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Integrated Drive Object Categorization in Cognitive Agents

An Activation-Based Multi-Criteria Exemplar Model

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Samer-Tamer Schaat
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Betreuung: o.Univ.-Prof. Dipl.-Ing. Dr.techn. Dietmar Dietrich
Mitwirkung: Dipl.-Ing. (FH) Clemens Muchitsch

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Advisor: o.Univ.-Prof. Dipl.-Ing. Dr.techn. Dietmar Dietrich
Assistance: Dipl.-Ing. (FH) Clemens Muchitsch

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(Signature of Author) (Signature of Advisor)

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Samer-Tamer Schaat
Pasettistrasse 91/8, 1200 Wien

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Abstract

The Artificial Recognition System (ARS) project uses a unitary cognitive process model to construct a cognitive architecture. This thesis provides a model to harness the ARS agent's memory for the support of perception. The associative character of the agent's memory is thereby used for associative activation-based memory retrieval. In designing a model of unconscious perceptual categorization bottom-up and top-down aspects of perception are considered.

Following a subjective and functional approach of cognitive modeling a model for the valuation of a stimulus as a drive object is designed as the primary purpose of the ARS agent's unconscious perceptual categorization. As the agent's bodily needs are represented as drives, this model is called *drive object categorization*, which is an exemplar model that uses the agent's concrete memory to categorize perceived objects as drive objects.

Following an integrated and holistic approach drive object categorization considers the integration of subjective influences. These influences are used to support perception by reducing uncertainty in choosing the most appropriate exemplars to base drive object categorization on. The integration of influencing factors into drive object categorization is inspired by the bionic concepts of top-down perception, particularly by the concept of memory-triggered expectations, and priming. Examples for such subjective influences are expected drive objects, which reflect affective priming in the ARS agent, or expected contextual objects which reflect semantic priming in the ARS agent. The former is considered in detail in this thesis.

To integrate the concept of expectation in drive object categorization, it is *transformed* to a categorization criterion by using *activation-based criteria application*. Together with the objective criterion of perceptual similarity, which represents bottom-up aspects of perception, subjective expectation-based criteria, which represent top-down aspects of perception, support the reduction of uncertainty in drive object categorization. A generic activation-based framework is designed to integrate these criteria. The usage of this activation-based framework enables directed memory retrieval and a considerable reduction of the search space.

Simulations of the model show different categorization results depending on the interplay of dynamic parameters. An evaluation of the simulations shows that the similarity criterion is more significant and more reliable to reduce uncertainty and that the expectation-based categorization criterion is only significant if appearance is weak or ambiguous.

The overall process represents the transformation of a stimulus with objective features to a subjective drive object. Additionally it provides information for top-down saliency by determining the perceived object's pleasure potential, which indicates the object's importance for the agent's actual needs.

Kurzfassung

Im Rahmen des Projektes ARS (Artificial Recognition System) wird ein autonomer kognitiver Agent für eine Artificial-Life-Simulation entwickelt. Dabei wird deutlich, dass nicht die rationalen Prozesse der menschlichen Informationsverarbeitung die entscheidenden Hindernisse für eine effektive kognitive Architektur darstellen, sondern jene Informationsprozesse, die der Mensch unbewusst vollführt. In dieser Arbeit wird ein Modell zur assoziativen aktivierungsbasierten Nutzung der Erinnerungen des ARS-Agenten zur Unterstützung der Wahrnehmung vorgestellt.

Einem subjektiven und funktionalen Ansatz der kognitiven Modellierung folgend wird dabei als primärer Zweck der unbewussten Wahrnehmungskategorisierung auf die Erkennung der Objektwirkung auf die körperlichen Bedürfnisse des Agenten fokussiert. Da in ARS die körperlichen Bedürfnisse des Agenten als Triebe repräsentiert sind, wird das Modell dieser Arbeit *Triebobjektkategorisierung* genannt. Dieses verwendet ein Exemplar-Modell, um wahrgenommene Objekte als Triebobjekte zu kategorisieren. Einem integrierten und ganzheitlichen Ansatz folgend berücksichtigt die Triebobjektkategorisierung die Integration von subjektiven Einflüssen. Diese werden im Modell verwendet, um die Kategorisierung durch Verringerung der Unsicherheit bei der Auswahl der geeignetsten erinnerten Exemplare zu unterstützen. Die Integration von Einflüssen in die Triebobjektkategorisierung ist durch die bionischen Konzepte der Top-down Wahrnehmung und Priming inspiriert. Insbesonders ist dies die Verwendung von unbewussten Erwartungen und die assoziative Erinnerungsaktivierung. Beispiele für subjektive Einflüsse sind erwartete bzw. gewünschte Triebobjekte und erwartete kontextuelle Objekte.

Für die Integration von Erwartungen werden diese als Kategorisierungskriterien spezifiziert. Zusammen mit dem objektiven Kriterium der Objektähnlichkeit unterstützen erwartungsbasierte subjektive Kriterien die Reduktion der Unsicherheit in der Triebobjektkategorisierung. Mittels eines *aktivierungsbasierten Multi-Kriterien Ansatzes* wurde ein generisches Framework entwickelt, um unterschiedliche Kriterien in die Triebobjektkategorisierung zu integrieren.

Die Simulation des Modells zeigt, dass das Ähnlichkeitskriterium zuverlässiger und signifikanter für die Triebobjektkategorisierung ist, insbesondere für die Reduzierung der Unsicherheit. Das erwartungsbasierte Kategorisierungskriterium ist nur bei schwacher oder mehrdeutiger Objekt-Erscheinung relevant. Der gesamte Prozess repräsentiert die Transformation eines Wahrnehmungsobjekts mit objektiven Eigenschaften in ein subjektives Triebobjekt. Zusätzlich bietet das vorgestellte Modell die Unterstützung der selektiven Aufmerksamkeitssteuerung durch die Bestimmung eines Lustpotentials von wahrgenommenen Objekten. Dieses repräsentiert die Bedeutung der Wahrnehmungsobjekte für die körperlichen Bedürfnisse des Agenten.

Acronyms

AGI	Artificial General Intelligence
AI	Artificial Intelligence
ARS	Artificial Recognition System
DM	Drive Mesh
GCM	General Context Model
kNN	k-Nearest Neighbor
MCDA	Multi Criteria Decision Aiding
SVM	Support Vector Machine
TP	Thing Presentation
TPM	Thing Presentation Mesh

Contents

CHAPTER 1

Introduction

Cognitive Architectures represent formal models of cognitive processes. They are implemented in software- or hardware agents (i.e. robots). In this case these agents are called cognitive agents. Different approaches for cognitive architectures exist. However, most of them do not follow a consistent and unitary cognitive model. Prominent examples therefor are SOAR [LNR87] and ACT-R [ABB$^+$04].

As opposed to such approaches the Artificial Recognition System (ARS) project[1] follows a unitary cognitive model to construct a cognitive architecture. In following a bionic approach, methods and patterns of human perception and decision making are evaluated and tested in an artificial life simulation. Therefore the principles of neuropsychoanalysis [2] are used. One principle is the distinction between unconscious and conscious processes, in the context of psychoanalysis called primary and secondary process.

Two of the challenges and key-areas in modeling the mind through such an approach are perception and the usage of memory therefore. The ARS project is a particular appropriate environment to approach these areas as it uses a holistic approach. The mentioned areas of perception and memory are the scope of this work, as they consider object categorization as a part of external perception, particularly for visual perception.

1.1 Motivation

When constructing a cognitive architecture the human mind is the best source of inspiration. Following a bionic human-inspired approach the ARS project emphasizes some key aspects

[1] `http://www.ars.ict.tuwien.ac.at`

[2] `http://www.neuropsa.org.uk/`

in human information processing that are crucial for cognitive architectures, particularly for perception, but are often neglected in cognitive systems. Some of those aspects, which also motivate this work are discussed next.

In cognitive architectures - as in humans - two qualities of information processes have to be distinguished. In following a human-inspired approach of information processing they are called unconscious and conscious processes. This distinction reflects a labor division that has evolved as a result of our adaption to the world during our phylogenetic development. These two kinds of processes operate under different rules and conditions. One of these conditions is the degree of structure used in the two processes. As highly structured information processing is often used in information processing, the rules of unconscious processing are often neglected in cognitive architectures although it is claimed [BC99], [Kah11, p. 4] that the majority of mental processes occur unconsciously. There are many possible ways to look at the distinction of unconscious and conscious processes and its advantages. One is to focus on the automated essence of unconscious processes. In this regard one can observe that already known perceived situations are processed automatically and hence with differing rules and under other conditions than new and unknown situations, which are coped by more costly conscious processing (cf. the Global Workspace Theory [Baa05]). Another perspective on this distinction is to interpret unconscious processes as preparatory work for conscious processes. This distinction is clearly reflected in perceptional processes. A good example therefore is the significance of top-down vision, which is an unconscious process (see Section 2.1). The idea of top-down vision proposes the primacy of memory in human vision. It claims that sensory information is only a secondary source of information and prior knowledge being the primary source for vision [Fri07, p. 134]. One can generally observe that memory and experience is a major factor in human problem solving. This approach also reflects the significance of subjective experience for perception, which is another aspect of the ARS approach that is often neglected in cognitive architectures.

The ARS model follows a subjective and functional approach of cognitive modeling. As opposed to an allocentric and objective approach to cope with the world a subjective approach focus on the subjective perspective of the agent (e.g. relative to the agent's needs and experience). In this regard perception is a mean to fulfill the agents needs and plans. An agent does not need an objective image of reality to fulfill its needs, but only a subjective one. This circumstance also reflects constructionist aspects of perception. But such a construction is a useful one that helps the agent to fulfill its needs in the world [Fri07, p. 131]. Hence perception is a functional and subjective process; it is only relevant that it works to support the agent's functions and needs in the world. In this regard one can say that the agent's perception of the world follows a model that is constructed to support fulfilling its needs and that works sufficiently therefore, i.e. it is compliant with an objective reality. This approach implicitly focuses on the subjective experience of an agent for perception. In this regard an agent is dependent on the use of its prior knowledge for the categorization process as an important part of perception. With the agent's experience as a basis therefore and the fulfillment of its needs and plans as the top concern, a holistic approach is needed.

Following a holistic approach, perception has to be integrated and has to interact with other processes of the cognitive architecture. Some of these processes are further inputs and influences for the perception process. These influences support perception and may help to interpret the perceived input and handle ambiguity and uncertainty. In this regard, the categorization process as an important part of perception has multiple influences. In a subjective approach perceptual categorization is primarily the interpretation of the perceived data in comparison with the agent's experience and relative to influencing internal and external factors. Such an interpretation leads to subjective semantics of a perceived situation and object.

As already implied, the primary purpose of subjective perception is the categorization of perceived objects regarding different influences of which the most important one is the agent's needs. The result of this semantic perception is recognizing the meaning of a perceived object for the agent's needs and concerns. This is a subjective and functional approach to the semantics of a perceived object.

This subjective and functional approach can be mapped to the generic pattern of goal-oriented dynamic problem solving that considers multiple aspects in an integrated and holistic fashion. In such a processing pattern uncertainty and ambiguity are handled by a goal-centered, functional and subjective approach by using domain-experience (= memory), context, needs and other influences. This in turn leads to goal-oriented semantics.

1.2 Problem Statement

The task of this thesis is to design a model that uses the agent's memory to support perception. The work has to comply with the requirements and rules of ARS, particularly the rules of the primary process, and has to be integrated in the ARS architecture.

After an analysis of the given task in the scope of the ARS approach, a more detailed description of the problem can be given. The prime goal of an agent, when perceiving an object, is to value the object regarding its semantics for the agent's needs. The question to be answered in this regard is „What does the object *mean* for the agent's needs? Is the object appropriate to fulfill these needs?“. The agent uses its experience with similar objects to fulfill the task of valuation and to answer these questions. This is a subjective and functional approach to an object's semantic and is part of the ARS primary process. As part of this process the agent has to categorize the perceived object and has to decide which objects in memory are similar to it and fulfill the agent's actual needs. Hence the work of this thesis comprises the design and implementation of object categorization for external perception in the primary process of the cognitive architecture ARS. Following a neuropsychoanalytic approach the agent's memory should be used to categorize perceived objects. In the scope of this work, visual perception is used representatively for perception.

After finding all similar objects in the agent's associative memory it has to be decided which object features of those objects should be used to extend the perceived object's features. The result of this step is a constructionist entity that is associated to similar objects in memory and leads to subjective semantics.

The result of this process supports the perception of an object's semantics in various ways. First, the consideration of the actual agent's needs leads to a directed and dynamic categorization. Second, the valuation of an object regarding its suitability to fulfill the agent's needs leads to functional categorization. Third, it constructivistically extends the object features which leads to a better subjective understanding of an object.

In summary, the task is to design and integrate a bionic model of perceptual categorization in ARS which follows the rules of the primary process. The implementation of the work is evaluated by use cases in an Artificial-Life-Simulator.

1.3 The ARS Approach

The usage of bionic approaches and process models for the development of technical systems has proved to be successful in the past. Unfortunately in information processing such an approach has often been neglected. Especially in Artificial Intelligence (AI) researcher often develop task models instead of process models. An appropriate inspiration for a process model of human information processing is given by neuropsychoanalysis, which is used in the ARS project. On the one hand neuropsychoanalysis merges insights from neurology with insights from psychoanalysis, on the other hand it addresses the neurobiological background of mental processes. The resulting theories and models are appropriate [Deu11, p. 4] for the application in cognitive architectures, particularly for a holistic top-down approach.

The need for a top-down design approach derives from the insight that handling complex models is not manageable with a bottom-up design approach [Deu11, p. 56]. The problems that are caused by processing an immense amount of data, which are produced by a high number of sensors, lead to this conclusion and reveal the need to find a new approach. Current technological systems lack the ability to process huge sensor data in a goal-oriented way to find patterns and decisions dynamically. This lack of current systems becomes obvious in an unobservable or uncontrollable dynamic environment (as opposed to a controllable environment). In other words: The skills that even human children show in everyday life, especially regarding situation awareness and decision making, is not achieved by any technical system today.

To find an approach that addresses the lacks of conventional systems of AI, the ARS project uses a bionic approach for modeling information processing of the human mind. After evaluating some models of the human mind, neuropsychoanalysis is used as the most appropriate framework for ARS because it is the only model [Deu11, p. 4] that handles the mind in an holistic and unitary fashion. Another important aspect is the top-down approach of the psychoanalytic model described by Sigmund Freud [Fre23]. In this regard psychoanalysts use the term *metapsychology*. Such a unitary approach ensures consistency in a model of the human mind, as opposed to the inconsistencies when trying to combine different psychological approaches, which each focus on a specific topic.

As already mentioned, psychoanalysis is the only approach that fulfills the requirement for a holistic, functional top-down model for the ARS project [Deu11, p. 4]. Using psychoanalysis, a functional model of the mind is developed in the ARS project. With such a functional model a generative approach is followed that describes the functions which generate behavior instead of building a behavior model. This approach complies with the Artificial General Intelligence (AGI) approach. For developing the functional model the second topographical model [Fre23] of the human mind with the three abstract functional units *Id, Ego and Superego* is used as the topmost layer and starting point in the top-down design approach. From there, a finer grained, more detailed description of the functions in the ARS model is generated with each new layer of description (see Section 2.5).

In the construction of the ARS agent it is emphasized that the basic processes in cognitive architectures has to resemble the unconscious processes in human information processing. Conventional AI has neglected this aspect and focused on the logical and rational processes of the mind. However different evidences show that a majority of human's skills are not based on structured and logical processes [BC99], [Kah11, p. 46]. That is one of the main reasons why a computer is able to beat a chess champion but is not able to cope with situations that are unconsciously coped with by human children.

In this regard the ARS project distinguishes unconscious and conscious processes. In following a psychoanalytical approach these are called primary- and secondary processes. The two processes follow different rules, priorities and principles. According to psychoanalysis, the primary process is structureless. That is, it does not consider logic or order, e.g. temporal and spatial relations. The central principle the primary process follows, is the pleasure principle. In psychoanalytic terms this represents the dynamics of drive wishes: psychic activity aims for maximal pleasure gain along with avoidance of unpleasure. That is, the main goal in the primary process is the maximal and immediate satisfaction of the agent's needs, represented by drives. The primary process does not consider any hurdles or negations in satisfying drives. Primary and secondary processes also have different psychic contents. In ARS this means that the two processes use different data structures (see Section 2.6).

Considering the distinction between primary and secondary process, the work of this thesis is assigned to the former. This means that this work does not cover topics of the secondary process and will not consider the rules of it. Regarding categorization, this is primarily the abstraction and conceptualization of perceived objects. In this regard one has to distinguish the usage of semantics in the secondary process, as addressed by concept-based models of semantic memory and subjective semantics in the primary process, as addressed in this work (see Section 3.3). Regarding the embedding of this work in ARS, one can observe that it builds on the symbolization of sensory input (see Section 2.5) and uses categorization to value perceived objects.

1.4 Thesis Overview

First the *motivation* of this thesis is given, where the need for an integrated, subjective and functional approach for perception in a cognitive architecture is motivated.

After an analysis of the given task in the scope of the ARS approach, a more detailed description of the *problem* is given and the purpose of perceptual categorization in the ARS primary process is emphasized, namely to categorize a perceived object regarding the agent's needs, which leads to subjective semantics of an perceived object. Furthermore the input and output of perceptual categorization is discussed and the most important requirements for fulfilling the problem are mentioned, namely the usage of the agent's memories and the consideration of the ARS rules.

An overview of the *ARS approach* summarizes the motivation of the ARS project and emphasizes the need for a bionic and unitary approach to cognitive systems. Additionally it discusses the ARS design approach and shows why neuropsychoanalysis is used for cognitive modeling in ARS.

Next a survey of the *state of the art* in those areas that are relevant for solving the problem of this work is given. Additionally it is checked which approaches and methods are appropriate for this work and fulfill its requirements. The central topic in this survey of the state of the art is perceptual categorization. Top-down perception and priming are discussed as bionic methods of influencing perceptual categorization in an holistic approach. After summarizing the details of the ARS model that are central for this thesis a comparison and evaluation of the state of the art is given.

The development of the *model* follows a requirements-driven methodology. To enable the integration of this thesis' model into the ARS model, first the rules and conditions of the ARS approach are analyzed with respect to the problem statement and conceptual requirements for perceptual object categorization in ARS are derived. After discussing how specific high-level concepts fulfill the conceptual requirements, the general approach of this work is presented, which reflects this work's conceptual model and considers all conceptual requirements. In this regard not only the fulfillment of the single requirements is considered; the focus also lies in the integration of all conceptual requirements to a consistent model. The general model gives an overview of *drive object categorization*, i.e. the valuation of a perceived object regarding its suitability as a drive object to satisfy the agent's bodily needs. After that the details of the general model are discussed. This includes the presentation of *integrated multi-criteria categorization*, i.e. a generic framework for the activation-based integration of categorization influences into perceptual categorization by transforming perceptual expectations into categorization criteria. This leads to a consistent model of perceptual categorization in the primary process of ARS.

In developing a detailed model further requirements are handled. This leads to the implementation model, i.e. a model which can be used for implementation, without the inception of further requirements.

After specifying the model, the documentation of its *implementation* is given. Thereby the adaption and extension of existing system components and the introduction of new components are discussed.

This thesis' model is *evaluated* using use cases. By using different stimuli, memories and bodily needs various scenarios are evaluated. The results gained from the simulation are summarized and discussed.

Finally, the *conclusion* summarizes the contributions of this thesis and discusses the results and possible *future work*.

CHAPTER 2

State of the Art

After introducing the topic of this thesis, next an overview of the state of the art in those areas that are relevant for solving the problem of this work is given. Additionally appropriate approaches and methods for this work will be analyzed and their fulfillment of this work's requirements will be examined.

When dealing with perceptual object categorization in a human-inspired cognitive architecture the starting point for analyzing the state of the art has to be models of object categorization in humans. On the one hand psychoanalytic requirements of ARS approach and introductory mentioned requirements in analyzing models of human object categorization have to be considered. On the other hand the technical and formal realization of such models have to be considered. As the basis of this work is an unconscious, subjective and functional approach to perception, the discussion of the state of the art starts with discussing top-down and bottom-up perception. After that categorization models and their technical implementation are described. Finally, priming, as a generic concept of perceptual influences, and its usage in the categorization process is discussed.

2.1 Top-down and Bottom-up Perception

Perception, especially vision, can be regarded as a bottom-up process, with sensor-data as the primary source for vision, or a top-down process [1], with prior knowledge as the primary source. This distinction implicitly raises the question how an interface between perception and cognition

[1] Here the term „top-down" is used to describe a process approach. The term is also used in this thesis to describe a system design approach. To differentiate between the two, the former is called „top-down process", the latter „top-down design".

may look like. Different opinions emphasize the primacy of bottom-up [Pyl99] or top-down processes [HRP97], [Bar97].

In both approaches perception can be interpreted as building a model of the world. In a top-down process the point of departure to build such a model is our prior knowledge, i.e. information from our memory. The constructed model of the world is used to drive perception and the sensory input is only used to „fill the gaps“ of the memory-based model of the world. The bottom-up approach operates in an opposite direction. Here the construction of a model of the world is build on the basis of sensory information, hence the model is the result of perception.

Helmholtz already recognized the significance of memory in vision over a hundred years ago and coined the term *„unconscious inference“* [Fri07, p. 41], [vH85, pp. 366-381]. It expresses that vision can only be the result of making assumptions and conclusions from incomplete sensory data, based on previous experiences. This reflects the significance of prior knowledge for perception, but can still be considered as a bottom-up approach as the process starts with sensory information, even if this opinion emphasizes that it is impossible to construct the perceived environment from sensory information alone and that prior knowledge about the environment is needed to interpret incomplete and ambiguous sensory information.

Since top-down perception starts with prior knowledge it emphasizes the role of subjective memory for perception more strictly than bottom-up perception. According to a top-down approach of perception our brain constructs a transparent model of the world [Met09, p. 72-77], i.e. the construction of this model happens actively and unconsciously. We recognize the model of the world (as our subjective reality) but do not recognize the process of constructing the model, i.e. the process of perception. That is, we have the impression of a direct, consistent and comprehensive contact to the world. Only because of this circumstance we can live with a stable, consistent perception and without uncertainty in perceiving the world. Particularly, the recognition that we only perceive a model of the world would not bring an evolutionary advantage [Met09, p. 70-73]. These features of top-down perception emphasize the unconscious and subjective nature of top-down perception.

After building the model of the world, in a top-down approach it is primarily used for perception via prediction [Bar09b]. Hence a top-down approach of our perception uses memory to predict which objects or situations to *expect*. In a memory-driven top-down approach memories trigger prediction by activating associated representations [Bar09b]. It is even claimed that the concept of predictions triggered by associated memory is a universal principle in the operation of the human brain [Bar09a]. These associations may be based on different similarities, e.g. perceptual, conceptual or functional similarities. In this regard, the perception of an object triggers the expectation of associated representations. This approach of triggering expectations based on the activation of associations with past experience and memories complies with the concept of *„memory of the future“* [Ing85], [Bar09b]. In this regard a top-down approach of perception is based on the associative character of memory.

2.2 Perceptual Categorization

Different approaches exist that try to describe the process of perceptual object categorization. In the scope of this discussion of the state of the art that is, given sensory information in a symbolic form, i.e the *stimulus*, how do humans use this information to reduce it to a higher-level label, i.e. its category, which subsumes the sensory information by comparing it to their memory (i.e. exploiting regularities between experiences). This process supports object understanding; it particularly helps to understand what the agent may do with the categorized object by evaluating former objects of that category. In this regard perceptual object categorization is a prerequisite to be able to assign non-perceptual, e.g. functional, object features to a perceived object.

Categorization includes category recognition and conceptualization. Since the scope of this work is perceptual categorization in the primary process of the ARS agent, the focus lies in the former, i.e. recognizing the category of an perceived object. Hence, in the remainder of this thesis the term category recognition is used interchangeably with categorization.

Based on category recognition further cognitive processing leads to the conceptualization of the recognized object. This is a hierarchical, abstract and relational (to other categories) view on the categorized object and leads to high-level semantics. In the ARS model these kind of processes occur in the secondary process. An example for such conceptualization is shown in [MR03]. Here a conceptualized representation, modeled by a semantic net, is used to reason about object properties and relations to other objects for semantic cognition. Such methodology follows a rule-based approach of hierarchical and abstract reasoning, which can be used for category recognition and conceptualization. This reflects the possibility to consider categorization as a reasoning or comparison process.

Following the rules of the primary process the focus of this thesis lies on a memory-based approach to category recognition as a comparison process. Such an approach uses an agent's memory to solve the problem of object categorization. Hence, in the remainder of this chapter the focus lies on memory-based categorization models. In such similarity-based processes categorization requires the comparison of the perceptual representation of an object with some representation of stored knowledge and can be seen as a function of the similarity of a perceived object to stored objects [PG04]. In this regard prior knowledge is represented as the agent's memory, particularly the representation of categories. Most similarity-based categorization models use a multidimensional psychological space [PG04] with using a dimension for every object feature. In such models similarity between objects is calculated as a function of distance. In the scope of perceptual categorization the most significant factor for similarity is the object's structure.

In a structured sense „... *a model of categorization specifies three things: (1) the content and format of the internal categorical knowledge representation, (2) the process of matching a to-be-classified stimulus to that knowledge, and (3) a process of selecting a category (or other response) based on the results of the matching process*" [Kru08, p. 269].

Since this work considers object categorization in the ARS agent, the basic knowledge representation is given by the ARS information representation (see Section 2.6). Still, a detailed representation of a category is not defined and is flexible. Regarding category representation, different approaches to represent a category also reflect different approaches of object categorization. For instance in prototype models a category is represented by a single prototype representation whereas in exemplar models a category is represented by all objects that are members of it.

Aspects of Categorization Models

Before discussing different categorization approaches, some aspects of perceptual object categorization that these approaches, if at all, address in different ways, are listed. Besides the already mentioned representational aspect there are other important aspects one has to consider when dealing with perceptual categorization. These aspects are often interdependent and associated. The following list is inspired by some aspects mentioned in [PG04], [Kru08], [Mur02], [MR03].

- The focus and goal of the categorization model. E.g. it may be a category recognition or conceptualization.
- The definition of categorization criteria: On which criteria is category membership based?
- Similarity measures: the calculation of similarity.
- The consideration of typicality.
- Identification and categorization/recognition and generalization: Are these handled as separate processes? Do they have separate representations?
- Levels of categorization: Is abstraction and hierarchy considered? Is (graded) multiple category membership considered?
- Borderline cases: How are objects categorized that are equally similar to multiple categories?
- Basic and entry level: What is the first level of categorization that a perceived object is categorized in?
- Top-down or bottom-up Categorization: Does the categorization process (and the category formation) starts with general categories or specific ones?
- Attention: Task-specific, selective attention of relevant feature-dimensions.

Overall, the key aspects of perceptual categorization are „... *the representations and transformations that link the input and response representations*“ [Kru08, p. 269]. When considering these key aspects one can distinguish exemplar, prototype, rule-based and theory categorization models [Kru08]. Rule models build on a classical definitional view on categorization (initiated by Aristotle [Mur02, p. 11]) that specifies sufficient and necessary properties for membership in a category [Kru08]. In this case categories are mentally represented as definitions. This „classical view argues that every object is either in or not in the category, with no in-between cases" [Mur02, p. 15]. Since for many categories it is very difficult to specify the necessary and sufficient features and many objects are not clearly in or out of a category the classical view is not applicable for common categorization [Mur02, p. 16]. The classical, rule-based, view was challenged by the idea of using typicality to categorize objects. This idea leads to the prototype approach. A prototype is the best example of a category. Objects that are very similar to the prototype are categorized as being very typical or good members [Ros75], [Mur02, p. 28]. A prototype can also be interpreted as a summary representation, which is a description of a whole category, rather than describing a single, ideal member [Mur02, p. 42]. Of course such prototype representations of a category are rarely real-world examples. Opposed to that, in exemplar models a category is represented by all members of the category [Kru08]. In this case category-membership is a function of similarity of an object to all known exemplars.

As already mentioned, the current information representation in ARS and the rules of the primary process favor a similarity-based categorization model. Hence, in the next sections prototype and exemplar models, which follow the similarity-based approach, are discussed in detail.

