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Agent-based Simulation of Animal Behaviour*

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Abstract

In the biological literature on animal behaviour, in addition to real experiments and field studies, also simulation experiments are a useful source of progress. Often specific mathematical modelling techniques are adopted and directly implemented in a programming language. Modelling more complex agent behaviours is less adequate using the usually adopted mathematical modelling techniques. The literature on AI and Agent Technology offers more specific methods to design and implement (also more complex) intelligent agents and agent societies on a conceptual level. One of these methods is the compositional multi-agent system design method DESIRE. In this paper it is shown how (depending on the complexity of the required behaviour) a simulation model for animal behaviour can be designed at a conceptual level in an agent-based manner. Different models are shown for different types of behaviour, varying from purely reactive behaviour to pro-active, social and adaptive behaviour. The compositional design method for multi-agent systems DESIRE and its software environment supports the conceptual and detailed design, and execution of these models. A number of experiments reported in the literature on animal behaviour have been simulated for different agent models.

Keywords: computer simulation, agent, animal behaviour, delayed response, reactive, pro-active, social, adaptive

1 Introduction

In the study of animal behaviour within Biology it is more and more recognized that in addition to real experiments and field studies, also simulation experiments are a useful source of knowledge and verification; e.g., see [3], [17], [23], [30], [36]. Viewed from a software engineering and AI perspective the techniques used to build such animal behaviour models are limited. Often specific mathematical techniques (such as game-theoretic or connectionist models) are adopted and directly implemented in a programming language. In accordance with the chosen (mathematical) content of the models, the types of intelligence within the animal are kept limited. This provides a useful perspective if the study of social patterns emerging from simple individual behaviours (and interaction with each other and certain physical environments) is concerned: an interesting research area as such. However, animals may also be able to show more complex patterns of behaviour. Modelling more complex agent behaviours is less adequate using the commonly adopted mathematical techniques. The literature on AI and Agent Technology offers more specific methods

* A preliminary and shorter version of this work was presented at IEA/AIE'98

to design and implement (also more complex) intelligent agents and agent societies on a conceptual level; e.g., [5], [6], [12], [20], [21], [28], [33], [35], [42].

The aim of this paper is to show that modelling techniques from AI and Agent Technology may provide useful tools to build animal behaviour models. In particular, the use of the compositional design method for multi-agent systems DESIRE (see [5]) to design, implement and experiment with agent-based simulation models for animal behaviour is discussed. It is shown how (depending on the complexity of the required behaviour) different types of animal behaviour can be modelled and simulated at a conceptual level on the basis of DESIRE. Different (variants of) reusable compositional agent models were used to model the different required behaviours. The advantage of this approach is that the models are designed at a high conceptual level, in terms of the processes, information and knowledge that is needed, and abstracting from implementation details. Nevertheless they can be executed by the DESIRE software environment.

Simulation of animal behaviour is an interesting type of application for multi-agent systems. Both areas can benefit from a more extensive study of this type of application. The area of multi-agent systems can benefit from the more detailed analyses and distinctions that have been made for different types of animal behaviour. The study of animal behaviour can benefit from software tools for agent modelling at a conceptual level that support simulation.

In Section 2 a problem description (a description of a pseudo-experiment) is presented; in Section 3 the principles behind the modelling approach used are briefly discussed. In Section 4 a generic model of a *purely reactive agent* is introduced which is an adequate agent model to describe the (immediate) functional character of stimulus-response behaviour. The black box is represented by the agent component. The stimuli form the input (observation results), and the response is formed by the actions generated as output.

In Section 5 a generic agent model is presented that can be used to model more complex behaviour. It includes not only components that represent the agent's memory (the agent's beliefs on the world and on other agents), but also components that represent the agent's capabilities to control its own behaviour (for example, via goal-directness, or adaptation), the agent's interaction with the world, and the agent's communication with other agents. This generic agent model has been used to obtain different agent models for different types of animal behaviour that go beyond purely reactive behaviour: *delayed response behaviour*, *deliberate pro-active behaviour*. In Section 6 an agent model is introduced for *social behaviour* and in Section 7 an agent model for *adaptive behaviour*. In Section 8 the behaviours of the different agent models introduced are compared for each of the situations defined in Section 2.

2 Problem Description

One of the most important aspects of agents (cf. [42]) is their behaviour. In the past, behaviour has been studied in different disciplines. In Cognitive Psychology the analysis of human behaviour is a major topic. In Biology, animal behaviour has been and is being studied extensively. Around 1900 a discussion took place about the manner in which observed animal behaviour can be interpreted in order to obtain an objective and testable description; for an overview, see [2], [40]. A risk of taking the intentional stance (e.g., [16]) as a perspective to explain behaviour, is that explanations are generated that make use of (a large number of) mental concepts that cannot be tested empirically. Therefore the *principle of parsimony* was introduced, stating that 'in no case may we interpret an action as the outcome of the exercise of a higher psychical faculty, if it can be interpreted as the outcome of the exercise of one which stands lower in the psychological scale'; see [31].

Building further on this perspective *behaviourism* was developed, e.g., [22], [34], [37], [41]. In this approach animal behaviour is explained only in terms of a black box that for each pattern of *stimuli* (input of the black box) from the environment generates a *response* (output of the black box), that functionally depends on the input pattern of stimuli; i.e., if two patterns of stimuli are offered, then the same behaviour occurs if the two patterns of stimuli are equal. This view was also extended to human behaviour. Because of the underlying black box view, behaviourism discouraged reference to internal (mental) activities of organisms: any speculation about the internal functioning of the black box (i.e., the processes that might mediate between sensory inputs and behavioural outputs) was forbidden; cf. [40], p. 4.

The deliberations put forward above are illustrated by a very concrete example, taken from the discipline that studies animal behaviour; e.g., [40]. The example was chosen because experiments with animals with respect to food have been performed and reported in the literature in extenso during the last century. Animals, for example dogs, sometimes show a *delayed response*: they look for food in places where they have seen food before. This suggests that these animals might have some internal representation or memory of stimuli received earlier. More systematic experiments on this delayed response issue, for example those reported in [25] and [39], support this suggestion.

2.1 The Domain

The type of experiment reported in [39] is set up as follows (see Figure 1). Separated by a transparent screen (a window, at position p_0), at each of two positions p_1 and p_2 a cup (upside down) and/or a piece of food can be placed. At some moment (with variable delay) the screen is raised, and the animal is free to go to any position. Consider the following three possible situations:

Situation 1 At both positions p_1 and p_2 an empty cup is placed.

Situation 2 At position p_1 an empty cup is placed, and at position p_2 a piece of food, which is (and remains) visible for the animal.

Situation 3 At position p_1 an empty cup is placed and at position p_2 a piece of food is placed, after which a cup is placed at the same position, covering the food. After the food disappears under the cup it cannot be sensed anymore by the animal.

Situation 4 At position p_1 an empty cup is placed and at position p_2 a cup and a piece of food is placed, in such a manner that the animal did not see the food.

In situation 1 the animal will not show a preference for either position p_1 or p_2 ; it may even go elsewhere or stay where it is. In situation 2 the animal will go to position p_2 , which can be explained as pure stimulus-response behaviour. In situation 3 the immediate stimuli are the same as in situation 1. Animals that react in a strictly functional stimulus-response manner will respond to this situation as in situation 1. Animals that show delayed response behaviour will go to p_2 , where food can be found. In situation 4 animals will behave as in situation 1; however, here they can find food and eat it, and therefore be reinforced in successful behaviour.

In the literature, many reports can be found of observed delayed response behaviour in experiments of the type described above: [40], p. 4-5. The animal species used in these experiments vary from rats and dogs to macaques, chimpanzees and human infants. Therefore, it is assumed that animals of the type studied maintain internal (mental) representations on the basis of their sensor input, and that they make use of these representations (in addition to the actual

sensory input that is used) to determine their behaviour. In a way it can be said that they may act as deliberate agents.

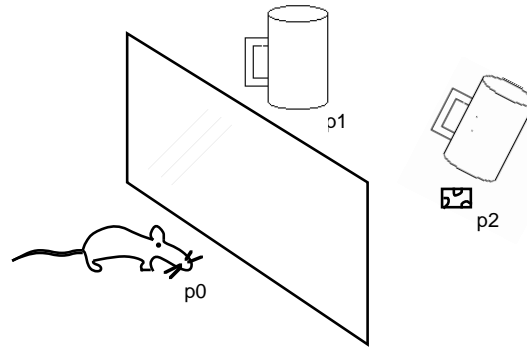


Figure 1 Situation 3 of the experiment

2.2 The Requirements

In this paper five agent models A, B, C, D and E for the experiment are described. The following requirements on their behaviour express possible hypotheses that can be made about the behaviour of animals in the experiments:

A. An agent with purely reactive behaviour should behave the same for the two situations 1 and 3 described above: doing nothing, as if no food is present. Only in situation 2 should it go to the position of the food.

B. An agent with delayed response behaviour should behave the same in the situations 2 and 3: it should go to the position of the food. In situation 1 it should do nothing.

C. A deliberate pro-active agent's behaviour in the situations 1, 2 and 3 depends on whether the agent has a motivation or goal to do so. E.g., the agent may start acting in a pro-active manner (without any specific stimulus) in situation 1.

D. A social agent is able to take into account communication with other agents. If another animal is present that communicates that it wants to have the food (e.g., by growling), and the agent believes that this other agent is higher in the hierarchy, then the agent will not try to get the food.

E. An adaptive agent is able to adapt its behaviour on the basis of experiences. If the cups have different colours, and a certain colour is used more often for cups under which food is hidden, then after some learning time the agent has a preference to look for food at positions with a cup of that colour with priority.

3. Compositional Development of Multi-Agent Systems

The agent-based models for animal behaviour described in this paper have been developed using the compositional development method DESIRE for multi-agent systems (DEsign and

Specification of Interacting REasoning components); cf. [5]. The development of a multi-agent system is supported by graphical design tools within the DESIRE software environment. Translation to an operational system is straightforward; the software environment includes implementation generators with which formal specifications can be translated into executable code of a prototype system. In DESIRE, a design consists of knowledge of the following three types: process composition, knowledge composition, the relation between process composition and knowledge composition. These three types of knowledge are discussed in more detail below.

3.1. Process Composition

Process composition identifies the relevant processes at different levels of (process) abstraction, and describes how a process can be defined in terms of (is composed of) lower level processes.

3.1.1. Identification of Processes at Different Levels of Abstraction

Processes can be described at different levels of abstraction; for example, the process of the multi-agent system as a whole, processes defined by individual agents and the external world, and processes defined by task-related components of individual agents. The identified processes are modelled as *components*. For each process the *input and output information types* are modelled. The identified levels of process abstraction are modelled as *abstraction/specialisation relations* between components: components may be *composed* of other components or they may be *primitive*. Primitive components may be either reasoning components (i.e., based on a knowledge base), or, components capable of performing tasks such as calculation, information retrieval, optimisation. These levels of process abstraction provide process hiding at each level.

3.1.2. Composition of Processes

The way in which processes at one level of abstraction are composed of processes at the adjacent lower abstraction level is called *composition*. This composition of processes is described by a specification of the possibilities for *information exchange* between processes (*static view* on the composition; for an example, see Figure 7 below), and a specification of *task control knowledge* used to control processes and information exchange (*dynamic view* on the composition).

Information exchange

Information exchange defines which types of information can be transferred between components and the information links by which this can be achieved. Within each of the components private information links are defined to transfer information from one component to another. In addition, mediating links are defined to transfer information from the input interfaces of encompassing components to the input interfaces of the internal components, and to transfer information from the output interfaces of the internal components to the output interface of the encompassing components.

Task control knowledge

Components may be activated sequentially or they may be continually capable of processing new input as soon as it arrives (awake). The same holds for information links: information links may be explicitly activated or they may be awake. Task control knowledge specifies under which conditions which components and information links are active (or made awake). Evaluation criteria, expressed in terms of the evaluation of the results (success or failure), provide a means to

further guide processing. Task control knowledge specifies when and how processes are to be performed and evaluated. Goals of a process are defined by the task control foci together with the extent to which they are to be pursued. Evaluation of the success or failure of a process's performance is specified by evaluation criteria together with an extent. Processes may be performed in sequence or in parallel, some may be continually "awake", (e.g., able to react to new input as soon as it arrives), others may need to be activated explicitly.

3.2. Knowledge Composition

Knowledge composition identifies the knowledge structures at different levels of (knowledge) abstraction, and describes how a knowledge structure can be defined in terms of lower level knowledge structures. The knowledge abstraction levels may correspond to the process abstraction levels, but this is often not the case.