Prototype Models

The usage of the concept of typicality to decide category-membership led to the prototype approach [Ros75], [Mur02, p.35]. There are different interpretations how a category representation, i.e. a prototype, should look like and how typicality should be defined. A prototype could be defined either as the most frequent instance or as a derived stimulus that is a combination of all the most frequent features [Kru08]. The most frequent definition of a prototype is a summary representation of a category, as opposed to an ideal best example [Mur02, p. 42].

When using typicality to decide category-membership one has to define what makes objects typical. The simplest determinant would be the frequency of perceiving an object. But this is not an appropriate determinant for typicality [Mur02, p. 31]. Rosch and Mervis [RM75] use family resemblance for typicality and define:

„...members of a category come to be viewed as prototypical of the category as a whole in proportion to the extent to which they bear a family resemblance to (have attributes which overlap those of) other members of the category. Conversely, items viewed as most prototypical of one category will be those with least family resemblance to or membership in other categories" [RM75, p. 575], [Mur02, p. 32].

That is, typical items tend to have the same properties of category members but tend not to have properties of members of other categories. Therefore each feature is weighted by the number of objects it occurred in - in relation to non-occurrence in members of other categories. Hence, the more frequent a feature appears in a category and does not appear in other categories, the higher its weight is. Finally, the overall score for the object is calculated as the sum of its feature's weights. This feature score is highly predictive of typicality [RM75], [Mur02, p. 35]. That is, items that are typical have features that are common in the category and less common in different categories.

Barsalou [Bar85] found following determinants of typicality: central tendency, frequency of instantiation and ideals [Mur02, p. 35]. Central tendency is similar to the idea of family-resemblance of Rosch and Mervis (see above). Frequency of instantiation is the frequency with which an object is categorized as a member of the category. Ideals reflect the degree to which each object fulfills the primary goal of a category. The last determinant is a functional and goal-oriented one and indicates the degree to which an object fulfills the primary function of a category.

As implied by the principle of family-resemblance, in prototype models a category is represented as a list of weighted features that are usually found in the category members. The categorization task is represented by a comparison of such a feature list with the stimulus object. Each feature the stimulus has in common with the feature list increases the feature's score. Otherwise the score for that feature decreases. This is also the case if the stimulus has a feature that is not represented by the prototype's feature list. After going through all features the next step is to check if the score is above a critical value (i.e. the categorization criterion) and decide if the stimulus is a category member [Mur02, p. 44].

One concern about such a feature list is that it does not represent any of the relations between the features [Mur02, p. 50]. Hence, feature lists are an unstructured way to represent categories. Based on the prototype approach schemata are introduced to consider a more structured view on category formation [RO77]. *„A schema is a structured representation that divides up the properties of an item into dimensions (usually called slots) and values on those dimensions (fillers of the slots). The slots have restrictions on them that say what kinds of fillers they can have. Furthermore, the slot may place constraints on the specific value allowed for that concept. The fillers of the slot are understood to be competitors"* [Mur02, p. 47].

Exemplar Models

In exemplar models perceived objects are categorized by comparing them to stored *exemplars* whose categories are already known. A category is represented by the set of all stored exemplars of that category. As opposed to other category models there is no explicit category representation or real concept as there is no summary representation [Mur02, p. 49].

In exemplar models a perceived object is categorized according to the similarity to stored exemplars. The higher the similarity of the object to exemplars in a given category, the more likely it is to be categorized into that category. Basically the number of similar exemplars and the degree of similarity determine how a stimulus is categorized. Hence, similarity calculation is the key determinant of category membership in exemplar models. As opposed to additive similarity calculation, as in prototype models, standard exemplar models use a multiplicative rule (see below) [MS78], [Mur02, p. 51]. The process of similarity calculation includes the comparison of the object's features with every exemplar's features. A part of this process is the decision about the degree of similarity and the importance of the feature for every matching and mismatching feature [Mur02, p. 52]. The next step is to multiply the scores for each feature which leads to the overall similarity score between the stimulus and the exemplar. Finally the similarity scores for each exemplar in a category are added up and the stimulus is categorized to the category with the most similarity to it.

Regarding typicality it can be observed that the degree of typicality correlates with the similarity to category members and the quantity of similar category members [Mur02, p. 50] *„Typical items would be categorized faster than atypical ones, because they are very similar to a large number of category members, and so it is very easy to find evidence for their being members.“* [Mur02, p. 50].

When addressing exemplar models one has to define what an exemplar is. This is not a feature of exemplar models per se, but rather depends on memory formation, respectively the storage of exemplars. The main question is if every encounter of the same object should be stored as an distinguished exemplar. As the quantity of stored exemplars have an impact on the categorization decision, this can be an important factor for exemplar models.

Exemplar models are first proposed by Medin and Schaffer with the presentation of their Context Model [MS78], [Mur02, p. 65]. This model is adapted by the General Context Model (GCM) [Nos86], which is the most influential exemplar model [Mur02, p. 65]. Before discussing exemplar models further, the GCM will be presented, as it is the most dominant one [Kru08]. In the GCM the categorization process can be structured in three parts. First, the distance between the stimulus and every stored exemplars is calculated. Second, the calculated distance is scaled with the result of weighting close similarity much more than moderate similarity. Finally category membership of the object is decided [Mur02, p. 65].

The distance between two objects is a function of how far apart they are on each of their dimension, where a dimension may be a feature or an adaption of features. The calculation of the distance d between an stimulus x and an exemplar y is given by following formula [Mur02, p. 66]:

$$d(x,y) = \sqrt{\sum_m w_m * (|x_m - y_m|)^2}, \tag{2.1}$$

where *m* is the dimension and w_m is the weight of a dimension. The weights are free parameter, i.e. they are calculated from the data (the exemplars) and are not specified beforehand.

The next step of the GCM is the derivation of similarity from the distance score. Experiments [She87] give evidence that „behavioral similarity between items is an exponentially decreasing function of their psychological distance“ [She87], [Mur02, p. 68]. Basically this is just another form of the multiplicative rule. The similarity calculation is given by following formula:

$$s(x, y) = \exp(-c * d(x, y)) \tag{2.2}$$

Hence in the GCM the distance is calculated on dimension-level (i.e. for every dimension) and the similarity on stimulus-level. The variable *c* basically modulates the effect of distance by determining the spread of similarity. A high value for *c* requires an item to be identical to a known exemplar to be used for comparison. If *c* is very low, the similarity to all items is used. Usually, *c* is a parameter estimated from the training data.

The last step of the categorization process in the GCM is deciding category membership. This is calculated by the ratio of a stimulus' similarity to a category relative to the similarity to the other categories. The following equation calculates the probability that the stimulus *x* will be placed into category *J* with consideration of the other categories *K*.

$$P(x|J) = \frac{\sum\limits_{y \in J} s(x, y)}{\sum\limits_{K} \sum\limits_{k \in K} s(x, k)} \tag{2.3}$$

The GCM is a powerful exemplar model that considers various aspects of categorization models but it assumes that a stimulus is represented as a point in a multidimensional interval-scaled space. Other scales are not considered by the formulas above. Additionally one has to consider that in the GCM similarity is affected by differences not by commonalities between dimensions [Kru08]. That is, if two stimuli have no differences, their similarity is 1.0. Finally one has to consider that in GMC-like exemplar models the *number* of matching dimensions has no impact on the similarity score. For such models it is not relevant if similarity is based on ten dimensions or one hundred dimensions.

Adaptive Models of Categorization

Recent categorization models try to follow a more flexible and adaptive way of category representation. An example therefore is SUSTAIN (Supervised and Unsupervised STratified Adaptive Incremental Network) [LMG04], [Kru08]. SUSTAIN is a categorization model that expects multivalued nominal features and is sensitive to the number of matches, but only if at least one mismatch is present. Instead of fixed representations, category representation follows the principle of adaptive clustering [MG11]. That is, similar exemplars form a cluster, which reflects a single representation of these exemplars. This allows a flexible form of category representation, which may act as an exemplar- or prototype representation. Hence in SUSTAIN, as opposed to classical exemplar- and prototype models, different categories may be represented in different ways. Different factors and configurable parameters determine how abstract or specific clusters are.

SUSTAIN can be used as a model of category formation. After the first categorization process (the encounter with the very first stimulus) a cluster is constructed, which is represented by the first stimulus [MG11]. When confronted with further target stimuli, the model tries to assign each stimulus to an appropriate existing cluster by comparing it with the stored clusters. When a new stimulus is assigned to a cluster, the cluster's representation changes to reflect the central tendency of the items that formed the cluster. That is, the cluster indicates the proportion of each feature. When the new stimuli does not fit in a cluster, a new cluster is created. Additionally to this unsupervised way of cluster creation a cluster may also be created by supervision in response to a misclassification. This procedure gives potential to various forms of category representation. Additionally to the already mentioned consideration of exemplar and prototype representation, clusters may belong to one or more categories and categories may be represented by one or more similarity-based clusters [MG11].

2.3 Classification Techniques for Perceptual Categorization

Computer science has developed different techniques to implement object categorization. They are called supervised machine learning techniques since they learn from previous data how to classify new input data.

The goal of most supervised machine learning techniques is to build a model of a domain using training data, i.e. already classified data, to be able to predict the class of new unclassified data. In such a *model-based approach* the training data is processed once to build a model (the so called training phase), which will be further used as a classifier. Such methods are also called parametric, since the goal is to learn parameters (from the training data) which are used to build a model. Wide used model-based classifier are decision trees, ANN (Artificial Neural Networks) and SVM (Support Vector Machines).

Another class of machine learning methods follows an *instance-based approach*. In that case, as opposed to a model-based approach, no training phase is necessary, because no learning of parameters is necessary since no model of the underlying data is built to predict an unknown stimulus. Instead, the stimulus is compared to every instance of the training data to decide its class membership. Instance-based machine learning methods are also called lazy, since the generalization process is made on-demand, i.e. it is delayed until classification is performed [Kot07]. That is, generalization is not a result of a training phase, as in model-based approaches. Lazy methods follow a problem-centered (i.e. stimuli-centered) approach to access and select experience (i.e. the training data) [dMA98]. This procedure results in an more costly classification process. On the other hand the costly training phase is omitted. It is quite obvious that instance-based classifiers correspond to similarity-based categorization models. The model-based approach basically follows the classical rule-based theory of categorization [Gag09]. Therefore instance-based classifiers will be discussed in detail.

The most prominent instance-based classification algorithm is the nearest neighbor algorithm, where the most similar (i.e. nearest in an multidimensional space) instance is considered for classifying a stimulus. An extension thereof is the kNN (k-Nearest Neighbor) algorithm, where the classification is based on the k-nearest instances. The nearest neighbor algorithm (or 1NN) corresponds to prototype models and the kNN to exemplar models; the instances would correspond to prototypes and to exemplars, respectively [Gag09]. The kNN algorithm is quite straight-forward: it chooses the k nearest instances to a stimulus according to a distance metric, identify the most frequent class label of them, and use it to classify the stimulus. Obviously the key factor in kNN is the calculation of distance. The distant metric should minimize the distance between two similar instances and maximize it between instances of different classes [Kot07]. An example for the distance calculation between two items, x and y, is the Manhatten metric [Kot07], which accumulates the absolute distance d of every dimension i:

$$d(x, y) = (\sum_{i=1 \in m} |x_i - y_i|^r)^{(1/r)} \tag{2.4}$$

As in similarity calculation in exemplar models one can distinguish the scale of the object features. After calculating the distance the final step of the kNN algorithm is to decide the most probable class c_j of the stimulus. That is, a stimulus *e* is classified such that

$$kNN(e) = max_{c_j \in J} P(c_j|e), \tag{2.5}$$

where

$$P(c_j|e) = \frac{\sum\limits_{X \in K_e} 1(x_c = c_j) \cdot K(d(x, e))}{\sum\limits_{X \in K_e} K(d(x, e))} \tag{2.6}$$

where K_e is the set of *e*'s nearest neighbors, *1(x)* is a function that results in 1 iff its argument is true, and *K* is a kernel function and usually the inverse of the distance function [dMA98].

kNN is a powerful and accurate classification algorithm [Kot07], [ZBMM06] and appropriate for various domains. Additionally it is a stable learning method. That is, small changes in the training set do not result in large changes in classification [Kot07]. Nonetheless the performance in kNN, particularly the accuracy is sensitive to the similarity function and the selection of k [Kot07]. Another disadvantage is the large storage requirement and performance issues since the procedure needs to process all instances for classification. Cross-validation or similar techniques to find the best value for k may increase computational costs further [Kot07]. It is also shown [Kot07], [OY03] that the accuracy of kNN can be considered as a function to some domain characteristics, such as „... *the number of training instances, the number of relevant and irrelevant attributes, the threshold number in the target concept, the probability of each attribute, the noise rate for each type of noise, and k*“ [OY03, p. 207]. [ZBMM06] emphasizes that the nearest neighbor approach - when using the right distance function - has outperformed other approaches for the most well-studied visual recognition datasets. Some reasons therefor are (1) that kNN does not need to construct a feature space, which may become intractable, (2) the effortless consideration of the multi-class nature of visual object recognition, and (3) an optimal error-rate, given a big training set [ZBMM06]. The last point implicitly also mention a significant disadvantage of kNN, namely high variance if the training data only provides limited instances.

Methods to reduce the disadvantages of kNN include feature selection, feature weighting and data reduction. Feature selection is a general method in machine learning with the goal to remove irrelevant and redundant features to get the algorithm to run faster and more effectively [Kot07]. Since kNN is very sensitive to irrelevant or noisy features this may be a crucial factor to consider [Kot07]. A more fine grained method to consider this factor is feature weighting, which leads to a more reliable distance metric.

Data Reduction

Data reduction methods try to reduce the instance set without losing significant information. One approach is using different kinds of filter mechanisms to identify and remove redundant and irrelevant instances [Kot07]. The basic idea of such approaches is that some instances may be very similar and do not add extra information. Other methods replace the instances using a model-based approach. That is, they construct abstracted representations (i.e a model) which should pertain all significant information of the original instances [GWB$^+$03]. Such approaches may lead to prototype models or cluster-models (cf. SUSTAIN, see Section 2.2). In using such approaches the risk of getting high variance increases if the remaining instances do not provide enough information [ZBMM06]. In that case more training data may solve the problem. Another possibility to handle this disadvantage (e.g. if the relevant subset of the training data cannot be increased) is to train a SVM on the k nearest neighbors and use the kNN's distant function as the SVM's kernel if the k nearest neighbor do not have all the same class [ZBMM06]. The essential idea of this approach is to use a nearest neighbor classifier to provide a smaller but more relevant training set for a SVM. To speed up kNN [ZBMM06] uses a further pruning method before the usage of a SVM. Therefore two distance functions in the kNN algorthm are used: One distance function with a computationally lower cost to omit the instances with a high distance to the stimulus and a more precise distant function, which only has to consider the instances left over from the first distance function. This procedure of coarse and quick discrimination, extended by successive finer but slower discrimination conforms with findings from psychophysics [ZBMM06], [TFM96].

2.4 Priming

„Priming is a nonconscious [2] form of memory that involves a change in a person's ability to identify, produce or classify an item as a result of a previous encounter with that item or a related item“ [SDS04, p. 853]. In this regard the target item is *primed* by the *the prime*, i.e. a previous encounter with that item or a related item.

As opposed to explicit memory tests, priming is experimentally assessed using indirect or implicit tests in which the task is to identify briefly flashed stimuli, to complete word stems, to classify words or objects, or to produce a category-example in response to a category cue. Previous perception of the target object improve performance on such tasks, even though subjects are not asked to recall the target items [SDS04].

Different forms of priming can be distinguished, among them perceptual, conceptual, associative and affective priming. In conceptual priming items with a similar meaning are primed. An example therefor is when objects prime other objects from the same category. A general form of conceptual or semantic priming can be described by associated priming. In this case, items that are associated in memory prime each other. A model often used for the representation of such form of priming is *spreading activation*, [CL75], [And83], where activation is spread through associated items.

In perceptual priming items with a similar appearance are primed. One can observe that the impact of priming increases with similarity between the stimuli and the primed item [WM98]. Hence, priming by repetition has the strongest effect. It has even been found that such priming remains over week-long delays [WM98]. Although the effects of priming decreases with changes in an object's exemplar, they are still considerable [WM98].

Another kind of priming is called affective priming. One form of its manifestation is the decreased time one needs to categorize a target as positive or negative when the process is primed with an item of the same valence [HHRW02]. Another form is priming by mood-congruent primes [SC08]. This reflects the influence of mood on a memory-based task. Typical studies have shown that sad people tend to recall more negative events and happy individuals rather recall more positive events [SC08]. One also has to consider the influence affects have on other forms of priming. In this regard some studies have been conducted on the impact of affects on semantic priming [SC08]. The results provide evidence that positive affects supports semantic priming, but negative affects do not. That is, positive valued stimuli activate semantic associations and increase their accessibility.

As a main explanation for semantic and affective priming spreading activation, a mechanism

[2] Some researchers use the term nonconsious instead of unconscious.

based on associated memory, has been used [SC08]. In such models activation spreads from prime to associated targets, and hence activates those targets. Such activation of associated memory is assumed to occur automatically and without intention for both semantic priming and affective priming [SC08].

Activation-based memory retrieval is used by different cognitive architectures for the consideration of various effects, amongst them priming-based processes such as recency and frequency-effects (i.e. the impact of recent or frequent input on cognitive processes), but also for representing capacity constraints in cognitive processing. Examples for cognitive architectures that considers activation-levels in memory retrieval are ACT-R [AL98, p. viii], an extension of Soar [Cho03] and 3CAPS (Capacity-constrained Collaborative Activation based Production System) [JC92], which all use a model of spreading activation.

Spreading Activation

Models of spreading activation represent an approach to memory retrieval in a generic network architecture [And83]. Particularly it models how activation spreads from a network-node to associated nodes. Such a process is also called *associated retrieval*, [Cre97]. In most cases semantic networks are used, but the principle is valid for all kind of associated networks, i.e. „*... a generic network of information items in which information items are represented by nodes, and links express sometimes undefined and unlabeled associative relations among information items*“ [Cre97, p. 458]. One feature which is often used in such networks is weighting of associations.

A spreading activation process can have multiple iterations, also called pulses, which can be divided in three steps [Cre97] and are ended if a termination condition is reached.

1. Preadjustment
2. Spreading
3. Postadjustment

The pre- and postadjustment step is optional and may implement some form of activation reduction to regulate spreading. This may be used to discard nodes that are not continually activated and to regulate the overall network activation [Cre97].

The spreading step begins with the calculation of the incoming activation from associated nodes [Cre97] or with the initial activation, respectively. Thereby the association weights may be considered:

$$I_j = \sum_i O_i * w_{ij}, \tag{2.7}$$

where
I_j is the total input of node j;
O_i is the output of unit i connected to node j;
w_{ij} is a weight associated to the link connecting node i to node j.

The input and weights may be binary or real-valued. After calculating the input value, the output value, i.e. the node's activation value, is computed. Therefore different activation functions may be used, where the most common used is the threshold function. Here it is only considered if the threshold is reached to decide if the node will be activated. Other wide used functions include the sigmoid and linear function [Cre97]. As before, the output value may be binary, i.e only indicating if the node is activated or not, or real, i.e. indicating the strength of activation.

After computing the node's activation value, it spreads to all associated nodes, usually sending the same value to each node. The next step includes a possible post-adjustment process, as mentioned above. Finally a termination condition is checked, e.g. the distance from the start-node. If the condition is fulfilled, the algorithm stops, otherwise the next iteration of the spreading activation process is processed. The result of the overall process is an assignment of activation values to the activated network nodes. The activation value represents the significance of the node for the information retrieval process.

2.5 ARS Model

As mentioned introductory, one result of the ARS project is the conclusion that psychoanalysis is the most appropriate approach to fulfill the requirement of an holistic and functional top-down model for constructing an cognitive architecture [Deu11, p. 4]. Using psychoanalysis, a functional model of the mind is developed in the ARS project. With such a functional model a generative approach is followed that describes the functions that generate behavior instead of building a behavior model. In this regard the ARS project models a system with the top goal of representing Artificial General Intelligence (AGI), i.e. broad human-like intelligence which is able to cope with complex and dynamic situations rather than with narrowly well-defined domains that are known at the design phase of the system. This enables the ARS agent to operate in dynamically changing environments.

Overview

The ARS agent is following the generic architecture of an agent in AI [RN03, p. 33], i.e. an entity that interacts with its environment through sensors and actuators. The ARS agent perceives

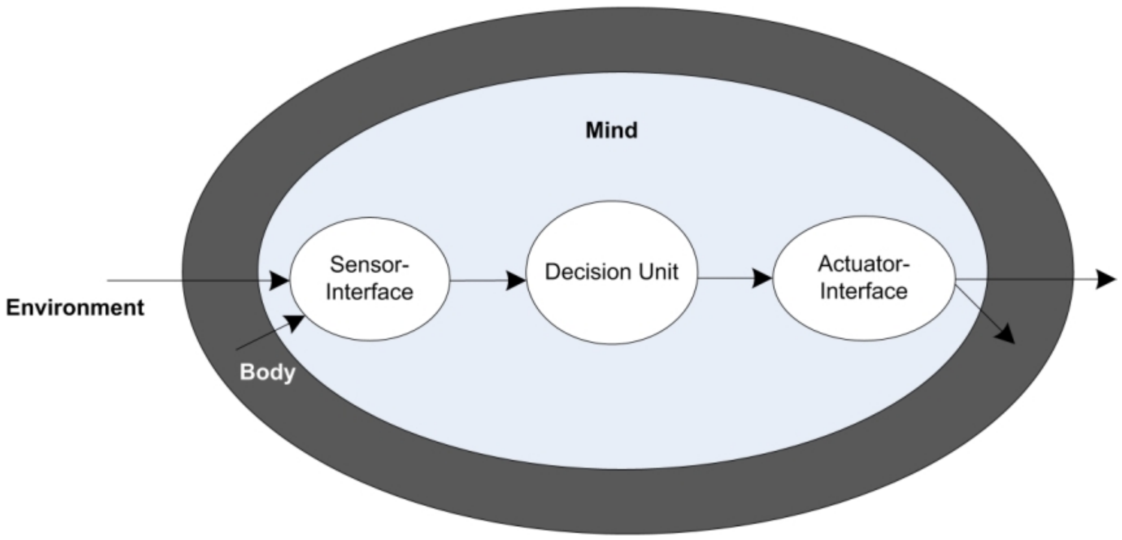

Figure 2.1: Artificial Recognition System agent architecture [Zei10, p. 62]

from its inner world - the body - and its outer world - the environment. The agent's decision unit processes the perceived information and acts upon its environment or body (see Figure 2.1).

For developing the functional model of the decision unit Sigmund Freud's second topographical model of the human mind with three subsystems, called *Id, Ego and Superego* is used. It is used as the topmost description-level and starting point in the top-down design approach in ARS (see Figure 2.2). From there, a finer grained, more concrete description of the model is generated with each new level of description. Id, Ego and Superego represent the three functional units in the topmost level. After splitting these functional units in more concrete functions in a top-down manner, they are resembled in the cognitive architecture of an autonomous agent in ARS.

The Id represents the ARS agent's bodily needs, such as stomach tension, blood sugar, oxygen saturation, etc [Deu11, p. 81]. The super-ego manages internalized rules in the form of prohibitions and orders. The Ego is responsible for mediating between the possibly conflicting claims of the other two instances, and the outside world. In this way it ensures the agent's capacity to act [DBMT09].

The ARS model, which is derived from the - above described - second topographical model of psychoanalysis, deals with motivation, wish-generation, decision making, planning and execution. It fulfills this by mediating between different demands. The Id demands the immediate satisfaction of the bodily needs. The reality demand represents possibilities and limitations of internalized knowledge about reality and external perception [DBMT09]. The superego demands the compliance with socio-cultural rules and prohibitions.

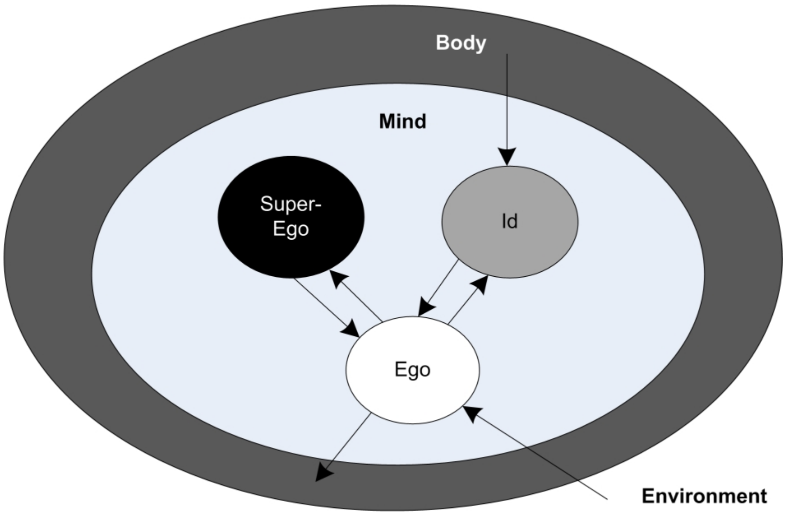

Figure 2.2: Artificial Recognition System functional model - first level [Zei10, p. 62]

ARS Functional Model

Following the top-down design approach, in the next step the three functional units *Id, Ego and Superego* are further split into smaller functional units with a more concrete functionality. The resulting second level of the functional model corresponds to the tracks shown in the overall function model, which is illustrated in figure 2.3. For this thesis particularly the drive track and perception track are relevant.

Drive Track

The drive track processes homeostatic data that is represented as drives. The concept of a drive is a theoretical construct and is the psychic representation of a bodily need. The drive comprises a drive source, a drive object and a drive aim. The drive source is the organ which signals the bodily need; the drive aim is the satisfaction of the drive by an act; the drive object is the object used in this act. Basically there are two kinds of drives: aggressive and libidinous ones. Every drive source triggers one of each kind. An aggressive drive is satisfied by an aggressive drive aim, a libidinous drive by a libidinous drive aim. After the triggering of a drive by a bodily need, the drive is rated by a quota of affect, which reflects the drive tension, i.e. the tension of the drive source. The higher the bodily need, the higher the quota of affect. The next step in the drive track, called hallucinatory wish fulfillment, is the search for possibilities to satisfy the drive, i.e. appropriate drive objects and drive aims (see Section 3.7). The agent uses its memory to determine drive objects and drive aims that satisfied a similar drive according to the agent's experience.

In this regard the drive track represents the central part of the agent's motivational system, which in further parts of the ARS model leads to desires and actions. The concept of the drive system represents the influence of the body on the psychic apparatus. In this regard embodiment is considered as a central factor of the ARS model.

Perception Track

The initial task of the perception track is the conversion of sensorial data to symbolic data that can be processed by the psychic apparatus. Therefor it merges sensor signals to semantic symbols in multiple steps. First the raw sensor data have to be converted into symbols in the sensor interface of the ARS agent. This is done by using the concept of neurosymbolization [VB08]. This process is inspired by neuroscientific principles. It uses multiple layers of so-called neurosymbols, which are the basic information processing units in neurosymbolization, and reflect features of neurons and symbols [VB08]. That is, every node in a neurosymbolic net has symbolic meaning. In this regard neurosymbols represent a layer between neural networks - the hardware layer - and symbolic representation. The neurosymbolization layer considers multimodal perception and merges sensor information from different modalities (related to the human five senses) to a multi-modal symbol by using a hierarchical concept of sensor fusion. As part of this process the binding problem is solved, i.e. all perceived information are assigned to a specific item. The result of the overall process is a symbolic item that is associated with its symbolic features (e.g. a symbolic item with the symbolic features „red“, „round“, „shiny“).

The next step in the perception track, which is handled by this thesis, is to categorize and recognize the result of neurosymbolization, i.e. a symbol. In the scope of the ARS project this is done by a memory-based approach. Hence the unknown symbol is compared to the agent's memory to identify and categorize it. As the ARS agent represents a thirty year old person, it is assumed that the agent recognize all perceived objects based on its memory and does not perceive completely unknown objects.

After identifying all perceived objects they are used to recognize the situation and activate similar situations. After that they are forwarded to the subsequent functional modules of the ARS model.