3.2.1. Identification of Knowledge Structures at Different Abstraction Levels

The two main structures used as building blocks to model knowledge are: *information types* and *knowledge bases*. Knowledge structures can be identified and described at different levels of abstraction. At higher levels details can be hidden. An *information type* defines an ontology (lexicon, vocabulary) to describe objects or terms, their sorts, and the relations or functions that can be defined on these objects. Information types can logically be represented in order-sorted predicate logic. A *knowledge base* defines a part of the knowledge that is used in one or more of the processes. Knowledge is represented by formulae in order-sorted predicate logic, which can be normalised by a standard transformation into rules.

3.2.2. Composition of Knowledge Structures

Information types can be composed of more specific information types, following the principle of compositionality discussed above. Similarly, knowledge bases can be composed of more specific knowledge bases. The compositional structure is based on the different levels of knowledge abstraction distinguished, and results in information and knowledge hiding.

3.3. Relation between Process and Knowledge Composition

Each process in a process composition uses knowledge structures. Which knowledge structures are used for which processes is defined by the relation between process composition and knowledge composition.

3.4 Generic Models and Reuse

Instead of designing each and every new agent application from scratch, an existing generic model can be used. Generic models can be distinguished for specific types of agents, of specific agent tasks and of specific types of multi-agent organisation. The use of a generic model in an application structures the design process: the acquisition of a conceptual model for the application is based on the generic structures in the model. A model can be generic in two senses:

- generic with respect to the *processes or tasks*
- generic with respect to the *knowledge structures*

Genericity with respect to processes or tasks refers to the level of process abstraction: a generic model abstracts from processes at lower levels. A more specific model with respect to processes is a model within which a number of more specific processes, at a lower level of process abstraction are distinguished. This type of refinement is called *specialisation*. Genericity with respect to knowledge refers to levels of knowledge abstraction: a generic model abstracts from more specific knowledge structures. Refinement of a model with respect to the knowledge in specific domains of application, is refinement in which knowledge at a lower level of knowledge abstraction is explicitly included. This type of refinement is called *instantiation*.

Reuse as such, reduces the time, expertise and effort needed to design and maintain system designs. Which components, links and knowledge structures from the generic model are applicable in a given situation depends on the application. Whether a component can be used immediately, or whether instantiation, modification and/or specialisation is required, depends on the desired functionality. Other existing (generic) models can be used for specialisation of a model; existing knowledge structures (e.g., ontologies, thesauri) can be used for instantiation. Which models and structures are used depends on the problem description: existing models and structures are examined, rejected, modified, specialised and/or instantiated in the context of the problem at hand.

3.5 Process hiding and external observation of behaviour

The notion of process hiding gives a sharp distinction in what is visible from outside an agent, and what happens internally. At the abstraction level of the whole agent no reference can be made to the internal concepts. Only the actions and observation results are specified at this process abstraction level. This corresponds to what an human observer can observe from the behaviour (from the black box perspective): the ‘stimuli’, and the ‘response behaviour’. For example, the term ‘the animal shows a delayed response’ refers to this process abstraction level, and leaves open by which internal processes the animal achieves its behaviour.

Descriptions that refer to processes that are assumed to take place within the agent are at one process abstraction level lower. A (theoretically debatable) phrase such as ‘the animal shows to have memory’ refers to this lower process abstraction level, and entails an assumption on how things are arranged internally.

4 An Agent Model for Purely Reactive Behaviour

An agent is *purely reactive* if it immediately responds to stimuli from its environment. Such agents are also called behaviour-based or situated agents; e.g., see [33]. These agents make their decisions based on a very limited amount of information, and simple situation-action rules. The stimuli can either consist of perceived changes in the external world or received communications from other agents. Changes in the external world are perceived by the agent by observation. The response behaviour of the agent affects its environment. Several architectures have been developed for reactive agents, see [1], [12], [28], [29]. In [33] an extensive overview of these architectures and the motivations behind them can be found.

Viewed from a Software Engineering perspective, modelling behaviour by a functional relation between input and output provides a system that can be described as a (mathematical) *function*

$$F : \text{Input_states} \rightarrow \text{Output_states}$$

of the set of possible input states to the set of possible output states. Such a system is transparent and predictable. For the same input always the same behaviour is repeated: its behaviour does not depend on earlier processes; for example, no information on previous experiences is stored in memory so that it can be remembered and affect behaviour. Well-known traditional programming methods are based on this paradigm; for example, program specification and refinement based on preconditions and postconditions as developed in, e.g., [18].

4.1 Process Composition

For the design and implementation of the different models the compositional development method for multi-agent systems DESIRE has been used; see [5] for more details. A generic agent model for purely reactive behaviour developed earlier within the DESIRE environment (and applied in chemical process control) was reused. The (rather simple) agent system in this model consists of two components, one for the agent (of type A) and one for the external world with which it interacts (see Figure 2).

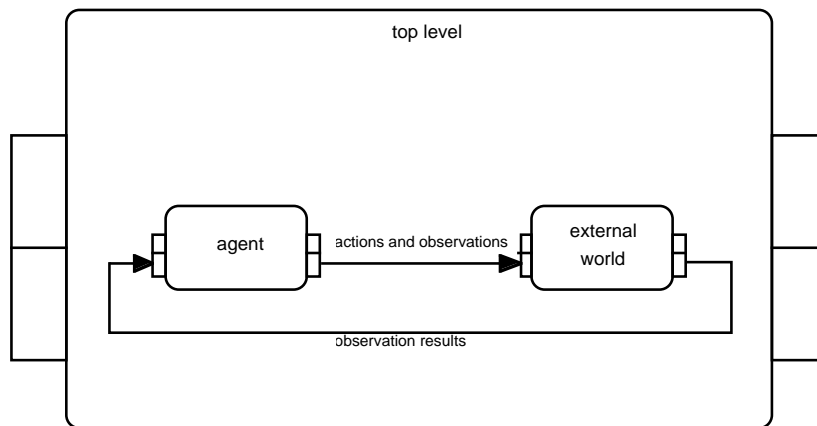


Figure 2 A generic agent model for purely reactive behaviour

In the current domain, the observation information that plays a role describes that certain *objects* (cup1, cup2, food, screen, self) are at certain *positions* (i.e., p0, p1, p2). This is modelled by two sorts OBJECT and POSITION and a relation at position between these two sorts. Moreover, two types of *actions* can be distinguished: eat and goto some position. The latter type of actions is parameterized by positions; this can be modelled by a function goto from POSITION to ACTION. E.g., goto(p1) is the action to go to position p1. The action eat that is specified assumes that if the animal is at the position of the food, it can have the food: if a cup is covering the food, as part of the action eat the animal can throw the cup aside to get the food. Variables over a sort, e.g., POSITION, are denoted by a string, e.g., P, followed by : POSITION, i.e., P : POSITION is a variable over the sort POSITION. The unary relation to_be_performed is used to express the information that the agent has decided to *perform an action*; for example, to_be_performed(goto(p1)) expresses that the agent has decided to go to position p1. The relation observation_result is used to express the information that certain information has been acquired by *observation*; e.g., observation_result(at_position(food, p1), pos) expresses that the agent has observed that there is food at position p1, whereas the statement observation_result(at_position(food, p1), neg) expresses that the agent has observed that there is *no* food at position p1.

4.2 Knowledge composition

In this section, first the information types to specify the knowledge are defined, and next, using these information types the domain knowledge is specified to obtain the required functionality.

4.2.1 Information types

Information types provide the ontology with which knowledge used in the processes can be expressed. Information types provide the *ontology* (or lexicon, or vocabulary) for the languages used in one (or more) components, knowledge bases and information links. In information type specifications the following concepts are used: sorts, objects, relations, functions, and meta-descriptions. Furthermore, information types can be composed from other information types.

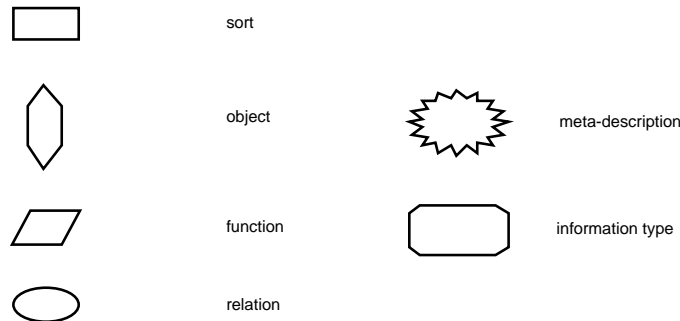


Figure 3 Information types: Legend

Each concept is represented graphically, see Figure 3. The icon for information types is used as depicted in Figure 4 containing only the name of an information type, but also as depicted in Figure 5 containing the sorts, object, functions, relations, and meta-descriptions used in the design of that information type.

All information types are (either directly or indirectly) composed of (1) generic information types and (2) domain specific information types. Generic information types are fully specified within the generic model. Domain specific information types are defined by references; they are instantiated for a specific domain of application. For example, the information type action info is composed of the generic information type actions to be performed and the domain specific information type domain actions.

The generic information type actions to be performed enables the agent to reason about actions; see Figure 4.

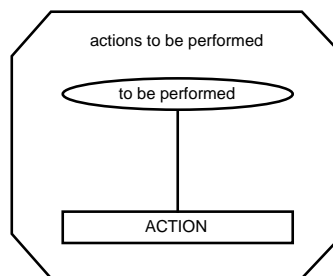


Figure 4 Generic information type: actions to be performed

The specific actions for a given domain of application are not specified within the generic model, but as part of the domain knowledge structures (see Figure 5).

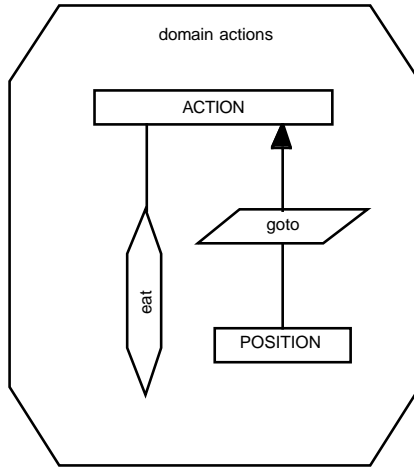


Figure 5 The information type domain actions

In a similar manner the information type observation result info is composed of the generic information types observation results and truth indication, and the domain specific information type domain meta-info. The generic information type observation results (see Figure 6) enables the agent to express statements on observation results. In the applications the observations are assumed *passive*: without taking any initiative, the agent automatically receives the observation results from the external world. The generic information type truth indication, which defines the two signs pos and neg in sort SIGN, is also used in the information type observation results.

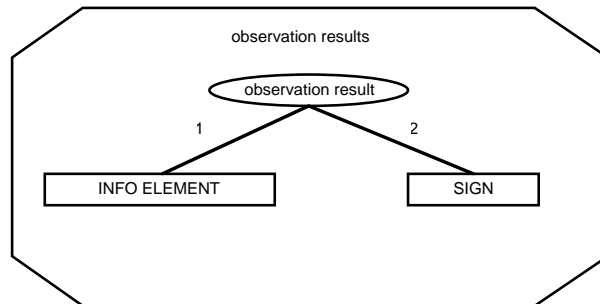


Figure 6 Generic information type observation results

By these information types it is possible to make statements about the process of observation of the state of the world in contrast to statements about the world. It is possible for the statement ‘my observation result is that food is present at p2’ to be true, while in the world state ‘food is present at p2’ is false. For example, a sensor could give the wrong information. Similarly, it could also be the other way around: the statement ‘food is present at p2’ can be true in the world state, while the statement ‘my observation result is that food is present at p2’ is false, simply because it was not observable, or at least I did not observe it. Note also that ‘I did not observe that food is present at p2’ means something different from ‘I observed that no food is present at p2’. A statement of the form ‘my observation result is that food is present at p2’ cannot be expressed using the information type that describes the world. For example, the statement ‘food is present at p2’ is not adequate. Therefore, another structure is necessary to express statements about statements. Statements about statements

are called *meta-level* statements. The statements that form the subjects of such meta-level statements are called *object level* statements.

4.2.2 Domain knowledge

Assuming that food is offered at at most one position (for example, position p2), the stimulus-response behaviour of agent model A expresses that if the agent observes that there is food at any position and that no screen at position p0 separates the agent from this position, then it goes to this position. This knowledge has been modelled in the following form:

```

if      observation_result(at_position(food, P:POSITION), pos)
and    observation_result(at_position(screen, p0), neg)
and    observation_result(at_position(self, P:POSITION), neg)
then   to_be_performed(goto(P:POSITION))

if      observation_result(at_position(self, P:POSITION), pos)
and    observation_result(at_position(food, P:POSITION), pos)
then   to_be_performed(eat)
  
```

4.3 The Behaviour of the Purely Reactive Agent

The requirement imposed on agent A was that it shows the same behaviour for Situations 1 and 3 in the problem description: do nothing. Moreover, in Situation 2 the agent is required to go to the position of the food. The agent of type A indeed shows behaviour as expressed by the requirements. For a more detailed account of the behaviour, see Appendix A.