ARS Function Model - Fourth Level

After giving an overview of the two most significant parts of the ARS model for this thesis, next the overall ARS model is shown in figure 2.3. This fourth level of the functional model is the most detailed one and is reached after another two levels of model concretization. It is the point of departure for the implementation in the ARS simulator. Figure 2.3 shows the assignment of the functional modules to the three functional units of the second topographical and the separation of the primary and secondary process, which follow different rules and principles (see

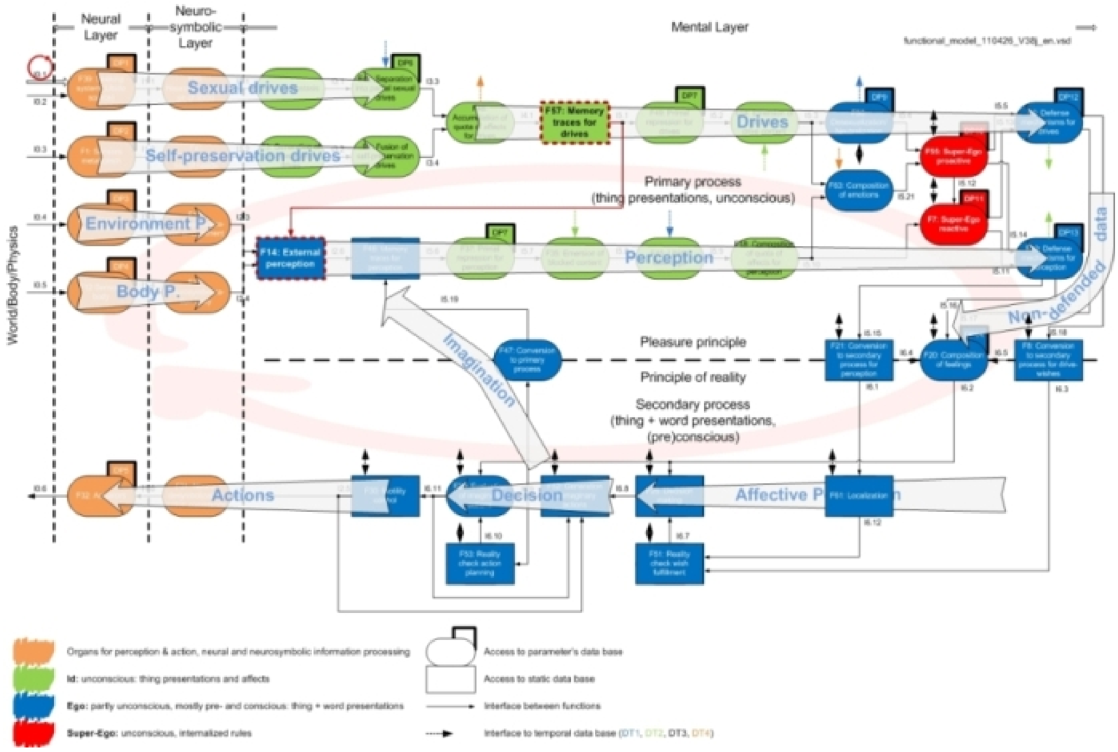

Figure 2.3: Artificial Recognition System functional model - fourth level [dl]

Section 1.3). A detailed discussion of the functional model is out of the scope of this thesis. In this regard the details of figure 2.3 are not relevant; only the track level (the arrows in the figure) are of interest.

For this thesis two functional modules, which are highlighted in figure 2.3, are particularly relevant, namely F14 and F57. The module F14 deals, amongst others, with object recognition. This thesis work, i.e. perceptual object categorization, is also part of F14's function. The second important module is F57, which implements the psychoanalytic concept of hallucinatory wishfulfillment (see Section 2.5 and 3.7).

2.6 Information Representation in ARS

An advantage of using psychoanalysis for a model of an cognitive architecture is its provision of an abstract concept for memory structures, which is used for modeling the information representation that is defined in the scope of ARS as follows:

Information representation summarizes the structural composition of data that is received by the *internal and external sensor system and the information management system* [Zei10, p. 9].

The central concept regarding information representation in psychoanalysis is the *memory trace*. In the ARS project a memory trace is defined as *„a psychophysiological concept of representing memories in the psyche*" [Zei10, p. 49], [DFZB09, p. 424]. A memory trace is a pattern for psychic data structures. Hence memory traces form the base for all psychic data structures but are not themselves data structures [Zei10, p. 49]. Incoming perceptions are matched against memory traces and activate them in case of a match. In case perceived information cannot be matched, new memory traces are constructed and stored. The concept of a memory trace implies that memory content is stored in a associated manner, with consideration of its co-occurrence, similarity and accessibility [Mer98, p. 75], [Zei10, p. 49] .

Psychic data structures are separated in thing presentations, which are processed in the primary process, and word presentations, which are processed in the secondary process. Their structure follows the rules of the respective process. For instance, thing presentations are not associated in structured form nor in any logical relation. The only associations used are co-occurrence and similarity.

Since the task of this thesis primarily considers object representations in the primary process, the remainder of this chapter will focus on them.

The psychoanalytically inspired technical concept of the data structures in ARS distinguish atomic data structures and composed data structures [Zei10, p. 50]. The atomic data structures in the primary process are thing presentations and associations. Associations are weighted connections between data structures. Regarding object representation a thing presentation (TP) evolves out of neuro-symbols and hence represents sensory information in a symbolic form. It is defined as *„the psychic representation of an object's sensorial characteristics in the form of acoustic, visual, olfactory, haptic, and gustatory modalities"* [DFZB09, p. 426], [Zei10, p. 54]. The sensor modality type from which it originates and an attribute value is the minimal definition of a TP. Associated TPs form the most important composed data structure of the primary process, a thing presentation mesh (TPM).

As it is assumed that every memory trace is created only once in memory [Zei10, p. 56], a TP may be associated to different TPMs. In the scope of this thesis a TPM represents a physical object, which is described by TPs that are associated through attribute associations. In this regard class attributes are distinguished from instance attributes. The former are essential for the physical definition, the latter are individually different. Additionally to attribute associations with TPs, a TPM may be attributed by TPMs. This is the case if a physical object has distinguishable object parts, which are also represented as TPMs.

Different TPMs may be associated with each other through primary associations, which reflect similarity and temporal associations, which reflect co-occurrence of objects. To distinguish physical objects from other forms of TPMs that are irrelevant for this thesis, TPMs that form representations of objects are called entities or entity-TPMs and TPMs that form representations

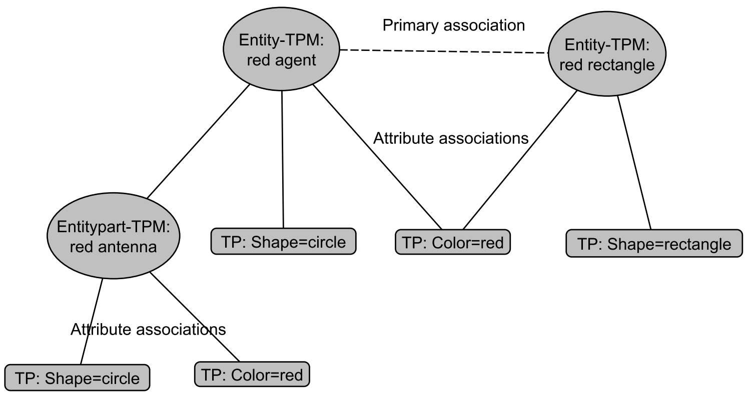

Figure 2.4: Thing presentation mesh

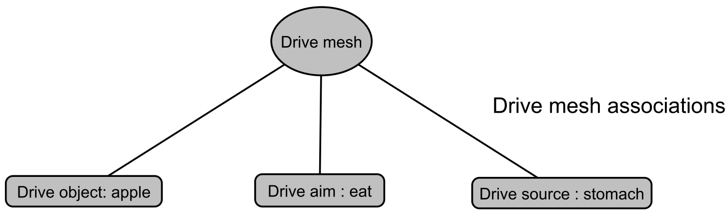

Figure 2.5: Drive mesh

of object parts are called entity-parts or entity-part-TPMs.

A drive mesh (DM) is another composed data structure that is processed in the primary process. It represent the psychoanalytic concept of a drive. As already mentioned, a drive is the psychic representation of a bodily need and comprises a drive source, a drive object and a drive aim. Technically the components of a drive are associated with the drive mesh by drive mesh associations (see Figure 2.5). As already mentioned the quota of affect reflects the drive tension in the drive source. Regarding further processing of the drive mesh the quota of affect represents the potential of drive satisfaction (i.e. reducing the drive tension in the drive source) by using the drive object in the drive aim's act. In case of a memorized DM the quota of affect reflects the amount of pleasure the associated drive object has brought in using the associated drive aim. In particular it represents the degree of reducing the according bodily need.

2.7 Comparison and Evaluation of Existing Approaches

After describing approaches in those areas that are relevant for solving the problem of this thesis, next the key topics of perceptual categorization, top-down vision and priming are briefly compared and evaluated with respect to the problem statement.

Top-down Vision and Priming

As this work is following a subjective approach and is located in the primary process, top-down perception is particularly significant. But even when giving top-down perception considerable relevancy, it is clear that perception of the world is not a self-fulfilling prophecy and bottom-up processes must also be considered. That is also the case in unconscious processing, because the expectations given by top-down processes can be revised by unexpected, but still known objects. Hence in the scope of this work, perception can be considered as the result of top-down and bottom-up processing working together. In this regard in perceptual categorization top-down perception will be considered in the form of priming and bottom-up processes will be reflected in the form of the consideration of symbolic object features that are based on the agent's sensors.

One can observe that priming complies with top-down perception. Generally, priming can be represented using an activation level in the agent's memory. Hence it is a good example how activated memory unconsciously influences and even may drive perceptual categorization .

Categorization

In the last decades the focus of research in human categorization was to emphasize the advantage of one categorization model and the disadvantages of others. This was particularly the case with the comparison of exemplar and prototype models. Currently there is an emerging consensus that exemplar-based models or derivates of them underlie important aspects of category representation [PG04]. Neurophysiological and empirical evidence support exemplar models [PG04], [Kru08]. Hence, when using aspects of process models as comparison criteria, exemplar models are favored by a significant amount of evidence. That makes them the most well studied and a richly explored class of categorization models [MG11], [Kru08]. Since one requirement of this work is the usage of a process model, exemplar models are favored in this regard.

When considering aspects of task models as comparison criteria the difference between prototype- and exemplar models decreases considerably. That is, both models make similar predictions in most use cases [Mur02, p. 95]. The difference in their prediction is primarily based on the fact that the feature list used in prototypes does not represent relations between the features [Mur02,

p. 96]. This aspect is also reflected by the linear separability of prototypes. That is, prototypes can be separated by a straight line in their according multidimensional psychological space.

Nonetheless exemplar models are inherently more powerful than prototype models [Mur02, p. 113]. They keep the representations of all the exemplars and hence have all the information about a category that could possibly be used in the categorization process, e.g for comprehensive similarity calculation [Mur02, p. 113]. In the process of constructing a summary representation, prototype models lose relevant information, e.g. the co-occurrence of particular features. In the end, exemplar models can always be used as a basis to build prototypes or other category representations and can account for prototype effects as prototypes are quite similar to a number of exemplars [Mur02, p. 114]. Additionally exemplar models can also account for advantages of abstraction [PG04]. This is very comprehensible, as when learning a new category exemplar information is the point of departure [Mur02, p. 114] (at least in unsupervised learning). Theoretically, although counterintuitive, perfect memory of all exemplar can be used to generate other category representations, even on the fly [Kru08].

Many intuitive arguments can be found against prototype- and exemplar models. On the one hand it seems counter-intuitive that every single stored exemplar is processed in the categorization process. But only because we do not *consciously* experience recalling every exemplar when categorizing a stimulus it does not mean that we do not [Mur02, p. 50]. On the other hand the idea that every category can be represented by a single prototype is questionable [Mur02, p. 43]. For example, it seems unlikely that a single prototype could represent all possibilities of bird-features. Generally, information about the variability of a category cannot be represented extensively by a single representation [Mur02, p. 41].

In summary, exemplar models can represent categories comprehensively and can account for prototype effects, but also for exemplar effects, which cannot be represented by prototype models. For instance, some experiments give evidence that the category decision is often based on apparently irrelevant perceptual information and/or on the reminding of a specific exemplars [Mur02, p. 86].

Instead of deciding the correctness of categorization models, recently some hybrid models where presented, which consider multiple category representations. An example is the already described SUSTAIN model [LMG04], which considers both exemplar and prototype representations. Other hybrid models use exemplar- and rule representations [AB01]. Still, such hybrid models are not flexible enough in distinguishing the usage of different category representations. The main reason therefor is that they do not follow an holistic approach and do not consider dynamic influences of the categorization process (which may be used to choose which categorization representation to use). For example, in SUSTAIN basically the frequency of categorization decides if an exemplar or prototype representation is chosen. Additionally, once a prototype for a specific category is constructed, there is no possibility to use an exemplar representation for this category in a future categorization process, i.e. in another situation.

In the end the decision which category representation to use is „... *probably a variety of task* *and personal variables. That is, stating this debate as „prototype vs. exemplar models" may itself be an error. Perhaps the issue should be discovering when people form generalizations and when they rely on exemplars, rather than deciding which model is correct and which incorrect"* [Mur02, p. 114]. This statement makes clear that a categorization model should consider dynamic influences. That is, the categorization process should be flexible, particularly regarding the factors and conditions that influence the decision about which category representation to use.

When considering the introductory mentioned functional and subjective approach and some of its analyzed manifestations, particularly priming, top-down perception and unconscious perception, some influencing factors of the categorization process can be observed that prefer the usage of exemplars. The avoidance of abstraction and conceptualization in the primary process favors exemplars over the more structured and abstract prototypes. Regarding priming (as a form of top-down perception) and activation-based memory retrieval, exemplar models provide more flexibility and fulfill the conditions for priming better than prototype models [Mal89]. This is particularly the case for perceptual and affective priming, which may be reflected by the influence of the agent's bodily needs (see Section 3.7). As already mentioned, one can observe that the impact of perceptual priming increases with similarity between the stimuli and the primed item [WM98]. It is obvious that concrete exemplars tend to be more similar to a stimulus than a prototype. Hence using exemplars in the categorization process is a prerequisite for perceptual priming of objects. When considering affective priming and the impact of affects in unconscious perception (the influence by drives in ARS, i.e. the pleasure principle) - and when assuming that drives are especially effective on concrete memory traces - exemplars are better suited to account for the role of affective priming in the categorization process. Hence the pleasure principle also favors exemplars over prototypes.

Additionally the access and consideration of memory traces is a basic principle in psychoanalysis and enable subjective valuation. Particularly the influence of drives can be considered in a more flexible and precise way if exemplars are used. This is also reflected by the intrinsic consideration of object identification in the categorization process, which also represents the impact of concrete memory traces on the categorization process and the interplay between identification and categorization.

Regarding semantic priming, the usage of exemplars does not seem to bring a significant advantage, compared to prototypes, although the flexibility regarding activation is better suited by exemplars. It primarily makes a computational difference if one prototype or multiple exemplars are needed to activate a concept. This is also the case for spreading activation, where the number of nodes correlates with the computational costs. But, of course, this is generally the difference between processing exemplars and prototypes. Computational arguments are often taken against the feasibility of exemplar models. In this regard one can observe that priming and activation-based memory retrieval decrease computational cost by directing the categorization process to the usage of a constrained set of relevant (i.e. activated) exemplars (see Section 3.5).

CHAPTER 3

Concept and Model

Following a requirement driven methodology, a top-down approach is used for the identification and analysis of the requirements. This leads to requirements in different levels of abstraction.

After analyzing and specifying the problem statement and recognizing the concrete topics that influence the task, the state of the art is evaluated according to the requirements, which are extracted from the problem statement. Next the rules and conditions of the ARS model are analyzed with respect to the problem statement and conceptual requirements for perceptual object categorization in ARS are derived. In the next chapters these conceptual requirements will be approached with the result of finding high-level concepts that fulfill them. As the key topic in this work is perceptual categorization, these requirements and concepts will be related to it.

After analyzing the conceptual requirements and high-level concepts, the general approach of this work is presented, which reflects this work's conceptual model and considers all conceptual requirements. In this regard not only the fulfillment of the single requirements is considered; the focus also lies in the integration of all conceptual requirements to a consistent model.

The next level of the top-down analysis is to find requirements and concepts for the implementation model, i.e. a model which can be used to implement the model without the inception of further model requirements.

After the model is implemented the results are evaluated in an Artificial-Life-Simulator by using different use cases.

3.1 Conceptual Requirements

The task of this work is to model and implement perceptual object categorization in the ARS agent's primary process by using the agent's memories. The fulfillment of this task has to follow the ARS approach. This aspect of the task is central, since an integration of a categorization model in the ARS agent requires the consideration of the ARS approach. Hence, a successful integration of this work in the ARS agent requires the analysis of the ARS approach and the recognition of those requirements that must be considered by a model of perceptual categorization. Only the consideration of these requirements enables the usage of this work in the ARS project.

From an analysis of the ARS approach and ARS model some central high-level requirements are extracted that have an significant impact on perceptual categorization. Next, these conceptual requirements and their impact on perceptual categorization are presented.

Bionic

The initial motivation of the ARS project was to model technical control systems in a bionic manner [DZBM09]. The motivation therefore is to find systems that cope with dynamic and complex situations - in the successful way humans do. As already mentioned, the psychoanalytic model is chosen as the most appropriate model of the human psychic apparatus. As showed introductory, the ARS project uses a top-down design approach, starting with Sigmund Freud's second topographical model and breaking it down until the fourth level of the ARS functional model. For many concrete domains the psychoanalytic model of the human mind only provides a loose guideline and no concrete model. This is also the case for perceptual categorization, where psychoanalysis provides a scaffold. In such cases models have to be found that comply with psychoanalytic guidelines that are given by psychoanalytical advisers. Since the ARS project follows a bionic approach, these models have to be bionic.

Rules of the Primary Process

As perceptual categorization in the primary process is modeled in this thesis, some requirements in this regard have to be considered. According to psychoanalysis the primary process is „structureless". That is, it does not consider logic or order. The central principle of the primary process is the pleasure principle. In psychoanalytic terms this principle represents the dynamics of drive wishes: psychic activity aims for maximal pleasure gain along with avoidance of unpleasure. That is, the main goal in the primary process is the maximal and immediate satisfaction of the agent's bodily needs, which are represented by the psychoanalytic concept of drives. Since the primary process uses primary data structures, additionally to the consideration of the primary process' rules, the available data structures have to be considered.

Regarding categorization this requirement constraints the representation of categories as well as the categorization process. A central requirement is the avoidance of reasoning processes. In this regard the usage of deduction, abstraction and hierarchy is not allowed in the categorization process. This requirement leads to the approach of categorization as an comparison process, as opposed to categorization as an reasoning process (see Section 2.2). The most significant requirement for perceptual categorization comes from the pleasure principle. In this regard the recognition of an perceived object's suitability as an drive object is the main purpose of perceptual categorization in the ARS primary process.

Subjective and Functional

Subjectivity is a key factor in psychoanalysis. Hence the ARS model, particularly the primary process, follows a subjective approach to cognitive modeling. In such an approach an agent's (subjective) experience is the basic source of information.

A subjective approach also induces a functional approach. In this regard *functional* refers to the central scientific principle of cause and effect. In a subjective and functional approach the effect on the subject lies in focus of the subject's cognition. The recognition of *something's* function leads to its utility and meaning, i.e. its semantics. This also complies with the scientific principle of evolution: From an evolutionary view *something* only „makes sense" if its function brings utility to the subject, i.e. it has a purpose for the subject, and hence supports its survival in the world. That is, in an evolutionary sense, the concept of *semantics* refers to functional utility for an subject. Hence, the recognition of function and its effect on a subject leads to subjective semantics.

Regarding perceptual categorization this means that perceptual information is intrinsically related to subjective experience and to subjective needs. In this regard perception is a mean to fulfill the agent's needs. This approach again complies with the evolutionary principle. The result of such semantic perception is the determination of an stimulus' effect on the agent's needs.

Holistic and Integrated

One of the most significant advantages of psychoanalysis for a cognitive architecture is the provision of a unitary and holistic functional model. On the one hand, this allows an abstract perspective on holistic aspects of the function model, which can be mapped to concrete aspects. On the other hand, it also considers different aspects of specific functions and the interplay with other functions. Hence a holistic approach induces an integrated approach. In this regard a *function* is not approached isolated, but integrated, with various influences.

For the *function* of perceptual categorization this means the integration of other significant influences of the cognitive architecture. In a subjective and functional approach these primarily are subjective influences that support the agent's needs. These influences support perception to handle ambiguity and uncertainty in recognizing an object, and help to interpret the perceived input regarding their functionality for the agent's need.

A holistic and integrated approach enables a dynamic system which considers the dynamic interplay of different influences. In this regard psychoanalysis refers to the concept of *psycho dynamics*.

Associative Memory

The psychoanalytic concept of memory traces and the derived technical data structures provide concrete rules for the representation and processing of physical objects. The representation of data structures in the primary process is already discussed in section 2.6. An important factor in this regard is the associative nature of the ARS data structures. On the one hand an object representation, in the ARS project represented as a TPM, is a associated mesh of its TPs (i.e. its attributes). On the other hand different TPMs are associated with each other according to their co-occurrence and similarity. Another important aspect of memory processing is their activation as part of the retrieval process. Finally, the rules of the primary process, which restrict the structure of TPMs and their processing also have to be considered.

Since the stimulus- and category representation are central aspects of a categorization model and impose processing-techniques, the concept of data structures has a strong impact on a categorization model in the ARS agent.

3.2 High-Level Concepts

After recognizing and analyzing the conceptual requirements and showing their impact on perceptual categorization in the ARS agent, next those high-level concepts that are appropriate for the mentioned requirements are presented. In this regard it is shown how those concepts fulfill the conceptual requirements.

Top-down Perception

Top-down perception is particularly appropriate to fulfill the conceptual requirements. The most significant feature of top-down perception in this regard is the central role of the concept of *expectations*, which is intrinsically subjective. This factor is also reflected by the significance of subjective memory in top-down perception. Expectations that are triggered by subjective memory and by subjective needs are particularly appropriate for the perceptual categorization model in the ARS agent. Subjective needed expectations also reflect an functional aspect. Hence, expectations may be triggered by the pleasure principle, i.e expected drive objects. But top-down perception also follows an holistic and integrated approach, since expectations - in principle - may be triggered by different sources. A central aspect of expectations in the scope of top-down perception is their unconscious triggering and processing. Hence in the scope of the ARS project it is located in the primary process. Finally, also the bionic requirement is fulfilled by top-down perception, as emphasized by various sources of the state of the art (e.g. [Bar09b], [HRP97], [Gre97], [OTCH03]).

But even when giving top-down perception considerable relevancy, it is clear that perception of the world is not a self-fulfilling prophecy and bottom-up processes must also be considered. That is also the case in unconscious processing, since the expectations given by top-down processes can be revised by unexpected, but still known objects. Hence in the scope of this work, perception can be considered as the result of top-down and bottom-up processing working together. In this regard in perceptual categorization top-down perception will be considered in the form of priming and bottom-up processes will be reflected in the form of the consideration of all sensorial object features.

Semantics per Valuation

Since this work is located in the primary process, perceptual categorization underly the pleasure principle. In this regard the primary purpose of perceptual categorization is to recognize the suitability of a perceived object as a drive object that fulfills the agent's needs. This unconscious, low-level valuation leads to the semantics of an perceived object in the primary process. That is, the recognition of an object's utility to satisfy the agent's drives is equal to the recognition of an object's *subjective semantic*. Such semantic categorization is a subjective and functional approach.

As opposed to the secondary process, categorization in the primary process does not use conceptualization, hierarchical processing and reasoning. Hence, as mentioned introductory, the categorization process focus on category recognition.

Exemplar Categorization

The rules of the primary process require categorization to be a comparitive process instead of an reasoning process. The significance of memory traces in the primary process and the prohibition to label objects make exemplar models the only possible approach for categorization in the primary process.

Additionally, an exemplar model is the most flexible categorization model since it operates on the most concrete level of object representation. This feature of exemplar models supports a holistic and integrated approach, since low-level object representation supports a flexible and direct integration of processes that influence perceptual categorization. In this regard the concerned object representations are directly affected from influencing processes. When considering an subjective and functional approach the usage of memory traces are more appropriate than abstracted memory structures. One significant reason therefore is that drives are especially effective on concrete memory traces. In this regard the usage of the pleasure principle favors an exemplar model, since the influence of drives can be considered in a more flexible and precise way if exemplars are used. Regarding the requirement for a bionic approach, exemplar models are supported by neurophysiological and empirical evidence [PG04], [Kru08]. Considering aspects of memory formation, exemplar models comply with the data structures in the primary process, i.e. particularly the concept of an exemplar complies with the concept of a thing presentation mesh. Additionally, exemplar models favor activation-based memory retrieval and support flexible memory activation.

Another significant aspect is the compliance of the central idea of exemplar models with the psychoanalytic idea of grouping similar memories to represent a „topic“ [Fre98, p. 290]. In exemplar models a category representation is formed by all members of the category. As the category criteria in exemplar models are similarity-based, exemplars which are similar regarding specific criteria form a category. A perceived stimulus would be compared to all exemplars and finally assigned to the most similar category. Hence, in the scope of perceptual categorization the „topic“ would be the category representation.

Priming

The search after a bionic form of a holistic and integrated approach to perceptual categorization leads to the intensively studied concept of priming. The consideration of different influences on perception is also considered in psychoanalysis, e.g. the influence by drives. Hence, the basic idea of priming is compliant with psychoanalysis. Priming is used in this work as an generic high-level concept for the integration of subjective expected objects in perceptual categorization. Priming is a bionic concept, which is located in the primary process and enables the integration of various influences in perceptual categorization in a generic form. This suffices holistic and integrated aspects, but also supports subjective and functional aspects, since priming provides a platform for the integration of subjective and functional influences, e.g. drives. Different forms of priming reflect the integration of different influences. Semantic priming complies with the significance of memory traces in the categorization process, i.e the influence of associative memory. The principle of affective priming complies with the pleasure principle, particularly the influence by drives. The single most important advantage of priming is its generic processing of all these influences regarding perceptual categorization. The integration of these influences help to handle ambiguity and uncertainty and reflect a dynamic categorization process. Regarding the memory formation in the ARS agent one can observe that associative priming complies with the concept of memory traces in psychoanalysis, particularly the activation of associated memories.

Since priming is per definition a preliminary step - i.e. priming occurs before the central process - it can be seen as configuring the categorization process. In this regard it operates as a bionic heuristic of data processing (see Section 3.5).

As already mentioned, the concept of spreading activation can be used to model important aspects of priming. This is particularly the case for representing the impact of a prime on primed entities. This is modeled by spreading of activation from the prime to its associated targets, i.e. the primed entities.