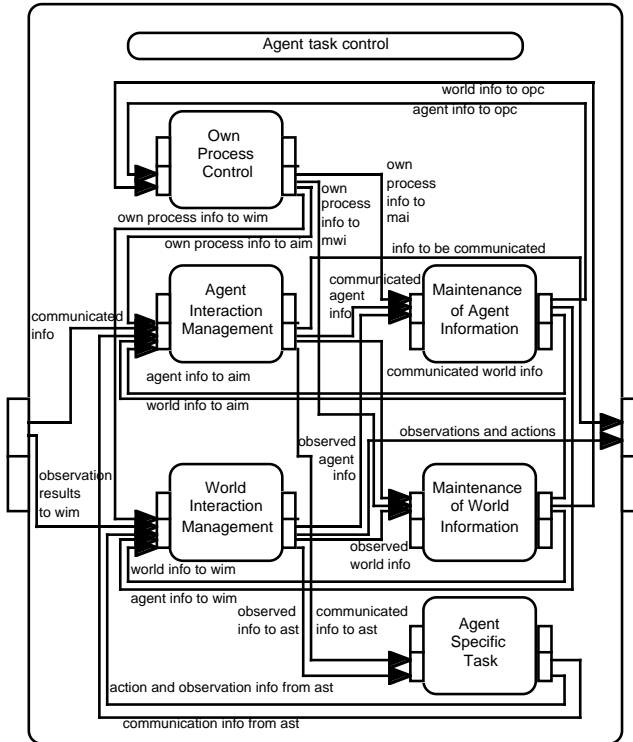


Figure 7 A generic agent model for deliberate reactive, pro-active and social behaviour

5 Agent Models for Delayed Response and Pro-active Behaviour

As opposed to behaviour defined by a purely functional dependency between input and output, as modelled in Section 4, an agent's behaviour often takes previous processes in which it was involved into account. For example, in delayed response behaviour, previous observations may have led to internal storage of information in a *memory* so that the same input pattern of stimuli can lead to different behaviour a next time it is encountered; the agent may be able to deliberate about it. Again viewed from a Software Engineering perspective, this makes that agents do not fit strictly in the paradigm based on a functional relation: to keep the functional relation, not only the actual input, but also the complete history of input should be taken into account, or the internal information in memory should be considered to be additional input.

To design an agent model that will show delayed response behaviour, the internal structure of the agent is made more complex. Within the agent a component maintenance of world information to maintain the observation results as beliefs (a memory) is distinguished from a component world interaction management that manages the interaction with the world. Moreover, the agent can generate its own goals in order to show pro-active behaviour, if a component own process control is added. If the agent has to show social behaviour, components are added to manage communication (agent interaction management) and to maintain beliefs on other agents (maintenance of agent information). The Generic Agent Model GAM depicted in Figure 7 (see also [8]) is composed of all of these components.

5.1 An Agent Model with Delayed Response Behaviour

For an agent with *delayed response behaviour* (type B), the component maintenance of world information is used, in addition to the component world interaction management. The only task performed by the component maintenance of world information is storage of observation information. No further knowledge is used within this component.

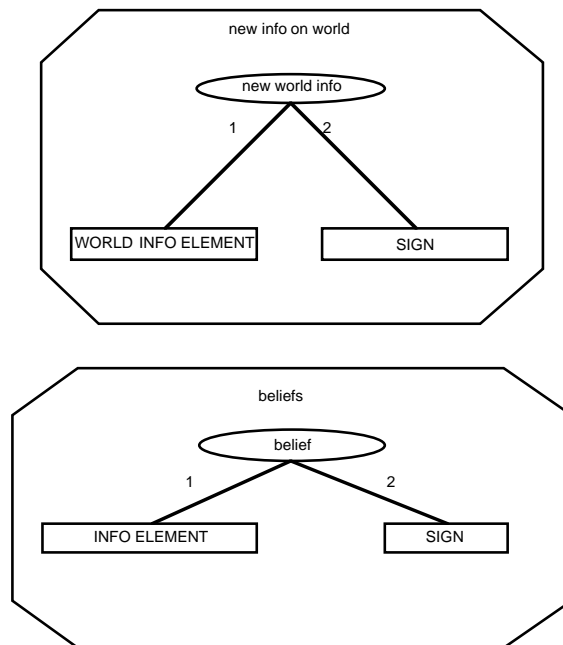


Figure 8 The information types new world info and belief info

The part of the knowledge of the component world interaction management that determines the actions is a variant of the knowledge used in agent model A. An additional part determines that the world information that was acquired by observation has *to be maintained*, expressed by the relation `new_world_info`.

```

if      observation_result(I:INFO_ELEMENT, S:SIGN)
then    new_world_info(I:INFO_ELEMENT, S:SIGN)

if      belief(at_position(food, P:POSITION), pos)
and     belief(at_position(screen, p0), neg)
and     belief(at_position(self, P:POSITION), neg)
then    to_be_performed(goto(P:POSITION))

if      belief(at_position(food, P:POSITION), pos)
and     belief(at_position(self, P:POSITION), pos)
then    to_be_performed(eat)

```

An essential difference with the knowledge in agent model A is that in the knowledge above the relation `observation result` is replaced by the relation `belief`. Not only can information from direct observation be used, but also information retrieved from memory: all input information gets the status of belief, in contrast to observation. The behaviour of this agent model in comparison to the behaviours of the other models is discussed in Section 8.

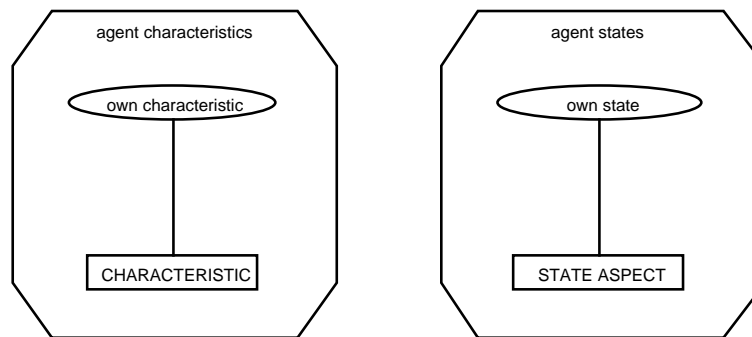


Figure 9 Composition and generic information types for agent properties

5.2 An Agent Model with Pro-active Behaviour

The third agent model to be discussed is a model for a *pro-active agent* (type C). A pro-active agent does not simply respond to stimuli, neither immediately, nor delayed. In addition to the observation information, its so-called *motivational attitudes* play an important role (e.g., see [42]) in determining its actions. These motivational attitudes can be based on the agent's own character (for example, an agent's character may be that it always wants to eat, or that it is totally apathetic),

but also on specific aspects of the agent's own state, such as being hungry, or being depressed. To determine the motivational attitudes of the agent, the component own process control is used; additional knowledge structures are introduced for this new component.