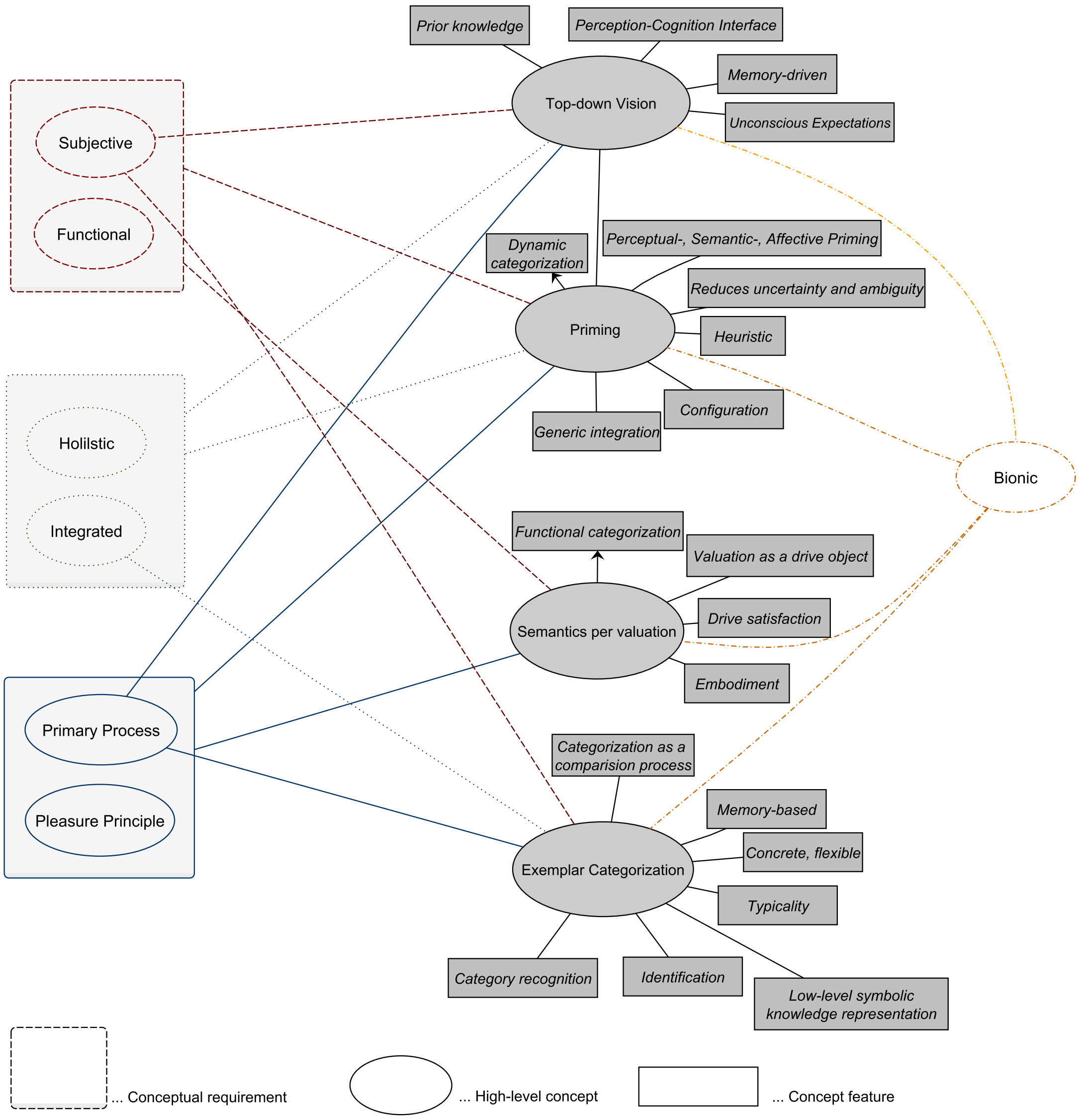

Figure 3.1: High-Level Requirements and Concepts

The conceptual requirements and their fulfillment by high-level concepts are summarized in figure 3.1.

3.3 Different Categorization Processes in the ARS Agent

Even if exemplar models are favored in the primary process, this does not mean that they are sufficient for categorization in the overall ARS model. An overall categorization model in the ARS agent needs to consider categorization in the secondary process and integrate it with categorization in the primary process. This complies with the different usage of semantics in the primary and secondary process. Since the scope of this work is the primary process, this aspect will not be discussed in detail, but only mentioned for further work.

The distinction between categorization in the primary process and secondary process complies with the distinction between categorization as a comparison process and categorization as a reasoning process. The former follows a similarity-based approach. The latter follow a rule-based approach and may arise from a similarity-based approach [Gol94]. This relation between similarity- and rule-based categorization considers aspects of grounding and induction. A similarity-based approach considers a grounded category formation, based on concrete experience. In further processing an inductive process may form abstract category representation that can be used in a rule-based categorization process [Slo03]. Additionally to an inductive category formation process one may also consider an deductive categorization process in the secondary process. This distinction also reflects two qualities of knowledge, namely experience-based unsupervised knowledge and theory-based supervised knowledge.

As already implied, categorization as a perceptually-based comparison process, i.e. categorization in the primary process, is not sufficient to consider all aspects of categorization [Gol94]. An inductive and deductive reasoning process in the secondary process has to extend similarity-based categorization. One reason therefor is that many categories are organized around tasks, goals or theories instead around perceptual similarity [Gol94]. Additionally to a perceptual similarity-based approach, one has to consider situation- and goal-dependent categorization. One example given in [Gol94, p. 133] is categorizing „things to retrieve from a burning house“. In this regard it is obvious that categorization may have multiple similarity-criteria additional to perceptual similarity, although the latter is still the most significant criterion [Gol94]. These aspects also consider the role of analogical reasoning in categorization [Gol94].

In summary, similarity-based perceptual categorization form the basis of the categorization process, particularly regarding aspects of induction and grounding. Or as [Gol94, p. 152] states: *„Similarity may not necessarily be sufficient for categorization, but similarity is sufficiently necessary to categorization...“* Hence, low-level perception-based aspect of category recognition should be extended by a high-level reasoning process of conceptualization. In a holistic and integrated approach the distinction and interplay between categorization in the primary- and secondary process has to be considered, but is not the scope of this thesis. Generally one can approach this topic by handling categorization in the secondary process as an extension of categorization in the primary process. That is, successful category recognition is extended by conceptualizing the recognized object, e.g. further reasoning about its categories and functions. This process leads to a hierarchical and abstract view on the categorized object and may provide further object understanding. Thus, this process extend the recognition of low-level semantics, i.e recognizing the similarity of an object, by high-level semantics, i.e. reasoning about the recognized category to further understand the function and effect of an perceived object (e.g. for abstract plans). Another aspect of the interplay of categorization in the primary- and secondary process is the corrective function of the secondary process, in case of wrong or uncertain category recognition in the primary process.

3.4 Perceptual Categorization in ARS - The General Model

In the previous sections the conceptual requirements are analyzed and their impact on perceptual categorization is shown. After that, high-level concepts are developed and their fulfillment of the requirements is shown. Next, the general model is presented, by specifying the input and output of perceptual categorization in the ARS agent and giving a definition of the categorization process. After that it is shown how the high-level concepts fit in this definition in a consistent form. In particular this includes the integration of the high-level concepts to a consistent model of perceptual categorization.

Before presenting the model some basic terms need to be defined. A *stimulus* is a *perceived object*. These two terms are used interchangeably. A *exemplar* is a stored entity-TPM. After the stimulus is categorized it is used as a *drive object*.

Drive Object Categorization

In a subjective and functional approach to perceptual categorization the recognition of an perceived object's suitability as an drive object is the main task of perceptual categorization in the primary process. Hence it is irrelevant to label a perceived object. For the agent in this stage of the primary process it is only relevant to answer the questions „Which effect does a perceived object have on the agent's bodily needs; what does this object *mean* for the agent's needs?". These two aspects of the question are correlated. When considering the first aspect of the question categorization can be described as *functional categorization*; the second aspect leads to *semantic categorization*. That is, the recognition of an object's utility to satisfy the agent's drives is equal to the recognition of an object's subjective semantics. Hence a perceived object's semantics in the primary process is recognized through the valuation of the object regarding its suitability to satisfy the agent's bodily needs.

Definition: *Drive object categorization* is the valuation of a perceived object regarding its suitability as a drive object to satisfy the agent's bodily needs.

The most important factors of a categorization model are the stimulus representation, the internal category representation and the process of deciding category membership. In the ARS perceptual categorization model the stimulus representation is given by the result of the neurosymbolic layer, which can be transformed to an entity-TPM; the category representation is given by the agent's experience, in the form of memorized entity-TPMs; and the category membership is decided based on multiple categorization criteria, amongst them the perceptual similarity of the stimulus to memorized TPMs. As already emphasized, such a model is called an exemplar or instance-based model. In the scope of perceptual categorization in the primary process the stimulus' category membership represents its suitability as an drive object. That is, all memorized entity-TPMs that served as a drive object for the satisfaction of a drive category form a drive object category. A concrete example is given in figure 3.2.

A *drive category* is defined by the drive source and drive component. In particular, all drives with the same drive source and drive component are member of the same drive category. A *drive object category* represents a formation of memorized entity-TPMs that satisfied drives from the same drive category.

In this regard a drive object category forms a psychoanalytic „topic" [Fre98, p. 290], which represents the grouping of similar memories (see Section 3.2). In case of a drive object category the similarity refers to satisfying the similar drives.

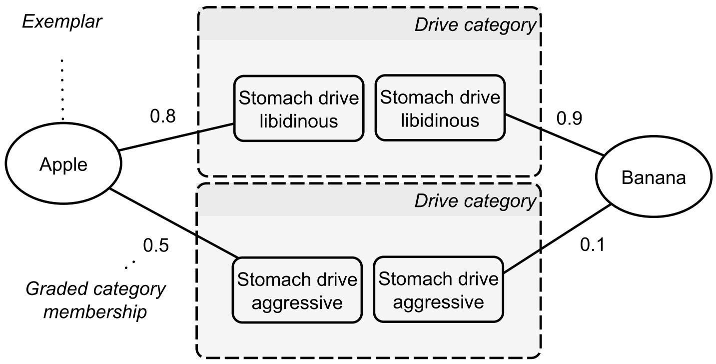

Figure 3.2: Drive categories

As mentioned in chapter 2.6 a drive object, i.e. an entity-TPM, is associated with a DM. The DM's quota of affect reflects the potential for drive satisfaction when using the associated drive object. Hence the quota of affect assesses the drive object regarding its potential suitability to satisfy the drive. As already emphasized, this is the purpose of drive object categorization. In this regard category membership in drive object categorization is *graded*. As a drive object may be suitable to satisfy different drives, drive object categorization considers *graded multiple* *category membership*. Hence, the result of drive object categorization is the association of the stimulus with drives from the according drive categories. The quota of affect of these drives represents graded category membership to drive object categories. The result of this process is the stimulus' valuation regarding its potential as a drive object. In this regard drive object categorization leads to the recognition of an stimulus' semantics in the primary process. This is particularly the recognition of a perceived object's meaning for the agent's bodily needs.

Exemplar Representation

When addressing exemplar models one has to clarify what an exemplar is. As already mentioned, in drive object categorization a TPM is used as an exemplar. Since TPs are only stored once and associated to entity-TPMs that are attributed by them, an entity-TPMs is defined by its TPs in a unique way. That is, it is not possible to retrieve two TPMs with identical TPs. This is not the most concrete level of object representation, since it is also possible to use every encounter of the same object as a distinguishable exemplar. But for drive object categorization this level of object representation would not bring any additional information, since the drive object category of an entity-TPM is not dependent on the object's context. That is, a drive object with identical attributes do not satisfy a drive differently in different situations. For example, a slice of bread is categorized in the same drive object category, if it is in the kitchen or in the bathroom.

In the primary process, following the pleasure principle, every perceived object is considered as a drive object. In this regard the first step in subjective perception in the primary process is to categorize the stimulus as a drive object. Therefore stored entity-TPMs are used. Following the pleasure principle, in drive object categorization only the usage of a stored entity-TPM as a drive object is considered. In further processing, particularly in the secondary process, entity-TPMs may be additionally considered in other aspects (e.g. for planning). Hence, in the scope of drive object categorization as an exemplar-based model an exemplar is a entity-TPM that represents a stored drive object.

Deciding Category Membership

In exemplar models perceived objects are categorized by comparing them to stored exemplars whose categories are already known. Basically the number of similar exemplars and the degree of similarity determine category membership. In such models similarity is a sufficient criterion to decide category membership. In an integrated and holistic approach the similarity criterion is *necessary but not sufficient* to determine category membership. Additionally to similarity further categorization criteria influence the category decision. Perceptually similarity represents an objective categorization criterion, which is extended by subjective categorization criteria (see Section 3.5). Hence, drive object categorization uses multiple categorization criteria to decide category membership.

The goal of conventional exemplar models is to find the most probable category by using the perceptually most similar exemplars to decide the stimulus' category membership. In this regard the result of using multiple categorization criteria is finding the most *appropriate* exemplars to decide the stimulus' category memberships. This category appropriateness reflects how appropriate the exemplar's category is to use it for categorizing the stimulus.

The *category appropriateness* of an exemplar reflects how appropriate it's categories are to base the stimulus' drive object categorization on it. The appropriateness of an exemplar is determined by multiple categorization criteria.

Drive object categorization has the goal to determine the suitability of a stimulus as a drive object. After finding the most appropriate exemplars to base this decision on, the goal is to determine *graded* category membership for the stimulus using all categories of the most appropriate exemplars (see Figure 3.3). In this regard the focus lies on grading the stimulus' category membership, i.e. to determine the potential quota of affect for every DM that the most appropriate exemplars are associated with.

Regarding the number of categories, drive object conforms with a multi-label categorization model. As opposed to conventional exemplar models, drive object categorization does not select which categories of the most appropriate exemplars to use, but rather uses all categories and decides graded category membership.

In terms of a kNN model, after the determination of the most appropriate exemplars, the first goal is reached by taking the k most appropriate exemplars and calculating graded category membership for every possible drive object category.

Identification and Generalization

In an exemplar model, the same object representation and the same process can be used for the identification and generalization [PG04] of categories. This is considered in drive object categorization. That is, an unambiguous full match with a specific exemplar lead to an identification of an stimulus' drive object categories. This is the case if an exemplar has the highest score for category appropriateness, with a maximal score regarding at least one criterion and the highest score for all other criteria. Theoretically it is not relevant which criterion gets the maximal score. Practically only the similarity criterion is significant to consider for reaching the maximal score (see Section 5.3). This case is called appearance recognition, i.e. a full match regarding appearance similarity. It must be emphasized that appearance recognition is not appearance identification, but only the recognition of an object's features, without considering object identification.

In case of such a *drive object identification*, the perceived object is categorized according to the categories of the unique exemplar that is found during the categorization process. Hence, drive object identification is concerned with identifying the drive categories and therefore includes drive object categorization. In the scope of this thesis this case is called *identified drive object*

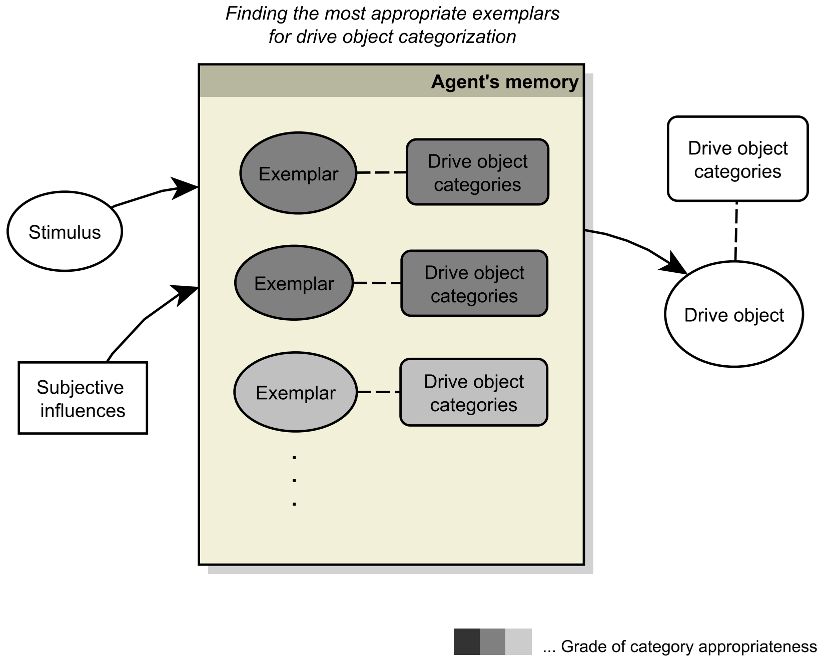

Figure 3.3: Drive object categorization - overview

categorization. Regarding object representation there is no need to differ between the identified perceived object and the according exemplar, since it would not be stored as a unique exemplar. Hence the exemplar is used to represent the stimulus in further processing (see Figure 3.4).

As the premise of the ARS agent is that it only perceives already known objects, identified drive object categorization should be the standard form of drive object categorization. But since objects may be ambiguous regarding their objective categorization criteria, i.e. their appearance, and subjective categorization criteria may not always reduce the uncertainty and ambiguity, the categorization process has to consider *generalized drive object categorization*. That is, deciding a perceived object's categories by generalization of appropriate exemplars' categories. In this case the drive object categories of the most appropriate exemplars are used (see Figure 3.4).

If the agent is not able to identify the stimulus' drive object categories due to high uncertainty, and hence generalized drive object categorization is needed, the most appropriate exemplar is used to represent the stimulus. In that case the exemplar's features are extended by those stimulus features that are not part of the exemplar. Hence, constructivistic aspects are considered. When using an exemplar to represent a non-recognized stimulus, the uncertainty of using the exemplar as an adequate representation must be considered. That is, the exemplar must reflect the degree of certainty of its usage as an adequate stimulus representation. The uncertainty in drive object categorization may be decreased by further processing in the secondary process. In this regard uncertain drive object categorization is the primary process' proposal that can be revised by reasoning in the secondary process.

In case the stimulus does not has *additional* features to the most appropriate exemplar but *different* features, the exemplar can not be used for further stimulus representation. In this case the stimulus representation is obtained and extended by the most appropriate exemplar's features.

In summary, the stimulus is categorized using identified- or generalized drive object categorization. This process is done by determining the category appropriateness of stored exemplars. Multiple criteria determine an exemplar's category appropriateness. After the stimulus is categorized, using the subjective information of stored exemplars, it is valuated as a subjective *drive object*.

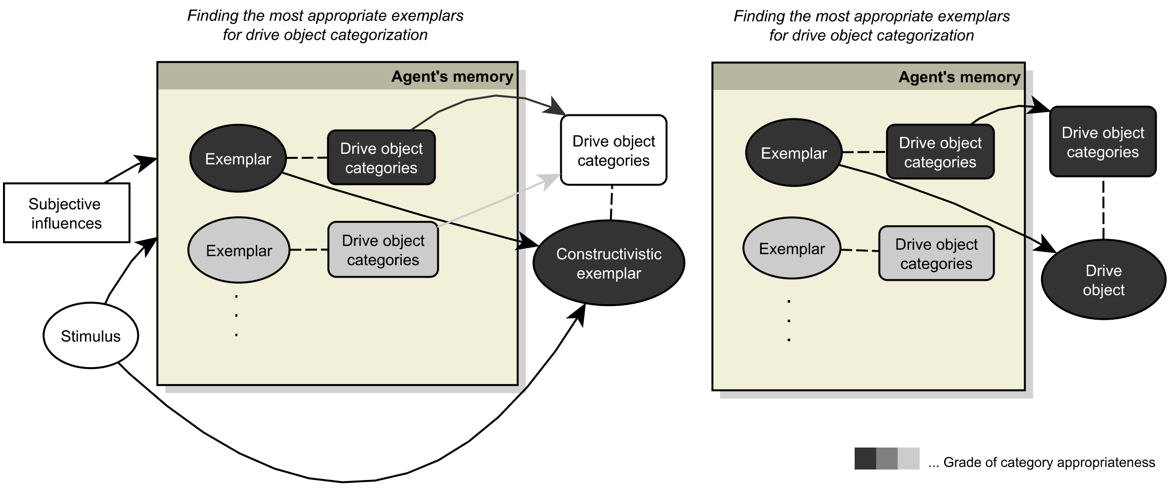

Figure 3.4: Generalized- and identified drive object categorization

3.5 Integrated Multi-Criteria Categorization - A Generic Framework

In the last sections drive object categorization is introduced. Therefore the general model of perceptual categorization in the primary process is described and the result of the process is specified. This process considers subjective and functional aspects by using an exemplar model and deriving an perceived object's semantics by valuating its suitability as a drive object. Such functional and semantic categorization suffice the rules of the primary process and the pleasure principle.

In an integrated and holistic approach perceptual categorization also has to consider various influences and their integration. In this regard perceptual categorization is primarily the interpretation of the perceived object in comparison with the agent's experience and relative to various influencing factors. In this thesis these influences are transformed to further categorization criteria. To reach this goal two high-level concepts are used, namely top-down perception and priming. After the description of the general framework of drive object categorization in the previous sections, next the integration of holistic aspects is considered in drive object categorization. Hence, the next step is to bring together all mentioned high-level concepts to form a consistent model of perceptual categorization in the ARS primary process.

Top-down Vision and Priming for a Holistic Integration of Infuences

The integration of influencing factors is inspired by the bionic concepts of top-down perception and priming. The former is used to handle influences in a generic way, namely as unconscious *expectations*, the latter is used to generically integrate these expectations for the configuration of the categorization process.

In top-down perception, expectations and predictions guide the perception process. In the scope of this thesis the concept of expectation in top-down perception is used to formulate a generic representation for different influences of the categorization process. To integrate this concept with the previously described exemplar model, categorization influences are represented by expectations, particularly by *expected exemplars*. Expectations can be triggered by different sources. For example, depending on the actual bodily needs the agent may expect certain drive objects (i.e. exemplars) that satisfied the needs according to the agent's experience. The generic result of such influencing processes is a set of exemplars that have different levels of expectation.

The concept of priming in the scope of this thesis is used as a configuration process to generically integrate various influences, i.e. expectations, in perceptual categorization. This is reached by introducing an *activation value* in exemplars, which represents the degree of expectation. Hence, a highly expected exemplar gets an higher activation value than a lower expected one. In the course of the categorization process the activation value represents an exemplar's category appropriateness. Hence, the result of activation processes is filtering and ranking the set of *appropriate exemplars*. To integrate the concept of expectation in the category decision process of the exemplar-based model, they are transformed to categorization criteria.

The activation-process by expectations can be seen as a bionic *heuristic*. That is, a technique that uses experience rather than explicit rules to solve ill-structured problems [SN58]. The problem to be solved is finding exemplars that are appropriate to base drive object categorization on them. The experience of the agent is reflected by choosing expected exemplars. Hence the heuristic is: using expectations to reduce the set of exemplars, i.e. the search space, to only include those exemplars that are expected, i.e. that are probable to be solutions. This heuristics speeds up the process of finding a satisfactory solution and also helps to reduce ambiguity and uncertainty. In this regard it guides the categorization process to find the most appropriate exemplars. This

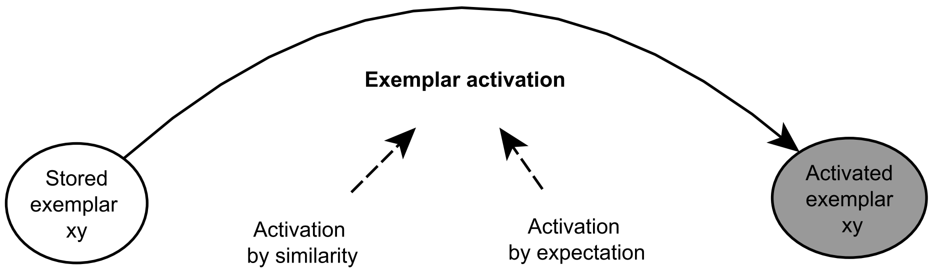

Figure 3.5: Exemplar activation

bionic heuristic handles a significant disadvantage of exemplar-based models, namely the big search space. When using preferred exemplars, which represent the most appropriate exemplars, only in the worst-case it is needed to process all exemplars.

The usage of priming and top-down perception handles ambiguity and reduces uncertainty in determining the most appropriate exemplars by using the subjective concept of expectation and activation (see Figure 3.6). Additionally it leads to data reduction, particularly search space reduction, and follows a subjective and functional approach.

Exemplar Activation via Application of Categorization Criteria

The key factor in the overall categorization process is to determine the most appropriate exemplars to base drive object categorization on. Various influences, which are represented as expectations, may be considered in deciding the most appropriate exemplars. To integrate these categorization influences in the categorization process they are transformed to categorization criteria. This is done by translating an influence's expectation to a criterion. Hence, the more an exemplar is expected regarding a specific influence, the better it fulfills the criterion of this influence.

Hence, multiple categorization criteria are used to decide the categorization process. The application of these categorization criteria lead to the activation of exemplars. This activation subsequently determine the category appropriateness of exemplars, which is the basis for drive object categorization.

Categorization criteria in drive object categorization can be separated in objective and subjective categorization criteria. Subjective criteria are based on information from the psychic apparatus. Objective criteria are based on an perceived object's information.

A significant objective categorization criterion is given by perceptual similarity, i.e. an exem-

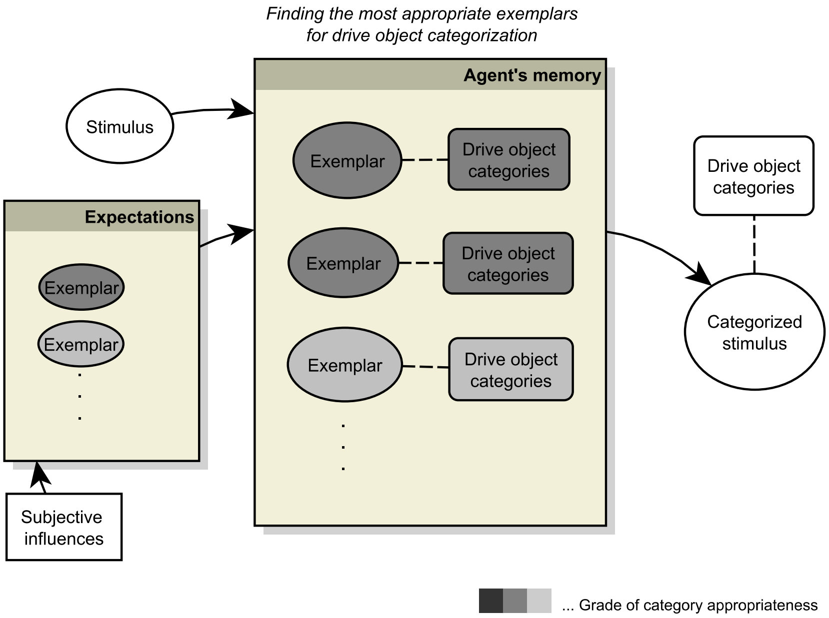

Figure 3.6: Integrated drive object categorization - overview

plar's similarity to the stimulus' appearance. Therefore the stimulus' features are used as categorization criterion. They are objective since they are the result of the neurosymbolic layer, which is not part of the psychic apparatus. The similarity criterion is a significant categorization criterion, since it influences the appropriateness of exemplars. In this regard the more an exemplar is perceptual similar to a stimulus' the more appropriate it is to base drive object categorization on it.

Subjective categorization criteria are the result of influences from the psychic apparatus, which are significant enough to be used as a categorization criterion. These influences are represented as expectations. An integrated and holistic approach of categorization considers various such influences. Considering the pleasure principle the most significant one is given by expectations that are triggered from the agent's actual bodily needs. Another significant categorization criterion is the influence of previously categorized objects and their associated exemplars. Since integrating influences in the categorization process is designed generically, every influence that can be reflected in a level of exemplar expectation, respectively activation, can be considered as a categorization criteria. The higher the expectation level of an exemplar, the more appropriate it is to base drive object categorization on it.

In the scope of this thesis additionally to the objective categorization criterion of perceptual similarity a subjective categorization criterion, namely the influence of the bodily needs, which reflects affective priming (see Section 2.4), will be considered. Another significant subjective categorization criterion is the context criterion, which represents aspects of semantic- and perceptual priming and is briefly discussed as future work in 7. This criterion uses internal context to form expectations. It is particularly appropriate to represent the impact and advantages of expectations and associative memory for perceptual categorization, but it is to extensive for a detailed discussion in this thesis.

Objective Similarity Criterion

The central factor in conventional exemplar models is the calculation of similarity. In this thesis' work perceptual similarity is only one categorization criterion amongst potential many. Nevertheless it is a necessary, although not sufficient, criterion to decide category membership.

The process of similarity calculation in exemplar models includes the comparison of the object's features with every exemplar's features. This aspect of exemplar models is a significant disadvantage. For a big amount of exemplars it is not feasible to calculate the similarity between a stimulus and every single exemplar. In technical terms, the search space would include all stored exemplar-objects. The associative structure of the ARS agent's memory enables the reduction of the search space by only using those exemplars that are significant for the comparison with the stimulus. Since a distinguishable feature, i.e. a TP, is stored only once, it can be associated to multiple TPMs (cf. 2.6). The usage of appropriate TPs (i.e. those TPs that are similar to the stimulus' TPs) as a starting point for the search after similar exemplars, reduces the search space to those entity-TPMs that are associated with them. Only those entity-TPMs are significant for similarity calculation (see Figure 3.7).

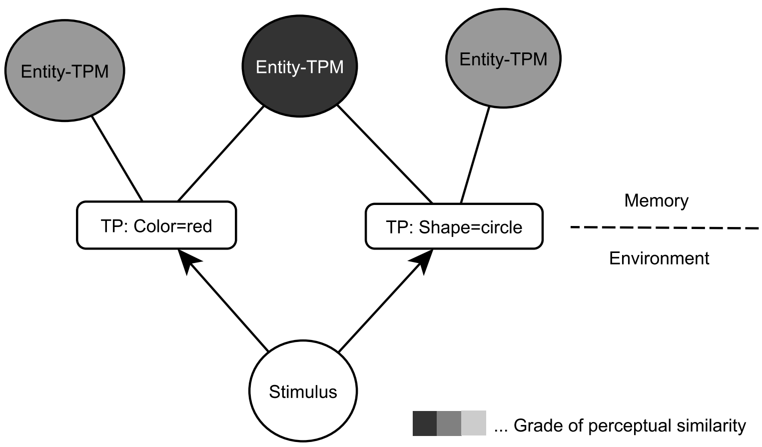

Figure 3.7: Associative similarity activation

Regarding the scale of the exemplar-features the current ARS information representation uses symbolic features, i.e. TPs that represent qualities. Hence a quantitative comparison of two TPs is not possible with the current ARS information representation; it is only possible to check the absence or presence of a TP when comparing two entity-TPMs. In this regard it would be advantageous to quantify qualities. An example therefor is to compare two colors or two shapes. To calculate the similarity between two colors, a quantitative value for the colors is needed. Different approaches (e.g. [CS93], [DK97]) to quantify symbolic features for the sake of similarity calculation use inductive learning techniques to calculate distance tables (with real-valued distances) from the training data. But such approaches do not comply with the ARS approach and the ARS data structures. Nevertheless, the quantification of qualities is currently not required in the ARS project, since the low number of possible objects enable their unique separation by binary comparison of symbolic features. Hence, for calculating the perceptual similarity between the stimulus and an exemplar only a nominal scale is used, since it is sufficient for the needs in the ARS project.

Another important factor in similarity calculation is selective attention to features. Selective attention is represented by feature weighting, which reflects the significance of a feature for the description of an exemplar. In particular two different exemplars may have the same features with different weights. This leads to more flexible and precise similarity calculation. In the course of similarity calculation the feature weight determine the feature's impact on the similarity score. Exemplar models that consider weighted features primarily use learning mechanism, e.g. gradient descent, to determine the weights [Kru93], [WAM97]. As learning mechanisms are not considered currently in the ARS agent and the agent resembles a thirty-year old person, the feature weights are already known and are represented by the attribute-associations' weight. Hence, local weights [WAM97] are used to determine the impact of a feature on the similarity calculation. That is, the determination of the feature weights is handled on exemplar-level and hence is a function of the exemplar.

One can observe that the activation of an exemplar by the similarity criterion also reflects aspects of perceptual priming. That is, the activation of an exemplar via the similarity criterion increases its category appropriateness for subsequent categorization processes.

Subjective Embodiment Criterion

A significant subjective categorization criterion in the primary process is the impact of expected drive objects that satisfied the agent's actual bodily needs according to its experience. In this regard the expected exemplars are those that are likely to satisfy the agent's actual bodily needs. The better the quota of affect of those drives that the exemplar has satisfied (according to the agent's experience) match the actual drives' quota of affect, the more it is expected. Regarding the kind of priming, one can observe that this categorization criterion represents affective priming.

Since the considerations of bodily needs represents the embodiment of the ARS agent, the influence of the agent's needs on the categorization process is called *embodiment categorization* *criterion*.

A concrete example is given: If the agent is hungry and its experience proposes that apples satisfy hunger, i.e. an apple is associated with the according DMs, the agent will expect an apple. The level of expectation correlates with the DM's quota of affect. That is, the better the apple satisfied these drives according to the agent's experience, the higher is the apple's expectation level.

The appropriateness of an exemplar regarding the agent's actual bodily needs can be described as follows. The more an exemplar has satisfied an actual significant drive according to the agent's experience, the more appropriate it is to base drive object categorization on it. Hence the exemplar is appropriate as an actual needed drive object. On the one hand this is a very subjective appropriateness, since it has no relation to a objective reality. That is, only because it would be appropriate for the agent to perceive a drive object that would satisfy its bodily needs (and hence the according exemplar would be appropriate to base drive object categorization on), it does not mean that this influence would support the recognition of the stimulus' real drive object categories. On the other hand, since the agent's drives co-determine the agent's actions, the probability of perceiving an object that satisfy the actual bodily needs is high. In this regard the embodiment categorization criterion supports reducing uncertainty and ambiguity in drive object categorization.

A concrete example therefor is given: The agent is very hungry, i.e the according actual drive has a high quota of affect, and the agent perceives an ambiguous object that could be categorized as a drive object that satisfies drives that represent hunger or a drive object object that do not satisfy hunger. The high quota of affect indicates that the agent is hungry for quite some time. Since the agent's plans are co-determined by its bodily needs, the probability for the agent to be in an environment with objects that satisfy its drives (e.g. the kitchen) is higher than the probability to be in another environment.

Apart from considerations of category appropriateness the embodiment criterion primarily reflects the impact of the body on the agent. This can also impede the recognition of an object's objective categories. For example, if the agent's drives are high and it is not in an environment with appropriate drive objects, the subjective impact of the drives impedes the recognition of objective drive object categories. This complies with the psychoanalytic requirement of the possibility to err („to err is human“).

But it must be emphasized that the advantage of considering various influences for categorization is the reduction of the agent's uncertainty in selecting appropriate exemplars. Hence, from the agent's subjective view it is not relevant if the reduction of the uncertainty in determining appropriate exemplars is based in objective or subjective influences.

In summary, the purpose of using categorization criteria is to support the determination of appropriate exemplars to base drive object categorization on. All criteria support the reduction of uncertainty in this process. In a subjective approach, additional to objective criteria subjective criteria are considered by using the concept of priming and top-down perception. Although the categorization criteria are separated in objective and subjective, they are still all functional criteria.

Activation-based Multi-Criteria Application

As showed in the previous sections, different categorization criteria determine the category appropriateness of stored exemplars. To handle these criteria generically, the concept of *activation* is used. The objective categorization criterion activates *perceptually similar* exemplars. The subjective categorization criterion activates *expected* exemplars. The degree of activation reflects the degree of category appropriateness. Such *multi-criteria activation* is a generic way to integrate multiple criteria, which may be based on subjective expectations or objective similarity, into drive object categorization.

Hence, exemplars are activated by applying different categorization criteria. Such consideration of multiple criteria to rank the appropriateness of exemplars pose a *multi-criteria decision aiding (MCDA)* problem. The main task of such a problem is to evaluate exemplars regarding different criteria and determine the impact of the individual criteria for the overall category appropriateness of an exemplar. This leads to the integration and aggregation of all categorization criteria for the overall ranking of appropriate exemplars. A widely used method for ranking alternatives (i.e. exemplars in this thesis) in MCDA is the definition of a utility function for each criterion, which determines a utility value for each alternative with respect to a criterion [ZD02]. In this thesis the activation of an exemplar by the application of a criterion represents the criterion's utility function. That is, an exemplar's fulfillment of a criterion is evaluated by an activation-based approach.

To determine the category appropriateness of all exemplars regarding the single categorization criteria, following steps are necessary. First, each exemplar has to be evaluated regarding every categorization criterion by using the criterion's utility function. In this thesis the utility function is implemented as a *criterion activation function*. This step is done by applying the categorization criterion on exemplars, i.e. by the activation of exemplars. Second, the activation values of all criteria are aggregated for each exemplar by using a *activation aggregation function*. As part of this step the impact factor of each criterion has to be determined. The aggregation of all activation values results in the aggregated activation value of each exemplar. Third, the exemplars are ranked with respect to their aggregated activation value, which reflects its category appropriateness.

An aspect that has to be considered is the possible dependence between the different criterion applications, i.e. activations, of an exemplar. In this regard two kinds of activations can be distinguished. The first kind is called *unconditioned activation*, because its application is not conditioned on other activation values. This activation kind represents categorization criteria that are independent from the application of other categorization criteria. The second kind is called *conditioned activation*, because its application is conditioned on other activation values. That is, the calculation of the activation value is dependent on activation value of another criterion. An example therefore is the application of the contextual categorization criterion (see Chapter 7). In this case an exemplar that is activated by the perceptual similarity criterion activates associated exemplars by applying the contextual categorization criterion. In case of unconditioned activation the order of applying multiple criteria is not relevant. Since in this thesis embodiment activation is considered exemplary for subjective criteria, i.e. the contextual criterion is not modeled in detail, only unconditioned activation is considered. Nevertheless, for the sake of comprehensibility the contextual criterion is mentioned in figure 3.8.

Regarding weighting the impact of each categorization criteria, i.e. weighting each criterion activation value, a dynamic weighting method is used and is separately defined for each categorization criterion. Hence for every criterion a *criterion activation function*, which serves as the criterion's utility function, and a dynamic *criterion weighting function*, which is needed for the aggregation of all criteria values, is defined.

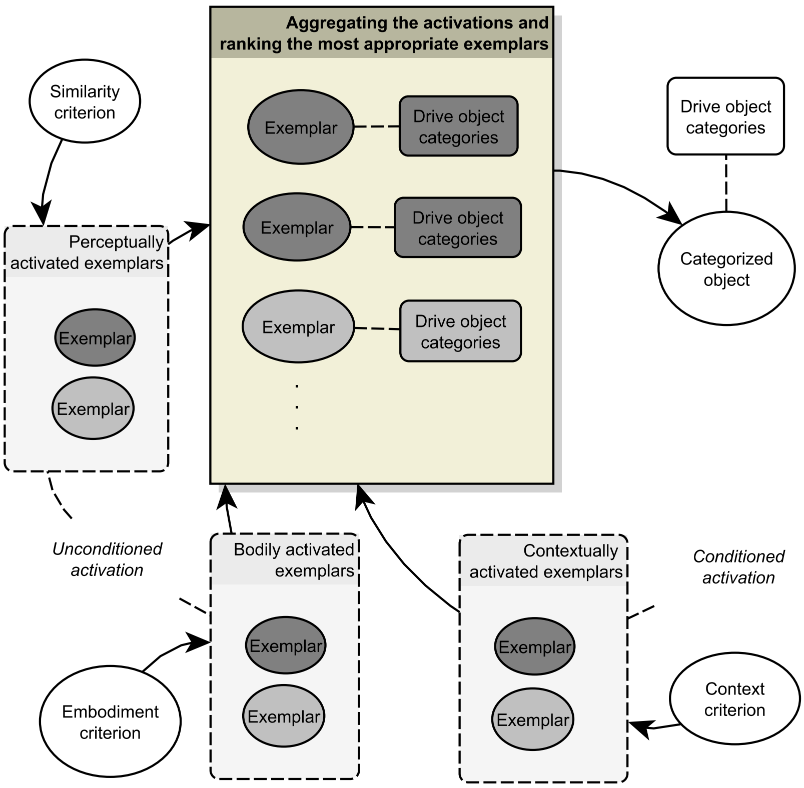

Figure 3.8: Activation-based multi-criteria ranking

The transformation of the problem of integrated drive object categorization to a multi-criteria decision problem and the usage of the criterion activation function as its utility function have various advantages. First, it provides a generic framework to integrate different categorization influences as categorization criteria. Second, the usage of multiple categorization criteria supports the reduction of ambiguity and uncertainty in category decision. Third, the usage of the concept of priming and activation for the criteria's utility functions enables the reduction of exemplar candidates that have to be considered for determining their category appropriateness. This advantage is next discussed in detail.

In MCDA theoretically all stored exemplars would have to be evaluated regarding every categorization criterion to determine the most appropriate exemplars for drive object categorization. This is particularly the case, if no point of departure exist that can be used to reduce the number of exemplars that have to be evaluated, i.e. the number of *exemplar candidates*. In such a case all stored exemplars are candidates. For example, the application of the similarity criterion would involve the comparison of the stimulus with every exemplar, since the stimulus potentially may be similar to any of the stored exemplars. As shown in section 2.2 conventional exemplar models and the k-nearest neighbor algorithm follow this procedure by considering all exemplars for similarity calculation. By using the concept of activation, the number of exemplar candidates is reduced. This is done by providing a point of departure, i.e. the activation sources, which activate those exemplars that fulfill a criterion in any form. This is possible, because the activation sources define the criterion. That is, a criterion is usually comprised of multiple activation sources (see Figure 3.11). Only those exemplars that get any activation from at least one activation source are considered as candidates. Subsequently the total amount of received activation from multiple activation sources (see Figure 3.10) determine the category appropriateness of an exemplar. An exemplar that gets the maximal amount of activation from all activation sources of a criterion is fulfilling the criterion in the best possible way and hence gets the highest possible criterion activation value, i.e. the highest category appropriateness regarding the criterion. In this regard the process is called application (instead of evaluation) of a categorization criterion, since the part of departure is the criterion's source activations, which activates exemplars. In the case of the similarity criterion - to continue the example given above - the stimulus' features are the point of departure (i.e. the activation sources which define the similarity criterion) for the application of the criterion and the determination of the most similar exemplars; only those exemplars are considered as candidates, which at least have one feature in common with the stimulus, since only in this case they get any activation at all (cf. Section 3.5). Exemplars that get the maximal amount of activation from all activation sources fulfill the criterion in the best possible way and hence are most appropriate regarding the specific criterion. Since exemplars from different drive object categories may get the maximal activation score, the determination of the most appropriate exemplars regarding a criterion may lead to ambiguous results. By considering multiple criteria, ambiguity and uncertainty in determining the most appropriate exemplars for drive object categorization are reduced.

Hence, the activation process on the one hand determines the exemplar candidates, which are considered for determining the most appropriate exemplars for drive object categorization, and on the other hand it is used for determining the most appropriate exemplars. This process is called *activation-based criteria application*.

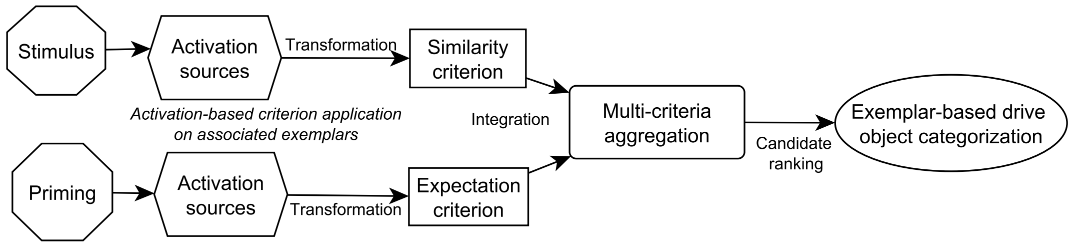

Figure 3.9: Activation-based multi-criteria categorization

In summary, *activation-based criteria application* uses an activation-based approach to apply a criterion and evaluate exemplars regarding a criterion. The overall process is summarized in figure 3.9.

3.6 From Objective Features to a Subjective Drive Object - The Overall Process

The overall process represents the transformation of an stimulus with objective features to a subjective exemplar. This reflects the primacy of subjectivity in the ARS agent, where perceptual information is intrinsically related to subjective experience and to subjective needs. In drive object categorization subjectivity is considered in multiple forms. First, drive object categorization focuses on the valuation of a stimulus regarding its suitability to satisfy the agent *subjective* needs. Second, the agent uses its *subjective* concrete experience in a comparison-based process to perform drive object categorization. Third, the stimulus' representation in further processing is based on the most appropriate exemplar. Fourth, subjective influences are considered in the determination of the stimulus' drive object categories.

Functional Categorization

The transformation from an objective stimulus to a subjective *drive object* follows a functional approach. Hence, drive object categorization is a form of *functional categorization*. The purpose of drive object categorization is not naming or labeling perceived objects, but to determine their function as drive objects. In a subjective and functional approach the effect of perceived objects on the subject lies in focus of the subject's perception. In this regard perception is a mean to fulfill the agent's needs.

In the scope of the primary process in the ARS agent, recognizing a stimulus as a drive object leads to its subjective semantics. That is, in an evolutionary sense, the concept of semantics refers to functional utility for an subject. Hence, the recognition of function and its effect on a subject leads to subjective semantics. In drive object categorization the recognition which effect the stimulus will have on the agent's needs leads to object understanding in the scope of the primary process.

Different categorization criteria are used to recognize an stimulus semantics and function. Although the categorization criteria are separated in objective and subjective, they are still all functional criteria.

Dynamic Categorization

As already analyzed in section 3.1 perceptual categorization in the ARS model has to be integrated and must consider subjective influences. The integration of influencing factors is inspired by the bionic concepts of top-down perception and priming. The former is used to handle influences in a generic way, namely as unconscious expectations, the latter is used to generically integrate these expectations. The transformation of expectations into categorization criteria and the integration with objective criteria by an activation-based multi-criteria approach enables *dynamic categorization*. It has to be emphasized that particularly subjective influences reflect flexible categorization influences. Hence, on the one hand such an approach supports reducing uncertainty in drive object categorization, on the other hand it enables different categorization results depending on dynamic influences. For example, when considering perceiving an *objectively* identical object in two different states of bodily needs, drive object categorization may lead to different *subjective* results.

3.7 Activation-Based Multi-Criteria Categorization - The Implementation Model

In this chapter the detailed model is presented. It is used subsequently as the implementation model of this thesis, i.e. a model which can be used for implementation, without the inception of further requirements. In designing the implementation model *modeling requirements*, i.e. requirements that the implementation model have to fulfill, are recognized and their fulfillment is shown.

As already emphasized, exemplars are activated by applying different categorization criteria. The aggregation of these activations leads to the aggregated activation value of an exemplar, which corresponds to its category appropriateness. Hence, the activation process supports the determination of appropriate exemplars to base drive object categorization on. After determining the most appropriate exemplars, category membership is decided.

Different factors have to be specified regarding the application of a categorization criterion and the determination of an exemplar's category appropriateness. First, the criterion's activation sources have to be specified. Second, the criterion activation function has to be defined. The specification of the activation sources lead to the definition of the criterion activation function, which serves as the criterion's utility function. Third, the construction of the activation aggregation function, which aggregate the various criterion activation values, has to be defined. As part of this step a criterion weighting function has to be specified, which determines the impact of a criterion to an exemplar's aggregated activation value. After ranking the exemplars with respect to their category appropriateness, the category decision is made.

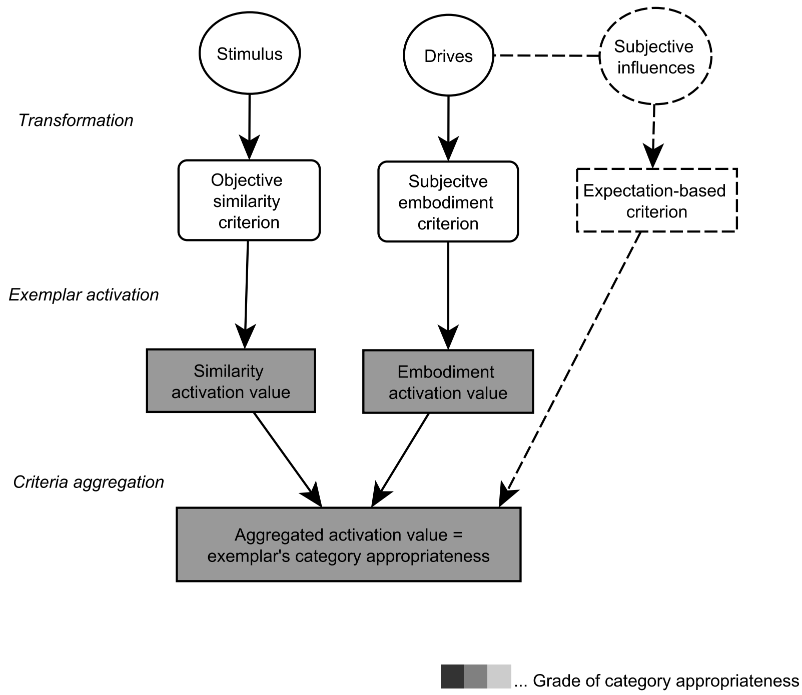

Figure 3.10: Determination of an exemplar's category appropriateness - overview

Application of Categorization Criteria - The Activation Process

Since a criterion usually consists of multiple activation sources, it has to be considered that the application of a criterion may activate the same exemplar multiple times, if the application of the criterion triggers multiple *activation sources* (e.g. if multiple drives activate the same drive object) (see Figure 3.11). Hence, additionally to determining the impact of each criterion activation value for an exemplar's aggregated activation value, the impact of each activation source for every criterion activation value must be determined. In this regard two aggregation functions are needed: One function to aggregate multiple source activation values from the same categorization criterion to one criterion activation value; and another function to aggregate multiple criterion activation values to one aggregated activation value. That is, the overall activation of an exemplar comprises of two aggregation functions. In the remainder of this thesis the former aggregation function is called *source activation aggregation* and the latter is called *criteria activation aggregation*. Source activation aggregation is represented by the *criteria activation function* and criteria activation aggregation is represented by the *activation aggregation function*.

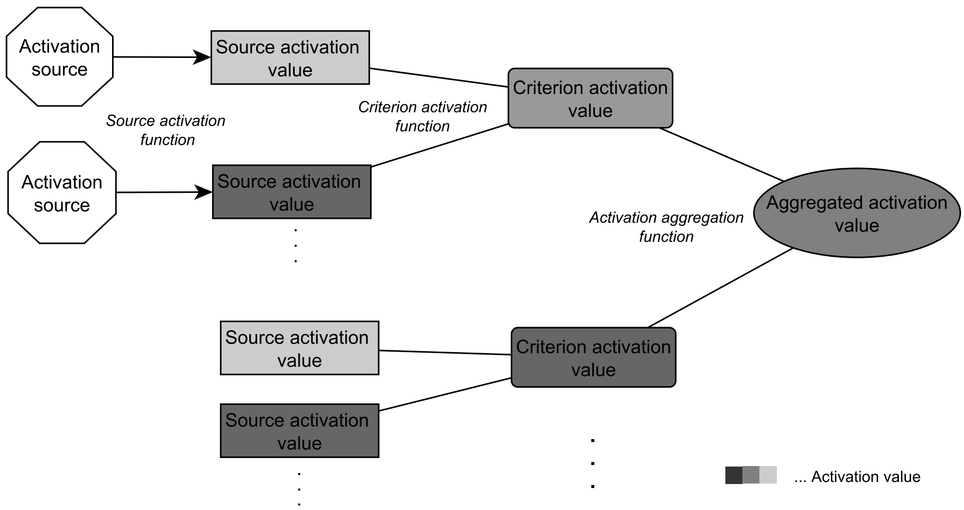

Figure 3.11: Composition of a candidate's activation value

Normalizing Activation Values

Since the activation values results from activation sources, which may have different scales, normalization must be considered. Additionally, the aggregated activation value of different exemplars may be grounded in different categorization criteria. For example, exemplar x may be activated solely by the embodiment criterion, whereas exemplar y may be activated solely by the similarity criterion. To aggregate values from different local scales, they have to be normalized with respect to a global scale, which serves as the norm. In the scope of the ARS implementation the global scale is [0,1]. Hence, the source activation values, criteria activation values and the aggregated activation value all have to be normalized with respect to the global scale. The normalization process has to be considered not only on a technical but on a conceptual level. That is, normalization should always consider the conceptual content that it processes. In this regard the choice of the normalization-procedure is dependent on the conceptual content. For example, in the case of normalizing the criterion activation value one has to consider the conceptual statement of the resulting value. That is, the criterion activation value should represent how well an exemplar fulfills the criterion. An exemplar that gets the maximal amount of activation from all criterion activation sources is fulfilling the criterion in the best possible way and hence gets the highest possible activation value, i.e. „1“. In summary, the normalization procedure is needed for the comparability of values with different scales, but also is needed for the representation of conceptual issues.

Criterion Activation Function

As already emphasized, in this thesis the criterion activation function is used as a criterion's utility function (in terms of MCDA). In this regard the criterion activation function's output, i.e. the criterion activation value, represents how well an exemplar fulfills the criterion. In *activation-based criteria application*, besides the definition of the criterion's activation sources, it must be specified how an exemplar gets activated by these. This requires the definition of a *source activation function*, which determines the calculation of the source activation value.

As already mentioned, the application of an categorization criterion can trigger multiple activation sources that activate the same exemplar. For example, two different drives may have the same drive object, i.e. an exemplar. In this case the exemplar has two activation sources regarding the embodiment criterion. In such case the source activation values have to be aggregated to a criterion activation value, which represents the exemplar's activation by this categorization criterion. Both, the source activation value and the criterion activation value have to be normalized to fit in the global scale [0,1]. It is assumed that the former is already done, since in ARS all present significant values are normalized. The normalization should not be considered only on a technical level, but rather should be consistent with the underlying conceptual content. For example, it would be misleading and conceptually wrong to just use a absolute normalization, which would lead to using the mean of all source activation values to aggregate them, since such aggregation may distort the criterion activation value. A concrete example therefore is given: if an exemplar is a drive object for a drive with a high quota of affect and also for a drive with a low quota of affect, the usage of their mean for the embodiment criterion activation value would not reflect the pleasure principle and the exemplar's correct category appropriateness. Instead the aggregation of multiple source activation values should be *accumulative*, but still must be normalized. This requirement results from the purpose of the criterion activation value, namely to provide the information of an exemplar's category appropriateness, represented by its activation value. In this regard a criterion activation value is a relative value, which should represent how well an exemplar fulfills the criterion.

To fulfill these requirements, first the *criterion's maximal activation value* has to be determined. That is the maximal activation score of the criterion's activation sources and reflects the best fulfillment of the criterion. Since this value is dependent on changing source activation values, a dynamic calculation of this value is required. Second, the accumulated source activation values have to be calculated, using the source activation function. The division of the accumulated source activation values by the criterion's maximal value would result in a relative value that fits the global scale [0,1] and indicates a relative activation score, i.e. how well the exemplar fulfills the criterion.

$$c = \frac{\sum_{i=1}^{n} s_i}{c_{max}} \tag{3.1}$$

c ... criterion activation value
s_i... source activation value of the *i-th* activation source
n ... number of activation sources
c_{max} ... criterion's maximal activation value

In summary, for every categorization criterion various factors have to be defined. First, the *criterion's activation sources* have to be specified. For example, in embodiment activation the actual DMs represent the activation sources. In case of a criterion that represents a subjective influence theses sources represent the *prime* (see Section 2.4). For both, subjective- and objective criteria, the direct or indirect association of activation sources to exemplars leads to the activation of these exemplars, which in case of a subjective criterion represents the *primed target items* (see Section 2.4). This process is compliant with using the concept of spreading activation (see Section 2.4) to model the priming process. After specifying the activation sources the *source activation function* has to be defined. This enables associative activation of exemplars and represents the activation-based application of a criterion. To determine how well an exemplar fulfills a criterion the *maximal criterion value* has to be defined. The *criterion activation function* then relates an exemplar's accumulated source activation values to the criterion's maximal criterion value, which is calculated dynamically. This leads to the determination of an exemplar's criterion activation value, i.e. its category appropriateness with respect to the criterion. To determine an exemplar's overall category appropriateness all criterion activation values have to be aggregated. Therefor the criterion's impact on the overall category appropriateness has to be determined using the criterion's weighting function.

Determining an Exemplar's Category Appropriateness - The Aggregation Process

After activating the exemplar-candidates by applying the categorization criteria, the different criterion activation values have to be aggregated to the exemplar's aggregated activation value, which represents the agent's certainty of using an exemplar for drive object categorization. Every criterion activation value represents the category appropriateness of an exemplar with respect to a categorization criterion. In this regard the criterion activation value represents the certainty the agent has regarding the respective criterion. The better the exemplar fulfills the criterion, the higher its criterion activation value and hence the more certain the agent is to use this exemplar regarding this criterion.

To reflect the agent's objective or subjective certainty of using an exemplar to based drive object categorization on, the criterion activation values have to be aggregated to the exemplar's aggregated activation value. The aggregation should reflect the impact of every single criterion activation value on the exemplar's aggregated activation value. This leads to the determination of an criterion's impact on an exemplar's category appropriateness. Particularly it may be the case, that an exemplar has a high criterion activation value, but the criterion has a low impact on the aggregated activation value.