In addition to the existing information types of agent model B, information types are required for knowledge on own process control; these information types express information on (see Figure 9):

- the agent's beliefs
- aspects of the agent's own state, such as being hungry, or being depressed, and specific characteristics of the agent, such as always eager to eat, or totally apathetic
- the agent's goals, such as be fed, just hang around, find food, or get food inside.

Information on the agent's *own state* can be expressed using the unary relation *own_state*; for example, the statement *own_state(hungry)* expresses that the agent is hungry. The agent's *own characteristics* can be expressed using the unary relation *own_characteristic*; e.g., the statement *own_characteristic(totally_apathetic)* expresses the information that the agent is totally apathetic. The *goal* that has been selected by the agent is expressed using the unary relation *selected_goal*. The knowledge to be used in the component own process control models (see Figure 10):

- an agent that is always eager to eat, always selects the goal be fed
- any not apathetic agent that is hungry or depressed selects the goal be fed
- a totally apathetic agent never selects a goal
- an agent which has be fed as a goal, selects the goal get food inside if it has a belief that food is present at a specific position; in the other case it selects the goal find food

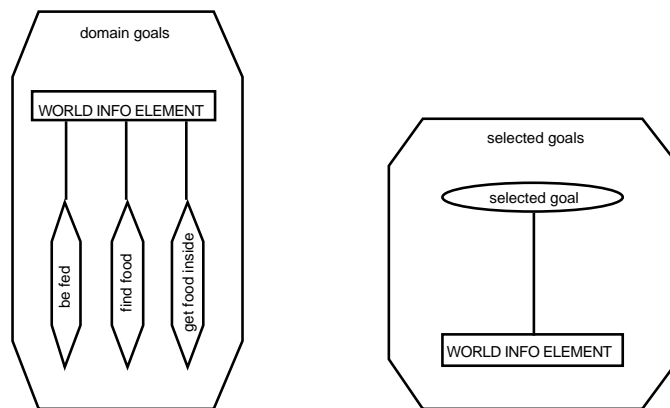


Figure 10 Generic and domain-specific information types for the agent's goals

The knowledge used in own process control knowledge can be formulated in a concise form as follows:

```

if      own_characteristic(always_eager_to_eat)
then    selected_goal(be_fed)

if      own_state(hungry)
and     not own_characteristic(totally_apathetic)
then    selected_goal(be_fed)

```

```

if      own_state(depressed)
and    not own_characteristic(totally_apathetic)
then    selected_goal(be_fed)

if      selected_goal(be_fed)
and    belief(at_position(food, P:POSITION), pos)
then    selected_goal(get_food_inside)

if      selected_goal(be_fed)
and    not belief(at_position(food, p1), pos)
and    not belief(at_position(food, p2), pos)
then    selected_goal(find_food)

```

Depending on the type of agent modelled, some facts can be added to this knowledge base, for example in the agent of type C:

```
own_characteristic(always_eager_to_eat)
```

(alternatively, for example, `own_state(hungry)`, `not own_characteristic(totally_apathetic)` could be specified, or `own_characteristic(totally_apathetic)`).

Depending on the agent characteristics specified, the agent determines one or more goals. To actually show certain pro-active behaviour, also suitable knowledge has to be specified on which actions are to be performed for a given goal. Moreover, not only actions can be performed in a pro-active manner, but also observations. In particular, if the animal visits a position for which it is not known yet whether there is food, it can decide to explore the position, e.g., by putting the cup a bit aside and/or activating its smell sensor (sniffing). To model active observations, the information type `observation info` is used, defining the relation `to_be_observed` on sort `WORLD_INFO_ELEMENT`. For example, the atom

```
to_be_observed(at_position(food, p1))
```

means that the agent has decided to observe whether food is present at position `p1`. Knowledge to initiate actions and observations is modelled in the component world interaction management. To determine actions related to the goal `get food inside`, two possible cases are considered:

- the agent believes that food is present at its own position; in this case it simply can start eating
- the agent believes that no food is present at its own position, but it believes that food is present at another position; in this case the agent can go to such a position (and if it arrives there it can start eating, according to the previous item)

This knowledge is expressed in a concise form as follows:

```

if      selected_goal(get_food_inside)
and    belief(at_position(food, P:POSITION), pos)
and    belief(at_position(self, P:POSITION), pos)
then    to_be_performed(eat)

```



```

if      selected_goal(get_food_inside)
and    belief(at_position(self, P1:POSITION), pos)
and    belief(at_position(food, P1:POSITION), neg)
and    belief(at_position(food, P2:POSITION), pos)
and    belief(at_position(screen, p0), neg)
then   to_be_performed(goto(P2:POSITION))

```

The goal get food inside assumes that the agent already knows at least one position where food is present. If this is not the case, the goal find food may be selected by the agent. To determine the actions or observations for the goal find food, the following cases are considered:

- the agent does not know whether food is present at its own position; then the observation to explore the own position is initiated (which determines whether food is present at the agent's own position)
- the agent believes that no food is present at its own position, and it does not know whether food is present at positions p1 and p2; in this case the action go to p1 is selected (and if it arrives there it can start exploring it, according to the previous item)
- the agent believes that no food is present at its own position and at position p1; it does not know whether food is present at p2; in this case the agent goto p2 is selected (and if it arrives there it can start exploring the position, according to the first item)

This knowledge is expressed in a concise form as follows:

```

if      selected_goal(find_food)
and    belief(at_position(self, P:POSITION), pos)
and    not belief(at_position(food, P:POSITION), pos)
and    not belief(at_position(food, P:POSITION), neg)
then   to_be_observed(at_position(food, P:POSITION))

if      selected_goal(find_food)
and    belief(at_position(self, P:POSITION), pos)
and    belief(at_position(food, P:POSITION), neg)
and    not belief(at_position(food, p1), neg)
and    not belief(at_position(food, p1), pos)
and    not belief(at_position(food, p2), neg)
and    not belief(at_position(food, p2), pos)
then   to_be_performed(goto(p1))

if      selected_goal(find_food)
and    belief(at_position(self, P:POSITION), pos)
and    belief(at_position(food, P:POSITION), neg)
and    belief(at_position(food, p1), neg)
and    not belief(at_position(food, p2), neg)
and    not belief(at_position(food, p2), pos)
then   to_be_performed(goto(p2))

```

For more details of the behaviour of the agent types B and C, see Appendices B and C.