The separation in objective and subjective categorization criteria has no influence on the determination of their impact on the agent's certainty in choosing the most appropriate exemplars for drive object categorization. This basically reflects an equal impact of top-down and bottom-up perception on perceptual categorization. But one can observe that the prerequisite of appearance recognition for identified drive object categorization (see Section 3.4) lead to the implicit preference of the similarity criterion in case of drive object identification (see section 5.3).

One can observe that the criterion activation value implicitly fulfills these requirements for a criterion's impact factor partially. As already mentioned, the criterion activation value represents the exemplar's fulfillment of the criterion. The better an exemplar fulfills a criterion, the more appropriate it is to base the category decision on it. That is, the better an exemplar fulfills a criterion, the higher the criterion's impact should be. Nevertheless, in case of a dynamic categorization criterion for the determination of an criterion's impact further consideration must be done. That is, the concrete conditions for their fulfillment are dependent on dynamic factors. The higher these factors, the higher the criterion's impact on the aggregated activation value should be. For example, in case of embodiment activation its impact should correlate with the drives' quota of affects. Hence a dynamic function is needed that determines the criterion's actual impact on the aggregated activation value.

After the determination of each criterion's impact, the calculation of the weighted average leads to the aggregated activation value a_{aggr}.

$$a_{aggr} = \frac{\sum_{i=1}^{n} w_i * c_i}{\sum_{i=1}^{n} w_i} \tag{3.2}$$

a_{aggr} ... aggregated activation value
c_i... criterion activation value of the *i-th* criterion
w_i ... criterion's weight
n ... number of criteria

As already mentioned, every exemplar that gets any activation is considered as a candidate for determining the most appropriate exemplars. Hence, the aggregated activation value is calculated for all candidates. After determining the aggregated activation value for all candidates, they are ranked with respect to it.

In summary, the criterion activation value is used on the one hand to determine the most appropriate exemplars. On the other hand it represents the certainty of a criterion and its impact on an exemplar's category appropriateness.

Embodiment Activation

The source of embodiment activation is a process called hallicunatory wishfulfillment. This is a psychoanalytic concept, which states that the bodily needs, represented as drive candidates, search after possibilities to be satisfied. A drive candidate is a bodily need that is not associated to a drive object and drive aim yet. To find suitable drive objects and drive aims that satisfy the bodily need the agent's experience is consulted by searching after memorized drive objects that satisfied a drive from the same drive category in the past. The result of this process is the association of memorized drives, which belong to the same drive category and are associated with a drive object and a drive aim, with the actual drive candidate.

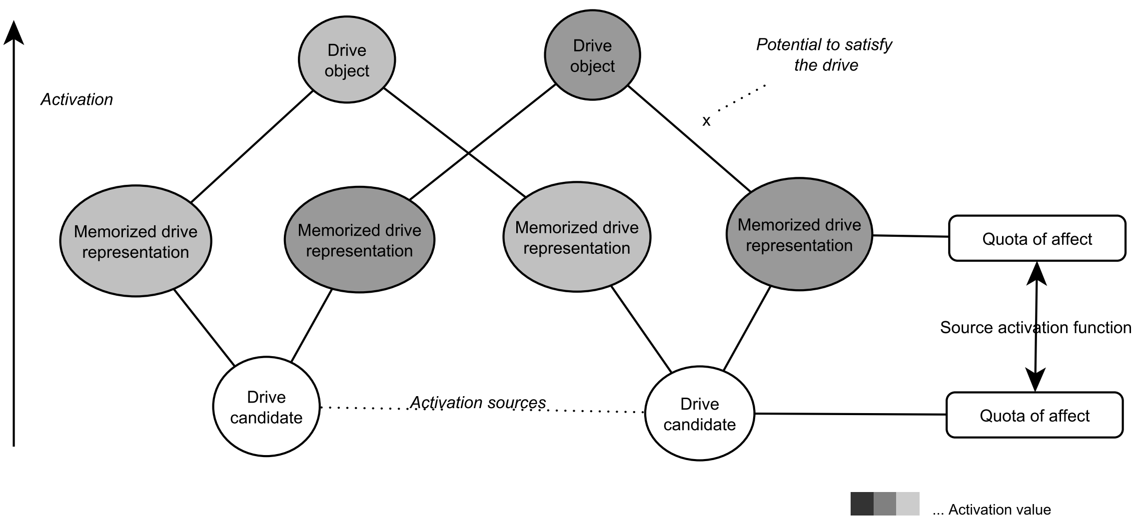

Figure 3.12: Embodiment activation

Following the pleasure principle, the drive candidate is then associated to the drive object and -aim of the memorized drive with the highest quota of affect. In summary, the drive candidate searches after the drive object and -aim that, according to the agent's memory, will satisfy the drive best. In further processing the drive aim and -object is used as part of the agent's decision making and planning.

Besides finding the best drive object and -aim, embodiment activation of exemplars is another result of the hallucinatory wishfulfillment (see Figure 3.12). Any memorized drive object, i.e. exemplar, that may be used to satisfy at least one of the agent's actual drives, is activated and used as a candidate for drive object categorization. The total activation reflects how well the exemplar would satisfy the agent's actual drives. As for other categorization criteria, the criterion activation function must be defined. Therefor the activation sources, the source activation function and the criterion's maximal value function must be determined.

The condition for fulfilling the embodiment criterion is to satisfy the agent's actual bodily needs. The embodiment activation function evaluates an exemplar in this regard. If an exemplar is associated with drives from every drive category and the quota of affect of those drives are the same (or higher) as the actual drives' quota of affect, the exemplar gets the maximal score (i.e. „1") for fulfilling the criterion. Hence, the activation sources are the agent's actual drives.

To evaluate the exemplar regarding the criterion the *embodiment activation function* compares every actual drive with the according associated drive of an exemplar. The source activation value represents how much of the maximal possible activation value the exemplar gets. That is, it represents how well the exemplar would satisfy the drive. For example, if an actual drive x has a quota of affect of 0.8 and an exemplar has satisfied a drive from the same drive category with a quota of affect of 0.6 (according to its memory), then the source activation value is $\frac{0.6}{0.7}$, i.e. the exemplar is suitable to satisfy 75% of the actual drive x. It must be considered that different activation sources may have different impact on the criterion activation value. Particularly, a possible satisfaction of a drive with a high quota of affect should have a higher impact on the criterion activation value than a possible satisfaction of a drive with a low quota of affect. Therefore the source activation values are weighted with the quota of affects of the actual drives. Additionally it has to be considered that two exemplars may satisfy a actual drive differently; particularly it has to be considered that their associated DM's quota of affect is higher than the actual drive's quota of affect. Following the pleasure principle, these exemplars should not get the same embodiment activation. Hence, the agent prefers the exemplar that brings the highest pleasure, even if it exceeds the actual bodily need. Therefor the exemplar's associated drive's quota of affect has to be considered as a additional weighting factor in calculating the embodiment activation value.

Hence, the source activation function is

$$s_i = \frac{p_i}{q_i} \tag{3.3}$$

s_i... source activation value of the *i-th* activation source (i.e. the actual drive)
q_i ... quota of affect of the *i-th* activation source (i.e. the actual drive)
p_i ... exemplars potential to satisfy the *i-th* actual drive

If s_i exceeds 1, it is rounded down.

The overall embodiment activation value c is then calculated as the weighted average of the source activation values:

$$c = \frac{\sum_{i=1}^{n} q_i * p_i * s_i}{\sum_{i=1}^{n} q_i} \tag{3.4}$$

The determination of an exemplar's embodiment activation value is also appropriate for determining visual top-down saliency (see Section 3.7) by indicating how well the stimuli may satisfy the agent's needs.

Dynamic Local Criterion Weighting

The impact of the embodiment activation value on the aggregated activation value is dependent on the actual drives' quota of affect. Therefore a weighting function is defined. The first approach is to use the actual drives' quota of affects to determine the impact of the embodiment activation value. That is, the higher the drives' quota of affects, the bigger their impact. But when being precise only those drives that would be satisfied by an exemplar are relevant for the calculation of the embodiment criterion's impact on the exemplar's aggregated activation value. In this regard it is not possible to use the same weighting for the embodiment activation value of every exemplar-candidate. Consider for instance an exemplar that is only used as a drive object for one drive, i.e. it is a member of only one drive object category. Drives from other drive categories should not have an impact on the embodiment criterion value. Hence the weighting function is dependent on the exemplar and only considers the quota of affects of those actual drives that are member of the same drive object category as the exemplar. The quota of affects of other actual drives have no influence on the weighting function. Such a weighting function is local, since it does not calculate a global weight that is used for determining the impact of the embodiment criteria for all exemplar-candidates, but for every single candidate separately; and it is dynamic, since it calculates the weight at every single categorization process due to the dynamic character of the actual drives.

In constructing the weighting function the pleasure principle must be considered. In particular the highest possible impact of the actual drives is not proportional to the sum of its quota of affects. In this regard *one* drive with a high quota of affect is sufficient for a high impact of the embodiment criterion. Additional drives increase the impact, but not proportionally.

This requirement is fulfilled by following weighting function. Considering the global scale [0,1], the weighting factor's maximal value is 1. Hence the initial range for the weighting factor is 1. After considering the first actual drive's quota of affect q_1, the remaining range is $(1 - q_1)$. The increase of the weighting factor by the next drive's quota of affect is only considered with respect of the the remaining range. That is, the weighting factor at this stage of the function would be $q_1 + (1 - q_1) * q_1$. Generally, the increase of the weighting factor comprises of the multiplication of a actual drive's quota of affect with the remaining range, and adding the result to the current weighting value.

$$w_{i+1} = w_i + (1 - w_i) * q_{i+1} \tag{3.5}$$

w_i .... current weighting factor (i.e. after the consideration of *i* actual drives)
w_{i+1}..... weighting factor after the consideration of *i+1* actual drives
$(1 - w_i)$ ... current available range (i.e. after the consideration of *i* actual drives)
q_{i+1} ... quota of affect of the *i+1th* actual drive

Similarity Activation

As already mentioned, the associative memory structure in ARS allows for an activation-based similarity calculation. This approach reduces the search space significantly. As opposed to conventional exemplar-based models it does not have to consider all exemplars, but rather only activate those exemplars that are similar to the stimulus. The first step of this process is the conversion of the stimulus representation into a psychic data structure, i.e. an entity-TPM. After that the stimulus' TPs are used to activate similar TPs in the agent's memory. In case of a nominal scale, only a binary match is considered. The activation of the according memorized TPs subsequently activates associated stored entity-TPMs (i.e. exemplars).

The goal of similarity activation is the evaluation of the similarity criterion. That is, evaluating exemplars regarding their perceptual similarity to the stimulus. As already described, the application of the criterion is done by an activation-based approach. In case of the similarity criterion associative activation can be realized directly. This is possible due to the associative information representation in ARS. Particularly, an exemplar's features, which are represented by TPs, are defined by its associations. As shown in figure 3.7 and figure 3.13, after transforming the stimulus in a TPM, its TPs (i.e. its features) are used as activation sources. Due to the usage of a nominal scale the source activation function comprises of a binary activation. In case of an activation the source activation value is 1. To reflect the impact of a feature its weight, which is represented by the according association weight, is used.

The criterion activation value is then calculated by following equation.

$$c = \frac{\sum_{i=1}^{n} w_i * s_i}{c_{max}} \tag{3.6}$$

s_i... source activation value of the *i-th* activation source (i.e. the TP)
w_i ... association weight of the exemplar's *i-th* TP
n ... number of stimulus' TPs
c_{max} ... criterion's max value

This criterion activation function represents an conventional exemplar's model similarity function. The summation of the weighted source activation values conforms with the similarity function of the featural ALCOVE model [Kru08]. Due to normalization and the consideration of weighted features, the summed weighted source activation values are related to the maximal criterion activation value.

An important factor of similarity calculation is the direction of the procedure. That is, when comparing the stimulus and an exemplar, one has to define the point of departure of the comparison. In activation-based categorization the point of departure in the comparison process is the stimulus, since its features are used as activation sources. In such an approach the similarity criterion value of 1 means that the exemplar is activated by all activation sources. *But the exemplar still may have additional features.* This case is not considered in conventional exemplar models, since they do not consider identification. This is sufficient for generalized drive object categorization but not for identified drive object categorization (see Section 3.4). For the former, similarity calculation has to consider the absence of exemplar-features in the stimulus. This requirement results from the purpose of drive object categorization, namely to value a stimulus regarding its suitability as a drive object. If the lack of an exemplar's feature still may lead to a full match (see Figure 3.13 d), identified drive object categorization would be distorted, since the exemplar's drive object categories are only valid for drive objects with the same features. Moreover the usage of the exemplar as the stimulus' representation in further processing (see Section 3.4) would be incorrect. A first approach to fulfill this requirement is to use the exemplar as the point of departure in the comparison process. That is, the unknown stimulus is searched in the known exemplars. One can observe that the usage of the exemplar's feature weights as the criterion's maximal activation value leads to such an approach. But this also leads to the opposite case of feature absence in a full match. That is, the lack of a stimulus' feature still leads to a full match (see Figure 3.13 b).

To fulfill the described requirement and handle this lack of the similarity criterion's activation-based application, the criterion's maximal activation value must be adapted. As already emphasized, the criterion's maximal activation value reflects the best fulfillment of the criterion. In case of the similarity criterion this is the case, if an exemplar and the stimulus have exactly the same features (see Figure 3.13 c). This case is called *appearance recognition* and is a practical requirement in the current ARS implementation for identified drive object categorization (see Section 3.4). Therefore the criterion's maximal activation value is represented by a combination of the exemplar's feature weights and the stimulus' features weights. In particular in a subjective approach the point of departure is the agent's memory. Hence, the exemplar's features weights are preferentially used to define the criterion's maximal activation value. Subsequently the criterion's maximal value c_{max} is extended by the weights of those stimulus-features that do not occur in the exemplar.

$$c_{max} = \sum_{i=1}^{n} w_i + \sum_{j=1}^{m} w_j \tag{3.7}$$

n ... number of exemplar features
k ... number of stimulus features
w_i ... *i-th* exemplar feature's weight
w_j ... *j-th* stimulus' feature's weight, with $j \in m$ and $m = |k - n|$

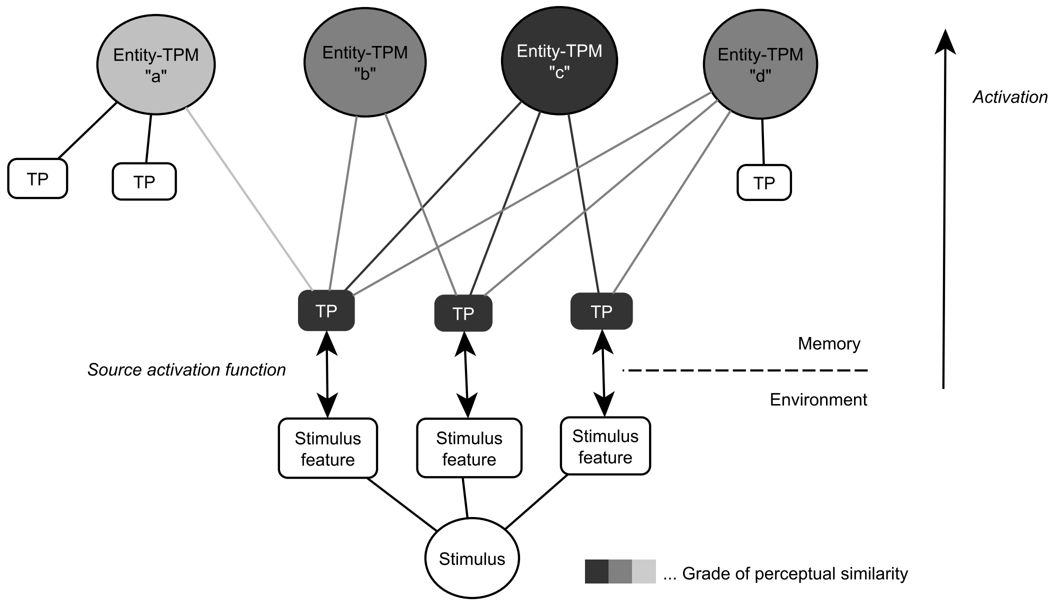

Figure 3.13: Appearance recognition in similarity activation

Criterion Weighting

As already mentioned one can observe that the criterion activation value may already fulfill the requirement for a criterion's impact factor. That is, the better an exemplar fulfills a criterion, the higher the criterion's impact should be. This is particularly valid for the similarity criterion. Additionally the number of stimulus features may be used to determine the impact of similarity activation. In this regard it is presumed that the ARS agent consolidates its experience to determine how the number of object features influences the criterion's impact. For example, if the agent's experience states that seven features is a high number of features for an object, a stimulus with seven features would lead to a high impact factor for the similarity criterion. In this regard appearance recognition of an stimulus with seven features leads to the maximal impact of the similarity criterion. This approach is compliant with similarity calculations that consider the number of matches [Kru08]. Due to the low number of stimulus features in ARS, the criterion activation value's implicit consideration of an impact factor is sufficient for current simulations (see Section 5.1).

Graded Category Membership

The aggregation of the criteria activation values of all exemplar candidates lead to the determination of their category appropriateness, which is the result of an *activation-based associative approach*. That is, activation-based criteria application processes determine the category appropriateness regarding every criterion. These values are combined to an exemplar's aggregated activation value, which represents its overall category appropriateness. In this regard drive object categorization is a *activation-based associative exemplar model*.

The next step is to determine the most appropriate exemplars to base the stimulus' drive object categorization on. In terms of the kNN algorithm this step includes taking the k most appropriate exemplars to determine the stimulus' drive object categories. As opposed to conventional kNN models, in drive object categorization the choice of k is dependent on the agent's certainty in determining the most appropriate exemplars. That is, the higher the category appropriateness of the most appropriate exemplar candidate, the higher the certainty in deciding the drive object categories and the lower k, i.e. the fewer exemplars are needed to base the stimulus' drive object categorization on. Particularly, in case of the highest possible certainty, i.e. in case of identified drive object categorization (see Section 3.4) k is 1, i.e. the drive object categories of the single most appropriate exemplar are used for categorizing the stimulus.

Hence, k is selected dynamically, i.e. in every categorization step. The more certain the agent is about the category appropriateness of the ranked candidates, the lower is k. Two factors influence this certainty. The first factor is the category appropriateness of the highest ranked candidate. The second factor is the distribution of the candidates' category appropriateness. This factor reflects the agent's certainty to distinguish the candidates and represents a scale for ambiguity. In this regard the worst case would be, if all candidates have the same category appropriateness. The second factor is not significant for selecting k in this thesis' model because of two reasons. First, it is assumed that the ARS agent does not encounter unknown stimuli. Of course, ambiguity still may occur. This leads to the second reason, namely the remaining risk of ambiguity is in most cases reduced by the application of weighted multi-criteria. The usage of multiple parameters (i.e. multi-criteria and their impact factors) in determining the category appropriateness reduces ambiguity. Nevertheless, in the worst case the usage of multi-criteria may increase ambiguity. In the case of generalized drive object categorization the implication of ambiguity is lower than in identified drive object categorization. That is, the consideration of remaining ambiguity is particularly relevant for determining identified drive object categorization. Hence, ambiguity that may remain after the application of multi-criteria is considered in this thesis to separate identified- from generalized drive object categorization. In the former case k is 1, in the latter case k is calculated by the function 3.8, which has the number of candidates and the first ranked candidate's category appropriateness (i.e. its activation value) as arguments. This procedure is represented in figure 3.14. Hence, the higher the agent's certainty, the lower the number of candidates that are used as k-exemplars. If a criterion is able to provide maximal certainty and no ambiguity occurs in choosing the most appropriate exemplar, identified drive object categorization is chosen, otherwise generalized drive object categorization is chosen to reflect the remaining uncertainty.

$$k = (1 - a) * n_c \tag{3.8}$$

a ... activation value of first ranked candidate
n_c ... number of candidates

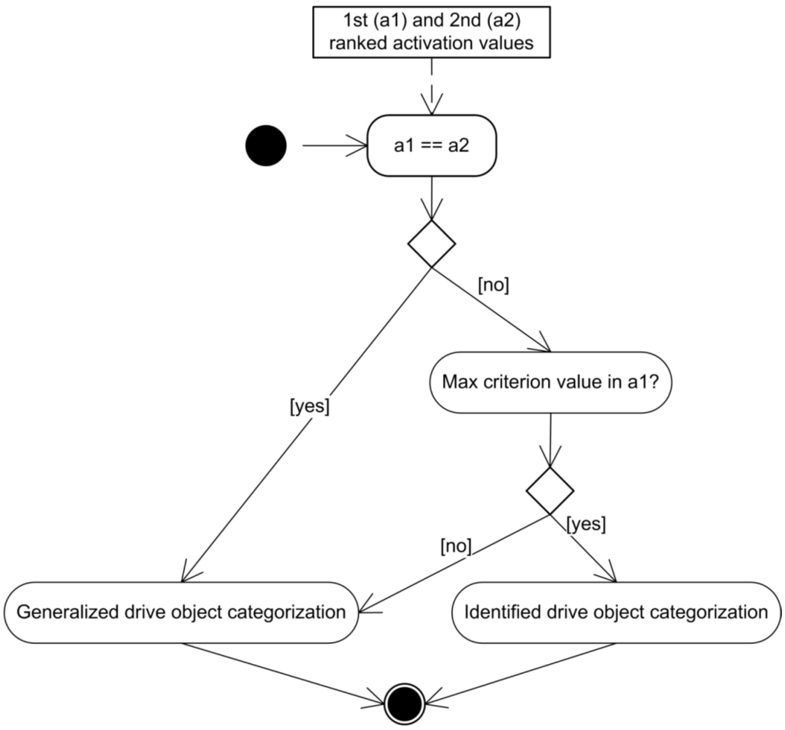

Figure 3.14: Dynamic selection of k - UML activity diagram

After finding the k most appropriate exemplars, the goal is to determine graded category membership for the stimulus using all categories of the k most appropriate exemplars (the *k-exemplars*). In drive object categorization the focus lies on grading the stimulus' multiple category memberships. In conceptual terms this means to determine the potential quota of affect for every drive category that the most appropriate exemplars are associated with. This leads to the valuation of the stimulus as a drive object and to determining how well the stimulus potentially may satisfy the agent's bodily needs that are represented by drives. One can observe that the latter aspect represents top-down saliency (see Section 3.7).

Drive object categorization includes the calculation of category membership to all drive object categories that are assigned to the k most appropriate exemplars. That is, drive object categorization corresponds to multi-label classification. In this regard the drive category decision do not has to consider which drive object categories to use, but only the graded category membership to each of the k-exemplar's drive object categories. Conceptually this grade represents how well the drive object is expected to satisfy the according bodily need. The stimulus' grade of category membership is derived from the k-exemplars' grade of category membership. This grade is represented by the DM's quota of affect. For example, if a k-exemplar is a member of a drive object category x, this drive's quota of affect reflects the graded category membership to the drive's category. Since different k-exemplars may be assigned to drives from the same category, multiple quota of affects have to be considered in determining the drive object's graded category membership regarding a category (see Figure 3.15 and 4.7). The first approach to consider this requirement is to use the arithmetic mean of all quota of affects to determine graded category membership.

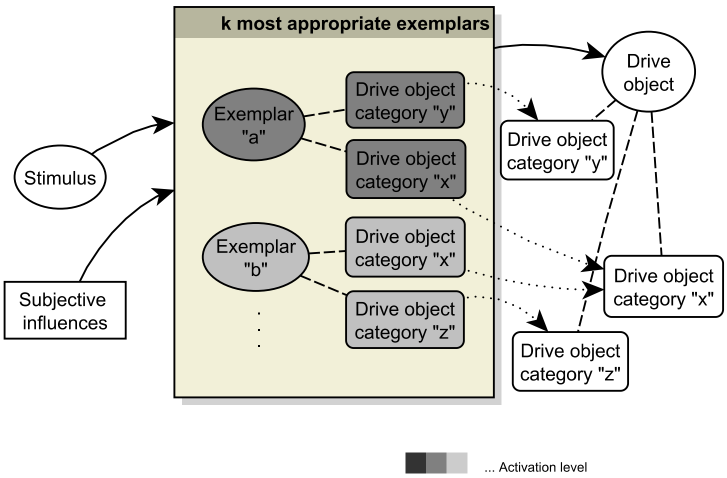

Figure 3.15: Graded category membership

The activation value of the k-exemplars, which reflects the exemplar's category appropriateness, represents the certainty the agent has in using their drive object categories as the stimulus' drive object categories. The higher an exemplar's activation value, the more certain the agent is in using its drive object categories as the stimulus' drive object categories. Hence, dependent on the exemplar's activation value the drive object categories of the k-exemplars may have different significance for the stimulus' drive object categorization. To formalize this requirement the arithmetic mean is not sufficient, hence a weighted average is used.

$$C_j = \frac{\sum\limits_{i=1}^{n} a_i * q_i}{\sum\limits_{i=1}^{n} a_i} \tag{3.9}$$

C_j ... graded category membership in drive category j

i .. i-th occurrence of drive category j, with $i = 1...n$
n ... number of k-exemplars in drive category j
q_i ... i-th drive's quota of affect
a_i ... activation value (category appropriateness) of the k-exemplar that is assigned to the i-th occurrence of drive category j

Pleasure Potential for Top-down Saliency

Another result of integrated drive object categorization is the provision of a basis for a visual saliency map. The determination of an exemplar's embodiment activation value is appropriate for determining visual top-down saliency according to the pleasure principle by indicating how well the stimuli may satisfy the agent's needs, i.e. how much pleasure the stimuli may bring the agent. In this regard it is not enough to consider an exemplar's potential to satisfy drives. This potential must be related to the actual drives and weighted by their quota of affect (see Section 3.7). Since the embodiment activation value is used for determining the potential satisfaction of drives, in this scope it is called *pleasure potential*.

After deciding drive object categorization the activation values are stored in the exemplars. The embodiment activation value indicates the importance of the exemplars, which at this stage represent stimuli, for the agent's actual needs. This subjective importance is a form of top-down saliency, which uses the internal state to determine saliency [Tre03]. Another form of visual saliency, which is not considered in this thesis, is given by bottom-up information, i.e. information from the incoming sensory signals. Converging evidence show that the interaction of bottom-up and top-down influences creates an integrated saliency map, which is used by an agent to guide visual attention [Tre03].

CHAPTER 4

Implementation

An important requirement in implementing this thesis' model is the integration into the existing ARS system architecture. Therefore a analysis of the according system components, particularly the ARS data structures and information representation management must be done. To fulfill this requirement the focus lies in adapting and extending existing components. Additionally, new components are needed in implementing this thesis' model.

4.1 Activation Framework

The introduction of an activation framework in drive object categorization comprises the extension of `clsThingPresentationMesh` by appropriate functions and variables. The class `clsCriterionActivation` is defined to represent the activation variables (see Figure 4.1). The enum-class `eActivationType` defines all valid types of activations; currently similarity- and embodiment activation are used.

Different functions are needed for activating a TPM. Therefore `clsThingPresentationMesh` is extended by the according functions (see Figure 4.1). These function are designed generically and hence the same source- and criterion activation function can be used for different criteria activation. A TPM may get activation from different sources. The activation is handled in the activating function. That is, the TPM's activation functions are called in the according function module. In case of embodiment activation the activating function is `hallucinatory-Wishfulfillment` in F57 (see 4.3); in case of similarity activation the activating function is `associativeSearch` (see Section 4.2), which is called by the `search` function in F14.

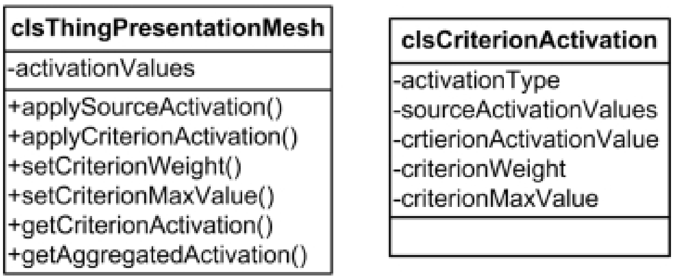

Figure 4.1: Criterion activation

4.2 Associative Search

In memory-based perceptual categorization memory access and memory search are key topics. In integrated drive object categorization memory search is used in two key processes and in the course of activation-based criterion application. In similarity activation the stimulus' features are used to find similar stored exemplars. In hallucinatory wishfulfillment and embodiment activation the actual DMs are used to find similar memorized DMs with associated drive objects and -aims.

An important requirement for the implementation is the integration into the existing ARS implementation, respectively its system architecture. Hence, to implement activation-based associative search, first the existing information representation management [Zei10, p. 80], i.e. the system architecture of memory access, must be analyzed. After that the integration into the existing system architecture is shown. This integration consists of adapting and extending the existing information representation management.

Information Representation Management

The information representation management provides an interface to the information representation layer [Zei10, p. 80], i.e. the agent's memory. The information management module is the key part of information representation management and provides data search and -retrieval from a persistent data storage. Due to the different structure of the ARS information representation the module is divided in secondary data structure management (SDSM) and primary data structure management (PDSM), which is further divided into the external perception management module (EPM) and the homeostatic perception management (HPM) module. These modules provide functions to compare the search patterns, i.e. the search query, to a set of stored data structures, which form the search space. Currently a list search algorithm is implemented to provide this functionality.

An overview of a search process in the course of the information representation management is given in figure 4.2. Regarding the procedure-arguments an abstracted notation is used.

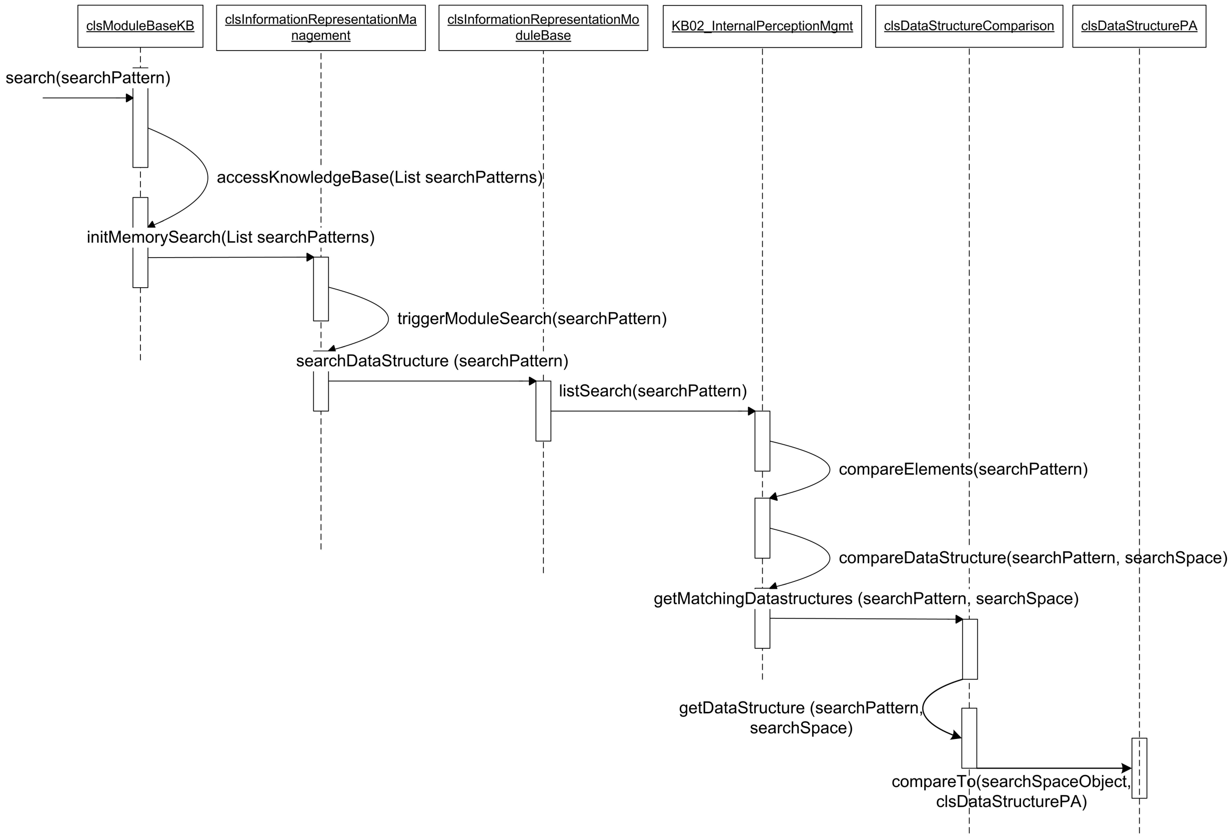

Figure 4.2: Information representation management UML sequence diagram

Associative Search

Currently a list search algorithm is implemented to provide memory search. This complies with a conventional instance-based algorithm that considers every item for similarity calculation. Due to continuous changes in the ARS data structures and search patterns the search algorithm provided rudimentary results. As mentioned in [Zei10, p. 133] the search algorithm should be adapted to the data structures. This requirement is fulfilled by the activation-based associative search algorithm that is used in similarity- and embodiment activation, where the associated structure of the TPM and DM is harnessed. Such an activation-based associative approach on the one hand follows an bionic approach, on the other hand enables goal-oriented search. That is, only those objects from the search space that may be relevant for search are considered in associative search.

To enable associative search, some adaptations in the ARS data structures and information representation functions are necessary. Amongst them are adaptations in `clsOntologyLoader` to consider associative search and a provision of association interfaces for the ARS data structures.

Association Interfaces

An important prerequisite for the generic processing of data structures in the course of associative search is the specification of their associations. Every composed data structure (see Section 2.6) contains internal- and external associations. Internal associations represents associations that are part of the data structure's identification. In case of a TPM these are *attribute associations* to TPs. As already mentioned, a TPM is composed of TPs, which are associated to a TPM through internal associations. In associative search only an data structure's internal associations are used to retrieve similar data structures. In this regard the *search pattern* consists of an data structure's internal associations. External associations do not identify a data structure and hence are not used in the search process. An example therefor is a TPM that is associated to another TPM via a similarity association.

To enable generic processing two interface-classes are specified that are implemented by data structures with internal- and external associations, respectively (see Figure 4.3). Data structures that implement the interfaces are guaranteed to support the respective functions.

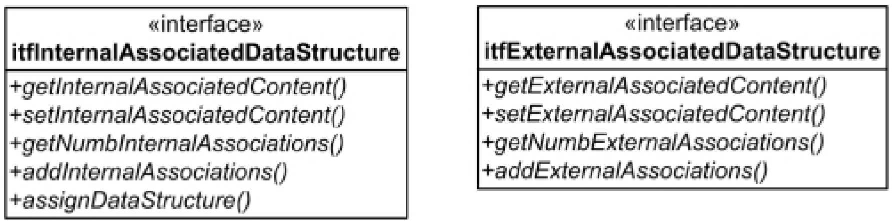

Figure 4.3: Association interfaces in UML

These interfaces enable the generic processing of search patterns. That is, every data structure that implements the interface `itfInternalAssociatedDataStructure` can be used generically in the associative search algorithm. For example, `clsThingPresentationMesh`, which is used in similarity activation, and `clsDriveMesh`, which is used in embodiment activation, implements the interface `itfInternalAssociatedDataStructure`.

Associative Search Algorithm

After analyzing and adapting the information representation management's implementation, the associative search function is integrated into the external perception management module (EPM) and the homeostatic perception management (HPM) module. The algorithm harnesses the associative structure of the ARS data structures to provide associated and directed search. Therefor the internal associations are used as the query representation. The significant difference to a list search is the provision of starting points for the search by using the internal associations. This bionic method enables a significant decrease of the search space and is compliant with an activation-based approach.

The basic idea of activation-based associative search is discussed in the scope of similarity activation (see Section 3.7). Nevertheless the algorithm is designed generically for all data structures that implements the interface `itfInternalAssociatedDataStructure`.

The algorithm is shown in 4.1 in abstracted form using pseudo-code. To enable a generic search, the class `clsDataStructurePA` is used, which is the top-most class in the ARS data structures (see Figure 4.4).

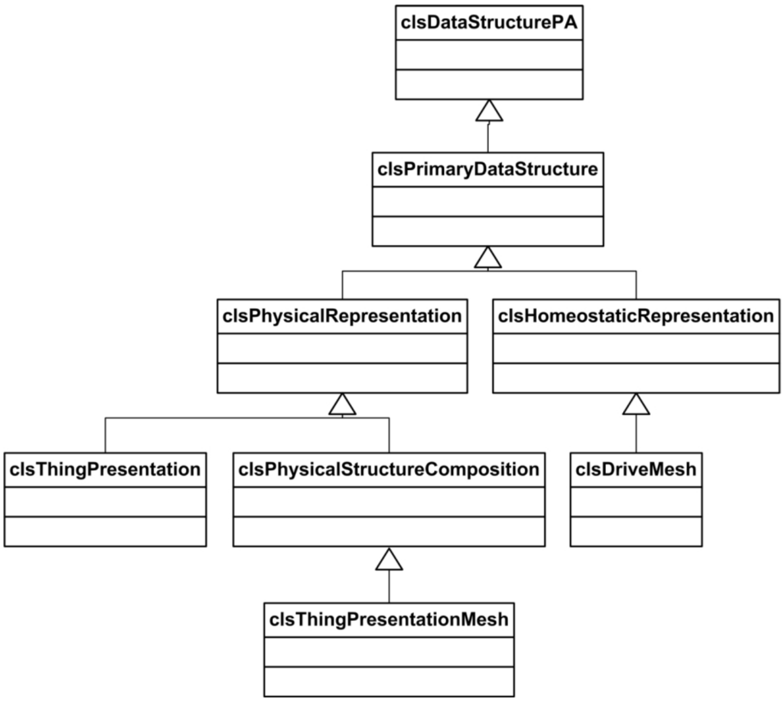

Figure 4.4: ARS primary data structures in UML

input : A unknown data structure $unknownDS$ and $returnType$ of associated data
output: A list of similar stored data structures $similarDataStructures$

```
if unknownDS instanceof itfInternalAssociatedDataStructure then
    // To avoid multiple entries a set is used
    searchFringe ← newHashSet()
    // Get internal associated data structures of unknownDS
       (e.g.  unknown TPM)

    foreach intAssDS of unknownDS do
        // Get matching data structures from search space
           (e.g.  TPs)
        intAssMatchedDS ← compareElements(intAssDS);
        intAssDSBestMatch ← getBestMatch(intAssMatchedDS);
        // Get associated returntype (e.g.  associated
           entity-TPMs of found TPs)
        returnType ← unknownDS .getDataStructureType() ;
        searchFringe .add(getAssociatedContent(intAssDSBestMatch,
        returnType));
    end
    foreach fringeObject of searchFringe do
        fringeObject .compareTo(unknownDS);
        // Get associated returntype (e.g.  associated DMs of
           similar entity-TPMs)
        similarDataStructures .add(fringeObject);
        getAssociatedContent(fringeObject, returnType);
    end
end
// If no associative search is possible, do list search
else
    similarDataStructures ← listSearch(unknownDS, returnType)
end
```

Algorithm 4.1: Associative search algorithm

4.3 Activation-Based Multi-Criteria Categorization

In figure 4.5 the communication between the concerned function modules is shown. After the hallucinatory wishfulfillment and embodiment activation of exemplars, which is done in F57, all drive representations are sent to F14. In this module similarity activation and integrated drive object categorization is accomplished.

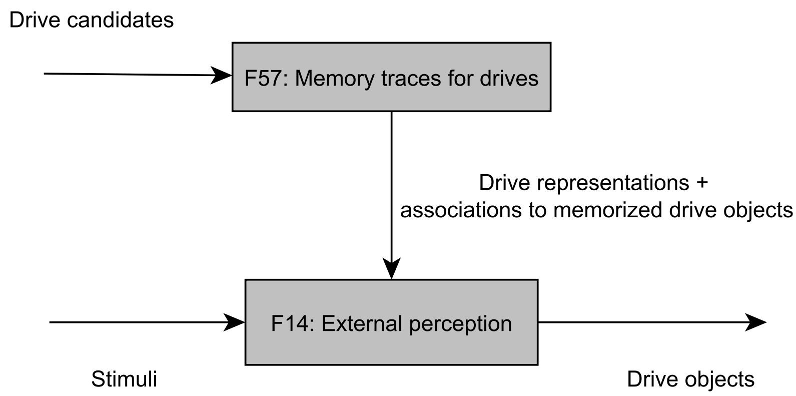

Figure 4.5: Function modules communication diagram

Integrated Drive Object Categorization

The basic procedure of integrated drive object categorization is shown in figure 4.6 and discussed in the following sections.

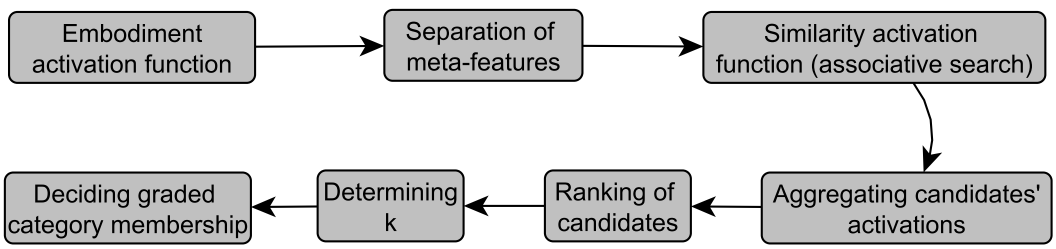

Figure 4.6: Drive object categorization - overview

Embodiment Activation

Embodiment activation is applied in the course of hallucinatory wishfulfillment in F57 (see Section 3.7). In this process the agent uses its memory to determine appropriate drive objects and -aims for every drive candidate. Following the pleasure principle those memorized drive object and -aim are used that brought the best reduction of the drive's quota of affect. After associating a drive object and -aim the drive candidate is called a drive representation since it comprises all components of a drive.

In the course of searching for drive objects, those exemplars that are appropriate as drive objects are also appropriate to base drive object categorization on, since they are expected, and hence get embodiment activation. The source activation value corresponds to the search matching factor, since the source activation function is considered in the drive mesh's `compareTo` function.

The algorithm 4.2 shows the procedure in abstracted form using pseudo-code.

input : A list of drive candidates $driveCandidates$
output: A list of drive representations $driveRepresenatations$ with activated drive objects

```
foreach driveCandidate ∈ driveCandidates do
    maxMatchFactor ← 0;
    maxMatchFactor ← 0;
    // Search for similar memorized DMs and return all
       associated TPMs
    memorizedDMs ← search( driveCandidate);
    foreach memorizedDM ∈ memorizedDMsdo
        // Associate memorizedDm to driveCandidate
        assSimilarDMs ← generateAssociation(driveCandidate,
        memorizedDM);
        driveObject ← memorizedDM .getActualDriveObject();
        // Embodiment activation.  source activation value
           complies with the matching factor
        driveObject .applySourceActivation(eActivationType,
        matchFactor);
        // Take drive object and drive aim of best match, this
           includes the highest QoA
        if matchFactor > maxMatchFactor then
            maxMatchFactor ← matchFactor;
            driveAim ← memorizedDM .getActualDriveAim();
            driveObject ← memorizedDM .getActualDriveObject();
        end
    end
    // Add to output
    driveCandidate .setActualDriveObject(driveObject);
    driveCandidate .setActualDriveAim(driveAim);
    ← driveCandidate;
    driveRepresenatations ← ;
end
```

Algorithm 4.2: Embodiment activation and hallucinatory wishfulfillment

Similarity Activation

To enable similarity activation first the stimulus' features must be separated into external- and internal features and associations. This is necessary because the stimulus is associated with meta-features, e.g. its position and distance to the agent. These *meta-features* are not relevant for similarity activation and distort its results. To separate these associations the enum-class `eEntityExternalAttributes` is defined, which list those meta-features that do not identify the stimulus and hence are not used in the course of similarity activation. After transforming the stimulus in an TPM, its associations are traversed to move those meta-features from internal- to external associations.

Similarity activation is then accomplished in the course of associative search (see Section 4.2).

Determining Aggregation

Every exemplar that gets any activation is considered as a candidate for drive object categorization. After all criteria activations are accomplished, for every stimulus its candidates-list is processed to determine their aggregated activation value using the weighted average of their criteria activation values (see Section 3.7).

Cloning

In the course of the activation processes of different perceived objects that are processed in the same simulation-step, an exemplar may be activated as a candidate for different stimuli. Hence, the candidates for every stimulus must be cloned to avoid cross-activation. Therefore the cloning-function of `clsThingPresentationMesh` is adapted.

Since the interface data is cloned in ARS by default and activated exemplars from F57 have to be considered as candidates in drive object categorization in F14, a merge of cloned objects with the same ARS data structure ids (`moDS_ID`) has to be done in F14. This ensures that the activation values of different java objects of the same exemplar are merged and enables their aggregation.

Ranking

Before deciding which candidates to use for the stimulus' drive object categories, the candidates must be ranked with respect to their aggregated activation value, i.e. their category appropriateness. Therefor the class `clsActivationComparator` is specified that implements the java utlitiy-class `Comparator`. This class implements the `compare` - function, which uses an exemplar's aggregated activation value to sort the candidates. After specifying `clsActivationComparator`, the static `sort` function of the `Collections` class is used to sort an candidate list using the implemented compare-function of `clsActivationComparator`.

Selection of k

The basic procedure of determining k is already shown in figure 3.14.

Graded Category Membership

After the determination of the most appropriate candidates, category membership is decided. Therefore all DMs of those candidates are traversed and graded category membership is decided by calculating their quota of affect's weighted average. The basic procedure is shown in figure 4.7, which also shows the detailed output of F14.

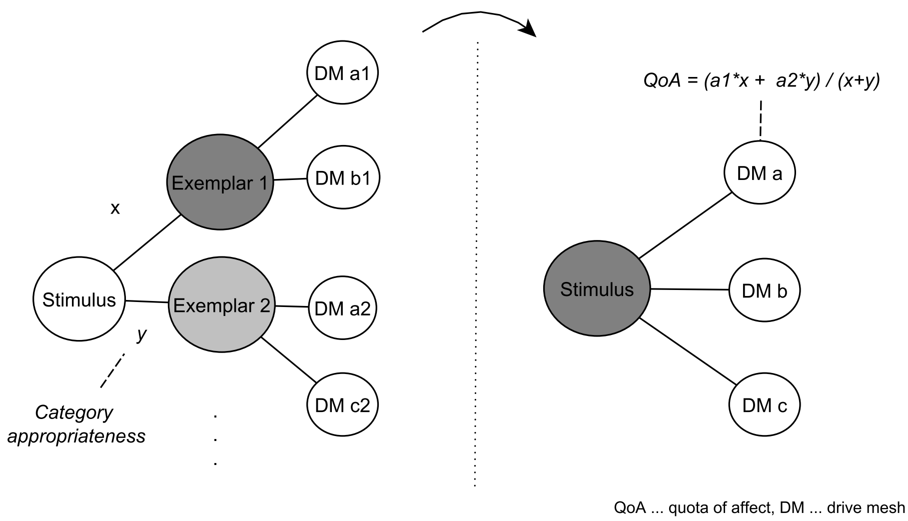

Figure 4.7: Calculating graded category membership

The following figure 4.8 gives an overview of the implemented functions in F14.

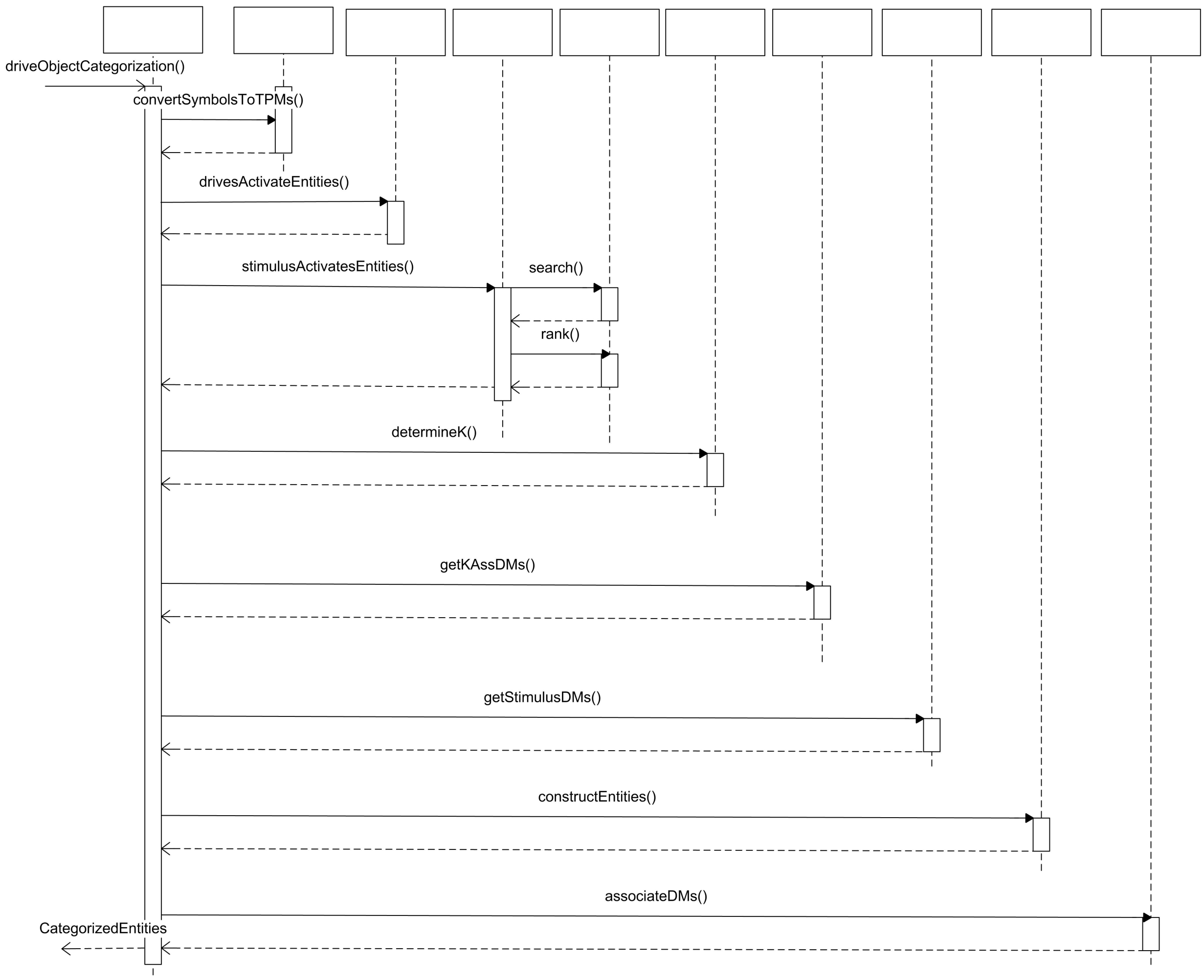

Figure 4.8: Drive object categorization - UML seqeucence diagrame

CHAPTER 5

Simulation and Evaluation

Integrated drive object categorization is evaluated by different use cases. The usage of different stimuli, memories and bodily needs lead to different use case scenarios.

The ARS project uses the MASON simulation framework [1] for simulation purposes. The virtual world that is used in simulation may comprise of different objects. An important purpose of the simulation is to show how the agent satisfy its bodily needs. Therefore it is central to recognize (1) for which drives categories perceived objects may be used as drive objects and (2) to which degree they satisfy the agent's current bodily needs. This part of the simulation is evaluated in the next sections.

After the agent recognizes how the perceived objects would satisfy its bodily needs, the agent heads towards the object that satisfies its needs best, i.e. the object with the highest pleasure potential, and performs the according action, which is based on the associated drive aims. It has to be emphasized that the pleasure potential considers the satisfaction of multiple drives by one object.

Next, the use case is described that guides the evaluation of integrated drive object categorization. After that it is shown how variations in the simulation lead to different use case scenarios, which are handled by integrated drive object categorization in different ways. This also emphasizes the dynamic aspect of drive object categorization.

[1] http://cs.gmu.edu/ eclab/projects/mason/

5.1 Use Case „Integrated Drive Object Categorization“

Integrated Drive Object Categorization is evaluated by a specified use case with different scenarios. The use case defines criteria that have to be fulfilled and evaluates the implemented model by showing how the agent valuates perceived objects as drive objects. The agent uses its experience with similar objects and its expectations to fulfill this task. In an subjective approach categorization is primarily the interpretation of the perceived data in comparison with the agent's experience and relative to influencing internal factors. The uses case shows how uncertainty and ambiguity in drive object categorization are handled by a functional and subjective approach by using domain-experience (= memory) and expectations.

In summary, the use case shows how the agent uses perceptually similar objects and expectations to fulfill the task of valuating perceived objects as drive objects.

Use Case Description

In this use case the agent perceives a fruit, a red apple or a red plum tomato. The agent has to decide which stored exemplars to use for deciding the stimulus' drive object categories. This decision is based on the agent's memory, i.e. the exemplars' activation values, which are determined by similarity- and embodiment activation. Based on the agent's certainty in choosing the most appropriate exemplars, two kinds of drive object categorizations are distinguished, namely identified- and generalized drive object categorization, which represents the two possible results of the use case. That is, if the categorization criteria are not able to provide the certainty that is needed for identified drive object categorization, generalization is used to value the stimulus as a drive object.

By changing specific conditions different use case scenarios are possible. A scenario is defined by conditions that lead to an alternative flow in the use case [Bal05]. These conditions are given by the stimuli, the agent's memory and actual bodily needs. Since drive object categorization is memory-based, changes in the agent's memory lead to different scenarios. The consideration of the agent's bodily needs as a categorization criterion also gives room for different scenarios. The sum of possible scenarios reflects the use case.

After giving a narrative description, the use case is specified in structured form in table 5.1 using a template from [Bal05, p. 68].

	Use Case „*Integrated drive object categorization*"
Goal	Valuation of a stimulus as a drive object
Precondition	Visual perception of a stimulus, memory formation, generation of actual drives
Postcondition	Graded valuation of a stimulus as a drive object
Actor	ARS agent
Trigger event	Visual perception of a stimulus
Description	1. Activate expected exemplars that would satisfy the actual drives 2. Activate exemplars that are perceptually similar to the stimulus 3. Determining criteria impact and aggregate criteria activation values 4. Selecting the most appropriate exemplars (k) 5. Deciding graded category membership
Alternatives	• 4 a Identified drive object categorization (k = 1) • 4 b Generalized drive object categorization (k > 1)

Table 5.1: Use Case „*Integrated drive object categorization*"

Scenarios

As already mentioned, changes in the stimulus, in the agent's memory and/or in the agent's actual bodily needs influence the categorization criteria and may lead to different scenarios. In this regard the model is evaluated by specifying conditions that lead to different scenarios, which are shown in figure 5.1. For the sake of comparability for every scenario the conditions, the categorization criteria values and the category decision are shown. Figures to depict the process of similarity- and embodiment activation are exemplary shown only for the first scenario.

Since the ARS agent does not perceive unknown objects, the focus in the simulation lies in appearance recognition. Since the numbers of parameters that lead to different results impede the evaluation of the model, some restrictions are made. To evaluate the model it is sufficient to use objects with two features, shape and color. This evaluates the model in an exemplary form. The features are all weighted with 1. When using a restricted number of object features the consideration of an impact factor for similarity activation is irrelevant (see Section 3.7). Hence in the following evaluations a similarity impact factor of 1 is used. For the consideration of the actual bodily needs, drives with the stomach as drive source are used in all scenarios.

As mentioned in section 2.5 a drive source triggers two kind of drives, i.e. an aggressive and a libidinous one. The libidinous stomach drive is satisfied by an libidinous action, e.g. nourishing; the aggressive stomach drive is satisfied by an aggressive action, e.g. biting.