6 An Agent Model with Social Behaviour

To obtain *social behaviour* (an agent model of type D), also the components agent interaction management and maintenance of agent information are used in the model.

A social agent is able to receive incoming communication and to generate outgoing communication. The generic information types for communication are depicted in Figure 11.

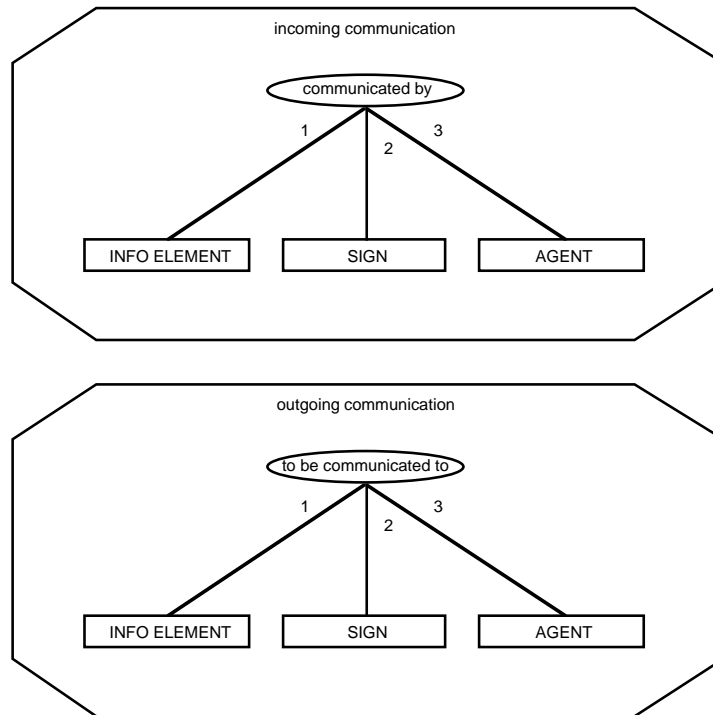


Figure 11 Generic information types on communication

By these information types it is possible to make statements about the process of communication (in contrast to, for example, statements about the world). It is possible for the statement ‘I was told that the pressure is high’ to be true, while in the world state ‘the pressure is high’ is false: the other agent may simply not tell the truth. It could also be the other way around: the statement ‘the pressure is high’ could be true in the world state, while the statement ‘somebody told me that the pressure is high’ is false, simply because nobody told me. Note also that ‘he did not tell me that the pressure is high’ does not mean the same as ‘he told me that the pressure is not high’. Similar to statements about observation, statements about communication are meta-level statements.

The information communicated to the agent may be used to extend or update an agent’s beliefs both on the world or on other agents. The information received is analysed, selected and prepared to be stored as information either on the world or on other agents; the related information types are depicted in Figure 12.

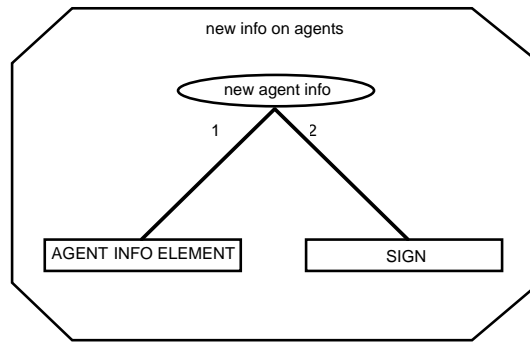


Figure 12 Generic information types: maintenance on agents

In the component agent interaction management knowledge is specified that identifies new communicated knowledge about other agents:

```

if      communicated_by(l_want_food, pos, A:AGENT)
then    new_agent_info(wants_food(A:AGENT))
  
```

Here, the statement `communicated_by(l_want_food, pos, A:AGENT)` expresses that the information `l_want_food` *has been communicated* (positively) by the agent `A:AGENT`. This *new agent information* (expressed using the relation `new_agent_info`) is stored in the component maintenance of agent information: the knowledge used in maintenance of agent information specifies the hierarchy between different animals, and whether another animal that is present wants the food. For example, if `an1` is an animal which is present and is *higher in the hierarchy*, then this can be specified within the knowledge base used in maintenance of agent information of the agent self as `higher_than(an1, self)`. It is also possible to model this information in a dynamic form, as an outcome of earlier experiences (fights). If the other animal wants the food, within the component maintenance of world information of the agent self it is derived that the food is protected, using the knowledge

```

if      wants_food(A:AGENT)
and    higher_than(A:AGENT, self)
then    food_protected
  
```

Within the knowledge elements used in the component world interaction management an additional condition **not** `belief(food_protected, pos)` is specified. For more details of the behaviour of agent type D, see Appendix D.

7 An Agent Model with Adaptive Behaviour

The agent models presented in the previous sections showed different types of behaviour, but they are not able to adapt their behaviour. In this section an agent model for adaptive animal behaviour is presented. To be able to learn from experiences it is important that for a given situation more than one option for an action is generated. By making decisions about the action that is selected from the options the animal can experiment with its behaviour, and, after evaluation, adapt its decision making process.

7.1 Process composition of the adaptive agent model

To be able to address and evaluate the action selection process explicitly, in this agent model the following more specialised processes are distinguished:

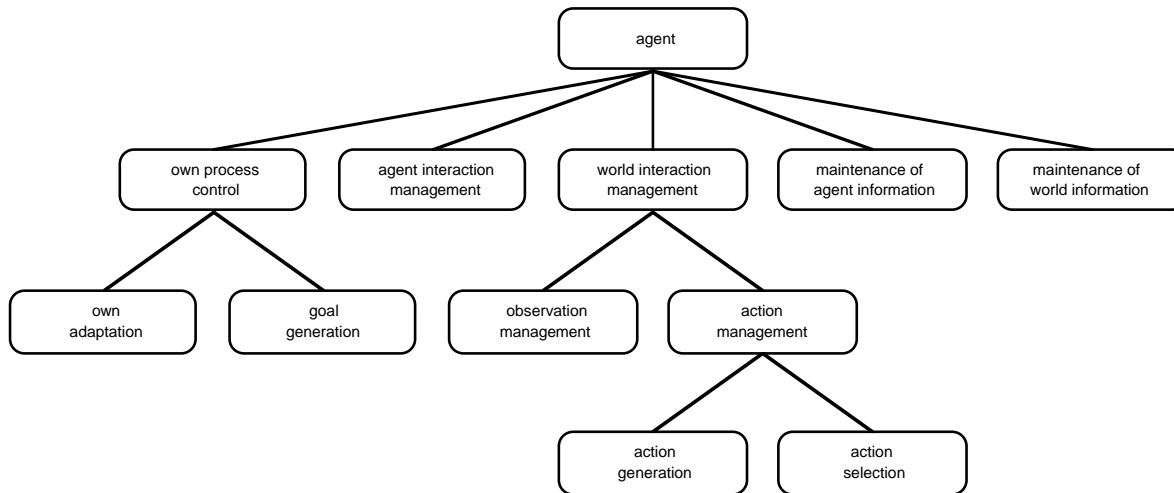


Figure 13 Processes and their abstraction levels for the adaptive agent model

- *action generation*

This process generates a number of alternative behaviours for a given (observed or believed) situation.