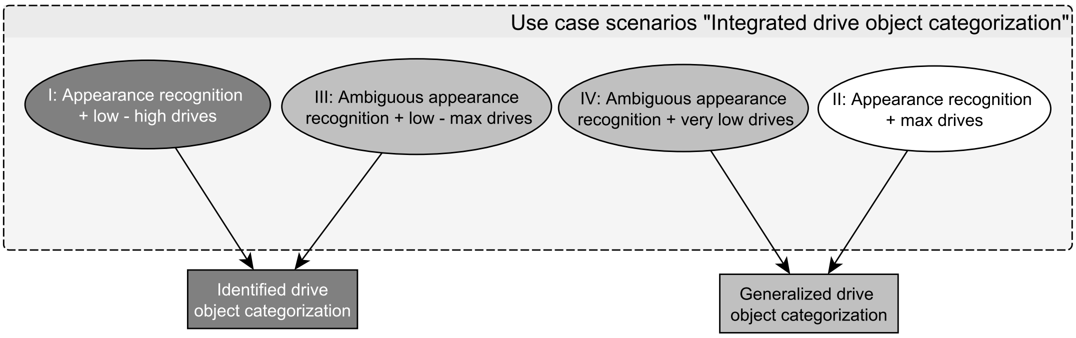

Figure 5.1: Use case scenarios *„Integrated drive object categorization“*

Scenario I: Appearance Recognition

The first scenario evaluates drive object categorization with actual drives that have low to high quota of affects, and without ambiguous stored exemplars. That is, expected exemplars get low to high weighted embodiment activation but always maximal similarity activation. The agent perceives a round and red stimulus (an apple) and tries to categorize it as a drive object (see Figure 5.2). In this scenario it is presumed that the agent only knows plum tomatoes (i.e. no round tomatoes). This ensures unique features for red apples and tomatoes and avoids ambiguity. According to the agent's memory an apple satisfies aggressive- and libidinous drives better than a tomato.

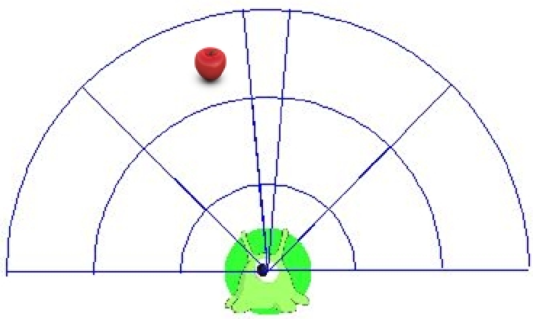

Figure 5.2: Use case scenario I

Table 5.2 summarizes the conditions of this scenario. Figures 5.3 and 5.4 show similarity- and embodiment activation in this scenario. The result of integrated drive object categorization in this scenario is shown in table 5.3.

Stimulus	Red round apple
Memories	Red round apple, red oval tomato, other fruits
Exemplar categories	• Red round apple: stomach drive libidinous: 0.7, -aggressive: 0.8 • Red oval tomato: stomach drive libidinous: 0.5, -aggressive: 0.3
Actual drives	Stomach drive libidinous: 0.2, -aggressive: 0.2

Table 5.2: Conditions scenario I

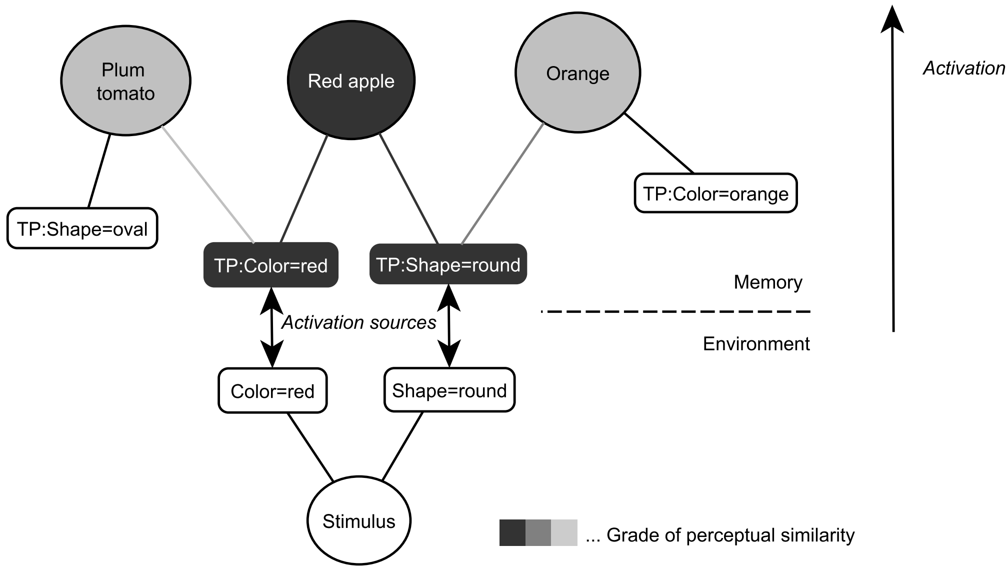

Figure 5.3: Appearance recognition - scenario I

In this scenario appearance recognition enables identified drive object categorization. The memorized red apple is activated by similarity with 1.0. Since no other exemplar gets such a high similarity activation and embodiment activation does not change the ranking, the stimulus is categorized according to the red apple's categories. One can observe that without additional weighting of the source activation value by the memorized DM's quota of affect the apple- and

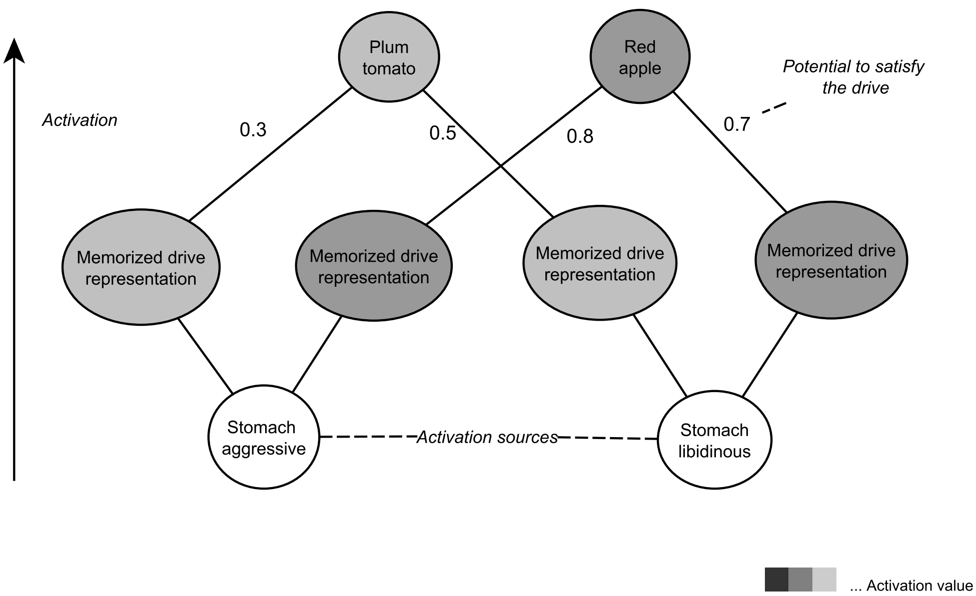

Figure 5.4: Embodiment activation - scenario I

Categorization variables	Red round apple	Red oval tomato
Category appropriateness	0.93	0.47
Similarity activation	1	0.5
Embodiment activation	0.75	0.4
Embodiment impact factor	0.36	0.36
k	1	
Category decision	Stomach drive libidinous: 0.7, -aggressive: 0.8	

Table 5.3: Results scenario I

tomato-exemplar would get the same embodiment activation value, since they have satisfied the according drives more than the actual drive's quota of affect. But since the apple-exemplar's memorized DMs have a higher quota of affects than the tomatoes' memorized DM's (see table 5.2) the apple gets a higher embodiment activation value.

Scenario II: Distorted Appearance Recognition

Simulations with different conditions show that in case of unique appearance recognition similarity activation is sufficient for identified drive object categorization. Additional embodiment activation does not affect the selection of appropriate exemplars until an exemplar's weighted embodiment value increases the aggregated activation value to a value that exceed a recognized exemplar's activation value. In this case identified drive object categorization based on appearance recognition is distorted by embodiment activation. With the premise of an agent that does not perceive unknown objects, in such a scenario the embodiment criterion may impede identified drive object categorization and generalized drive object categorization is chosen. Nevertheless, the additional embodiment activation in such a case is not sufficient for identified drive object categorization that is based on embodiment activation. That is, when perceiving a tomato the agent would not categorize it based on an memorized apple, even if the „worst case" occurs and the apple-exemplar gets the maximum weighted embodiment activation (see tables 5.4 and 5.5). This would only be the case if the stimulus is unknown or the similarity impact factor of a recognized exemplar is lower than the embodiment impact factor of an expected exemplar. In this scenario 0.9 is chosen as the maximal value for the memorized quota of affect that an apple has reduced, since according to psychoanalysis only so-called „primal objects", which are not considered in this evaluation, can reduce a quota of affect of 1. Hence, the maximum weighted embodiment activation in this thesis is 0.9.

It has to be considered that an exemplar that gets the maximum weighted embodiment activation has to satisfy the maximum of all actual drives' quota of affect. Only in this exceptional case identified drive object categorization is distorted and generalized drive object categorization is chosen. Only if an exemplar is a „perfect" drive object for the agent's actual drives, i.e. it gets maximum weighted embodiment activation, the criterion's impact factor can reach the maximum of 1.

In the „worst case" of maximum weighted embodiment activation, the thereby increased uncertainty in choosing the most appropriate exemplar leads to generalized drive object categorization. Such an scenario is shown in figure 5.5. In this scenario the agent perceives a plum tomato. After activating the plum-tomato-exemplar by the similarity criterion, it is ranked highest, since appearance recognition is reached. Applying embodiment activation with maximal possible values changes this ranking. The resulting uncertainty in choosing the most appropriate exemplar leads to generalized drive object categorization.

The conditions of this scenario are summarized in table 5.4. The results are shown in table 5.5.

As shown in these tables only with a drive object that nearly reduces the maximum quota of affect and with reaching an according gap between the embodiment activation of the apple- and tomato-exemplar, generalized drive object categorization instead of identified drive object categorization occurs.

In summary, the worst case of integrated drive object categorization of an agent that only per-

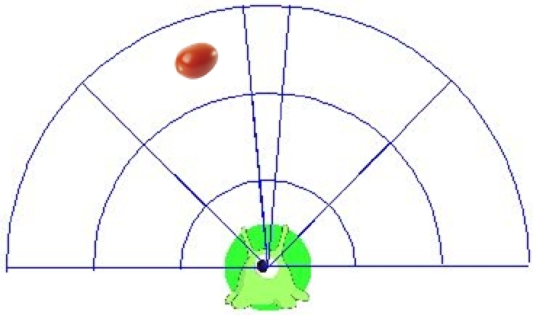

Figure 5.5: Usce case scenario II

Stimulus	Red oval tomato
Memories	Red round apple, red oval tomato, other fruits
Exemplar categories	• Red round apple: stomach drive libidinous: 0.9, -aggressive: 0.9 • Red oval tomato: stomach drive libidinous: 0.4, -aggressive: 0.2
Actual Drives	Stomach drive libidinous: 0.99, -aggressive: 0.99

Table 5.4: Conditions scenario II

Categorization variables	**Red round apple**	**Red oval tomato**
Category appropriateness	0.66	0.55
Similarity activation	0.5	1
Embodiment activation	0.82	0.1
Embodiment impact factor	0.99	0.99

k	1
Category decision	Stomach drive libidinous: 0.67, -aggressive: 0.58

Table 5.5: Results scenario II

ceives known stimuli is generalized drive object categorization despite appearance recognition. Therefore the maximum of actual drives' quota of affect must be reached and the „distorting“ exemplar (e.g. the apple in scenario II) must be memorized as a nearly perfect drive object that reduces the maximum quota of affect.

It has to be emphasized that an exemplar that gets the maximum weighted embodiment activation has to satisfy the maximum of all actual drives' quota of affect. Only in this exceptional case identified drive object categorization is distorted and generalized drive object categorization is chosen.

Scenario III and IV - Ambiguous Appearance Recognition

As already mentioned, the ARS agent only perceives known objects. Nevertheless, in case of perceiving an object that has the same features as different exemplars, ambiguity occurs. In such a case ambiguous appearance recognition occurs. The agent needs additional information to reduce its uncertainty in choosing an exemplar to base drive object categorization on. In integrated drive object categorization multiple categorization criteria are used to reduce uncertainty. An example therefore is the usage of the embodiment criterion.

In case of perceiving a red apple, two ambiguous exemplars with the same features exist in the agent's memory in scenario III and IV, a red round apple and a red round tomato. That is, these two exemplars get the same similarity activation value. Hence, in these scenarios similarity activation alone does not enable identified drive object categorization. Dependent on the expectation the agent has, one of the two exemplars gets a higher activation value. In case of embodiment activation the degree of expectation of an apple is higher than a tomato. This is the case, since according to the agent's memory an apple satisfies the agent's bodily needs better than a tomato. Hence, using similarity- and embodiment activation the agent is able to accomplish identified drive object categorization (see tables 5.6 and 5.7). In this regard the agent is able to identify the according drive object categories. Of course, this is a subjective certainty. In case of the perceived apple the categorization complies with an objective categorization; for the tomato this is not the case. But in a subjective approach only subjective certainty in choosing exemplars for drive object categorization is relevant.

Stimulus	Red round apple
Memories	Red round apple, red round tomato, red oval tomato , other fruits
Exemplar categories	• Red round apple: stomach drive libidinous: 0.7, -aggressive: 0.8 • Red round tomato: stomach drive libidinous: 0.5, -aggressive: 0.3
Actual drives	Stomach drive libidinous: 0.3, -aggressive: 0.4

Table 5.6: Conditions scenario III

Categorization variables	Red round apple	Red round tomato
Category appropriateness	0.91	0.76
Similarity activation	1	1
Embodiment activation	0.76	0.34
Embodiment impact factor	0.58	0.58

k	1
Category decision	Stomach drive libidinous: 0.7, -aggressive: 0.8

Table 5.7: Results scenario III

When defining exemplar-ambiguity as exemplars having exactly the same activation value, the embodiment impact factor, i.e. the quota of affect of the according actual drives, is not relevant in scenario III. A slightly higher increase of one of the two exemplar's activation values by embodiment activation is sufficient to reach a unique activation value. When defining exemplar-ambiguity as having a certain distance to the activation value of the next ranked exemplar, eliminating ambiguity is dependent on the embodiment impact factor. For instance, it is comprehensible that a difference of 0.03 (see table 5.9)in the activation values of two exemplars is not enough to reach the certainty that is needed for identified drive object categorization. An example is given in the next scenario, where the agent's actual drives are very low (see tables 5.8 and 5.9). This scenario leads to generalized drive object categorization, since the needed distance of 0.1 to eliminate ambiguity cannot be reduced by embodiment activation.

Stimulus	Red round apple
Memories	Red round apple, red round tomato, red oval tomato , other fruits
Exemplar categories	• Red round apple: Stomach drive libidinous: 0.7, -aggressive: 0.8 • Red oval tomato: Stomach drive libidinous: 0.5, -aggressive: 0.3
Actual Drives	Stomach drive libidinous: 0.05, -aggressive: 0.05

Table 5.8: Conditions scenario IV

Categorization variables	Red round apple	Red round tomato
Category appropriateness	0.98	0.95
Similarity activation	1	1
Embodiment activation	0.75	0.4
Embodiment impact factor	0.097	0.097

k	1
Category decision	Stomach drive libidinous: 0.6, -aggressive: 0.55

Table 5.9: Results scenario IV

5.2 Use Case „Pleasure Potential“

This use case briefly shows how the embodiment activation value may be used as an object's pleasure potential to determine top-down saliency (see Section 3.7). In this use case the agent perceives an red apple and a tomato (see Figure 5.6). After deciding drive object categorization the agent has to decide which perceived object would bring the best satisfaction of the agent's actual bodily needs. This decision is used to determine which object to approach from the primary process' view.

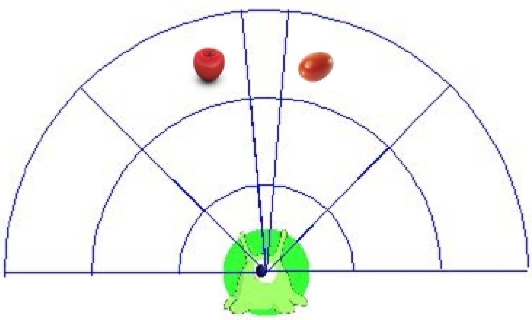

Figure 5.6: Use case „Pleasure potential“

As shown in 5.10 only the combination of different conditions, primarily the actual- and memorized drives' quota of affects, determine an object's pleasure potential.

5.3 Discussion of the Results

The presented simulations show how the agent uses its memories and memory-triggered expectations to reduce the uncertainty in choosing appropriate exemplars for drive object categoriza-

Actual drives (libid. / aggr.)		Drive object category stomach libid.	Drive object category stomach aggr.	Pleasure potential
0.3 / 0.7	Apple	0.4	0.7	**0.61**
	Tomato	0.5	0.3	0.24
0.7 / 0.3	Apple	0.4	0.7	**0.37**
	Tomato	0.5	0.3	0.34
0.6 / 0.7	Apple	0.3	0.7	0.45
	Tomato	0.6	0.5	**0.47**

Table 5.10: Use case „pleasure potential“ - conditions and results

tion. These simulations emphasize the need for two kinds of drive object categorization, namely identified- and generalized drive object categorization. If the agent's memory and expectations provides enough information to reduce uncertainty sufficiently, identified drive object categorization is accomplished. Otherwise the agent generalizes over the exemplars' drive categories to value a stimulus as a drive object. In this way the remaining uncertainty in the categorization process after applying all categorization criteria is still considered.

The usage of multiple criteria for the decision of multiple graded category membership shows the flexible and dynamic character of integrated drive object categorization. Dependent on various conditions multiple scenarios and results of integrated drive object categorization are possible. The interplay of these conditions leads to a variety of results. That is, given a stimulus, little changes in different conditions can result in categorizing the stimulus differently. These conditions are: the agent's categorized exemplars, particularly their graded category membership, the agent's actual drives, particularly their quota of affects, the number of stimulus features and their weights. One can observe that the category decision is dependent on all these conditions and their interplay. This fact emphasizes the dynamic and flexible character of integrated drive object categorization and gives an impression of the complexity of the interplay of determining conditions and parameters. This complexity and the according categorization-possibilities would rise with every additional criterion that is considered in integrated drive object categorization.

The restrictions of some conditions and the premise of perceiving only known stimuli enable a comprehensible evaluation of the model. With this premise standard scenarios and border-scenarios are simulated. Although the model does not prefer any criterion, the premise of perceiving only known stimuli implicitly gives the similarity criterion more impact. But even without this premise the similarity criterion would implicitly get more impact than the embodiment criterion, since in the majority of scenarios similarity activation is higher and the impact factor of the embodiment criterion is only considerable in exceptional scenarios. Hence the reduction of uncertainty by the similarity criterion is significantly higher than by the embodiment criteria. Simulations with different conditions show that in case of unique appearance recognition similarity activation is sufficient for identified drive object categorization. Only in the case of ambiguity in appearance recognition the embodiment criterion provides significant reduction of the agent's uncertainty in drive object categorization. It has to be emphasized that in this case the subjective uncertainty is reduced, which may not comply with the result of objective categorization. In summary, one can observe that the similarity criterion is more reliable to reduce uncertainty and that an additional categorization criterion is only significant if appearance is weak or ambiguous. When considering the similarity criterion as a bottom-up criterion and the embodiment criterion as a top-down criterion, one can transform above statement. In this regard, when using one top-down criterion, the bottom-up criterion is considerably more significant.

Besides reducing ambiguity in appearance recognition the embodiment criterion also may distort identified drive object categorization in exceptional scenarios and increase the uncertainty. This results in generalized drive object categorization. Nevertheless, the additional embodiment activation in such a case is not sufficient for identified drive object categorization that is based on embodiment activation. In summary, the worst case of distorting integrated drive object categorization by the embodiment criterion is generalized drive object categorization despite appearance recognition (which may be able to enable identified drive object categorization without the embodiment criterion). With the premise of an agent that does not perceive unknown objects, generally one can observe that only appearance recognition enables identified drive object categorization.

Besides the categorization as drive objects, the stimuli's pleasure potential is determined via the embodiment activation value. In this regard the simulations show that the combination of different conditions, primarily the actual- and memorized drives' quota of affects, determine an object's pleasure potential. In this regard the variety of combinations rises with the consideration of additional drive categories.

CHAPTER 6

Conclusion

The given problem of using an agent's memory to support perception in the ARS agent's primary process is analyzed and *integrated drive object categorization* is presented, which is a model of perceptual categorization in the ARS agent's primary process and is compliant with the ARS approach. The model approaches the problem of memory-usage for the support of perceptual categorization in various ways (see below).

After analyzing the ARS approach with respect to the problem statement, a model for the valuation of a stimulus as a drive object is designed as the primary purpose of the ARS agent's perception. In this regard perception in the ARS agent's primary process is a means to support the agent's bodily needs. The agent uses its experience to fulfill the task of categorizing a stimulus regarding its effect on the agent's bodily needs. Such a functional categorization leads to the recognition of subjective semantics.

Two opportunities of memory-usage for perceptual purposes, which are compliant with the ARS approach, are modeled in this thesis. First, an exemplar model is defined, which uses the agent's memory to find similar exemplars to base a stimulus' categories on. An exemplar-based model is used instead of a prototype model due its better compliance with the rules of the primary process. Additionally it is more compliant with the second form of memory-usage for perceptual purposes, namely the concepts of top-down perception and priming. The former is used to handle subjective influences of perceptual categorization in a generic way by using unconscious expectations that are triggered from memory; the latter is used to generically integrate these expectations by using the concept of associative activation. Examples for memory-triggered expectations are expected drive objects, which reflects affective priming in the ARS agent, or expected contextual objects, which reflects semantic priming in the ARS agent.

The central issue in integrated drive object categorization is the selection of appropriate memorized exemplars to base a stimulus' categories on. Two opportunities to reduce the uncertainty in choosing the most appropriate exemplars are modeled and integrated. The first follows a bottom-up approach in using the similarity to the stimulus' features to activate appropriate exemplars. The second opportunity follows a top-down approach in using the agent's expectations to activate appropriate exemplars. These two forms of memory-access to reduce uncertainty in selecting the most appropriate exemplars are transformed into categorization criteria to integrate them in a consistent model of perceptual categorization.

A generic framework is designed to transform and integrate all categorization criteria, by using an activation-based multi-criteria approach. Therefore a criterion is transformed into activation sources, which activate direct or indirect associated exemplars. The activation value is determined by the criterion's activation function. An exemplar that gets the maximal amount of activation from all activation sources of a criterion is fulfilling the criterion best and hence gets the highest possible criterion activation value. The multiple criteria activation values are then aggregated with consideration of a criterion's impact to an aggregated activation value, which represents the category appropriateness of an exemplar. Hence an exemplar can be activated from expectation-based subjective criteria and from a similarity-based objective criterion. That is, an exemplar's activation is dependent on how expected it is and how similar it is to the stimulus.

The usage of *activation-based criteria application* enables the reduction of exemplar candidates that have to be considered for determining appropriate exemplars. This represents a form of data reduction by reducing the instance set. The provision of activation sources as starting points for memory access enables activation-based and directed memory retrieval by reducing the search space. This eliminates a significant disadvantage of conventional instance-based algorithms, i.e. the big search space.

Simulations of the model show how the agent uses its memory and memory-triggered expectations to reduce the uncertainty in choosing appropriate exemplars for drive object categorization. These simulations emphasize the need for two kinds of drive object categorization, namely identified and generalized drive object categorization, which are chosen based on the agent's certainty in selecting the most appropriate exemplars. That is, if the categorization criteria are not able to provide the certainty that is needed for identified drive object categorization, generalization is used to value the stimulus as a drive object. In this way the remaining uncertainty after applying all categorization criteria is still considered.

One can observe that the category decision is dependent on various conditions, i.e. dynamically changing parameters. The interplay of these changing parameters can lead to different categorization results. This fact emphasizes the dynamic and flexible character of integrated drive object categorization and gives an impression of the complexity of the interplay of determining parameters.

Simulations of the model with different conditions show that in case of unique appearance recognition similarity activation is sufficient for identified drive object categorization. Only in the case of ambiguity in appearance recognition the embodiment criterion provides a significant reduction of the agent's uncertainty. In this regard the evaluations show that exemplar-ambiguity should be defined as two exemplars having similar but not ident activation values. It has to be emphasized that in case of handling ambiguity by expectation-based criteria the subjective uncertainty is reduced, which may not comply with the result of objective categorization. Besides reducing ambiguity in appearance recognition the embodiment criterion also may distort identified drive object categorization in an exceptional scenario and increase the uncertainty. This results in generalized drive object categorization.

Although the model per se does not prefer any criterion, the similarity criterion implicitly has more impact on determining appropriate exemplars. Generally, one can observe that the similarity criterion is more reliable to reduce uncertainty and that additional categorization criteria are significant only if appearance is weak or ambiguous. When considering the similarity criterion as a bottom-up criterion and the embodiment criterion as a top-down criterion, one can transform above statement. In this regard, when using one top-down criterion, the bottom-up criterion is considerably more significant. With the premise of an agent that does not perceive unknown objects, in general one can observe that only appearance recognition enables identified drive object categorization.

Besides the categorization as drive objects, the stimuli's pleasure potential is determined by the embodiment activation value. In this regard simulations of the model show that the combination of different conditions, primarily the actual- and memorized drives' quota of affects, determine an object's pleasure potential, which is an appropriate determinant for the agent's selective attention and can be used to support the agent's decision making.

CHAPTER 7

Future Work

For future work it would be interesting to analyze the primary process' interaction with the secondary process regarding perceptual categorization (see Section 3.3).

Additional future work could be an investigation if the application of multiple expectation-based criteria is able to reach the similarity criterion's significance of reducing the uncertainty in drive object categorization. Significant additional subjective influences which can be used as categorization criteria to support reducing uncertainty may be expectations that are triggered from planing and associative memory formation. The latter reflects contextual considerations in perceptual categorization and is discussed briefly next.

An important subjective categorization criterion is given by the associations of previously categorized objects' representations to stored exemplars. As introductory mentioned, stored entity-TPMs (i.e. exemplars) may be associated to co-occurent and similar objects. These associations can be used to support the determination of an exemplar's category appropriateness. If an exemplar is associated to a previously categorized stimulus it is expected and hence its category appropriateness increases. In this regard the subjective experience of co-occurent and similar objects influence drive object categorization. This is particular comprehensible for co-occurent objects, since co-occurent objects provide additional information about the stimulus. This subjective categorization criterion is also reasonable from an objective perspective. That is, the subjective co-occurrence association-strength reflect the objective co-occurrence probability of the associated objects.

A concrete example is given: if two exemplars, e.g. a banana and an apple, have a strong co-occurrence association, the agent has often perceived these two objects together. After the correct categorization of the banana, the stored association to the apple increases its category appropriateness. That is, after categorizing a banana, the expectation level of an apple is higher than e.g. of a tomato (which may have a similar appearance).

The usage of co-occurence associations to activate exemplars reflects semantic priming and contextual considerations. Since it uses associated content, i.e. internal context, it may be called *subjective context categorization criterion*. In this regard the subjective endogenous context that reflects co-occurence, i.e. the co-occurence associations of an exemplar, may be used for considering objective exogenous context, i.e. contextual physical objects. This complies with evidence that context consideration is the norm in object recognition [MBC11], and hence is also an important aspect in perceptual categorization. Human object perception does not occur isolated and contextual information provides a significant input for object recognition and categorization, especially when the object appearance is weak or ambiguous [MBC11]. Different kinds of context may be considered, amongst them semantic context, which basically refers to co-occurrence of objects and is the most valuable kind of context for object recognition [GB10]. Additionally, as opposed to other context types (e.g. spatial or scale context) the consideration of semantic context complies with the rules of the primary process.

Semantic priming is a bionic, integrated and subjective form of context consideration. It considers context by using *context-based expectations*, which is a bionic method to make object recognition and categorization more efficient [Bar04]. This method of context consideration complies with this thesis' generic pattern of integrating subjective influences of perceptual categorization by using the top-down concept of expectations. In this regard the stronger an exemplar is associated with previously categorized exemplars, the more an exemplar is expected, i.e. the higher it's category appropriateness.

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