- *action selection*

This process selects one option from the set of alternative behaviours, using selection knowledge based on earlier experiences.

- *own adaptation*

This process evaluates the selected action upon its successfulness, and adapts the knowledge used to make a selection. In particular, if the action was successful, in the future it will be chosen more often (under comparable circumstances), and the other options less often. If the action was not successful, it will be chosen less often.

The first two of these processes are modelled as a specialisation of world interaction management, whereas the latter process is modelled as a subprocess of own process control. The processes and their four abstraction levels are shown in Figure 13.

The process composition relations are straightforward. The relevance ordering relations are transferred from the component own adaptation via the input interface of own process control to world interaction management and within this component to action selection. Moreover, the actions generated by action generation are transferred to action selection as well.

7.2 Knowledge composition of the adaptive agent model

In this section the information types and knowledge bases for the adaptive agent model are discussed.

7.2.1 Information types

For the adaptive agent, information types are required to specify which options for actions are generated in a given situation, how the decision is made to choose between the options, and how this choice is influenced by experiences. The options for actions to achieve a given goal are expressed by the generic information type action alternatives; see Figure 14.

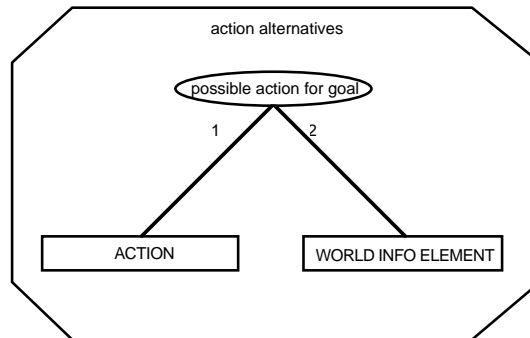


Figure 14 The information type action alternatives

The selection process first determines which actions are to be ignored; the remaining actions are considered appropriate: the generic information type action selection info; see Figure 15.

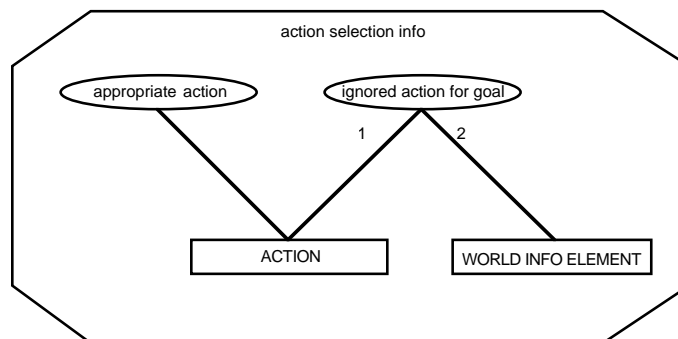


Figure 15 The information type action selection info

Within this selection process the domain specific information types food relevance info and action relevance are used; see Figure 16. The agent's experiences are formalised by a (dynamic) linear ordering of the colours: the higher a colour in this ordering, the more successful experiences the agent has in finding food at positions of that colour. This linear ordering is represented by

`has_higher_food_relevance(C1:COLOUR, C2:COLOUR)`

which means that colour C1:COLOUR is higher than colour C2:COLOUR in the linear ordering. The linear ordering is maintained and updated in the component own adaptation within own process control. It is only used in the component action selection.

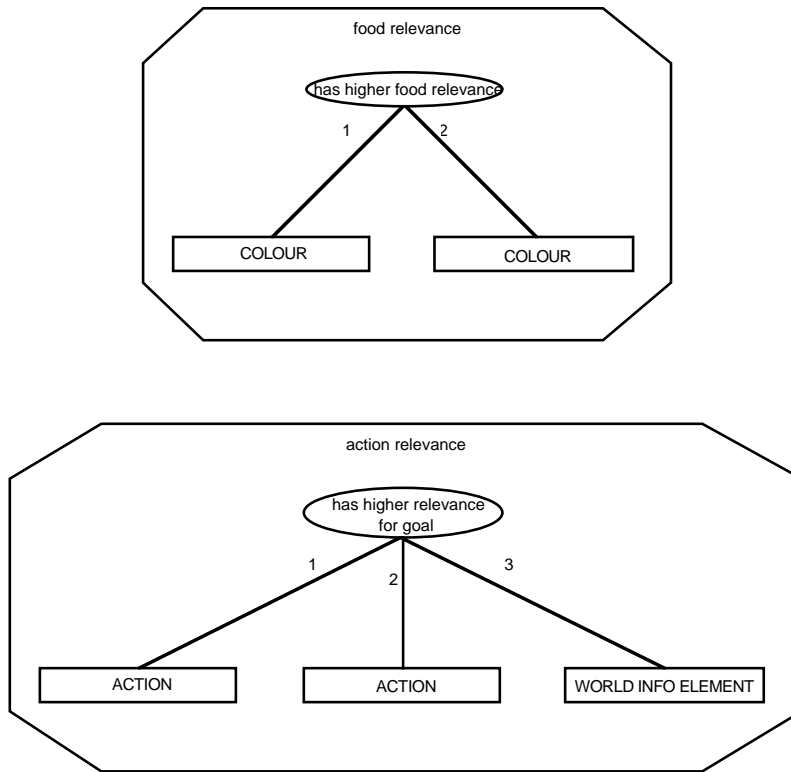


Figure 16 The information types food relevance and action relevance

The update of the relevance information makes use of the generic information type reinforcement info (see Figure 17), and the domain specific information type food precedence info (see Figure 18) are used. The food precedence relation expresses the immediate neighbours in the linear ordering on food relevance.

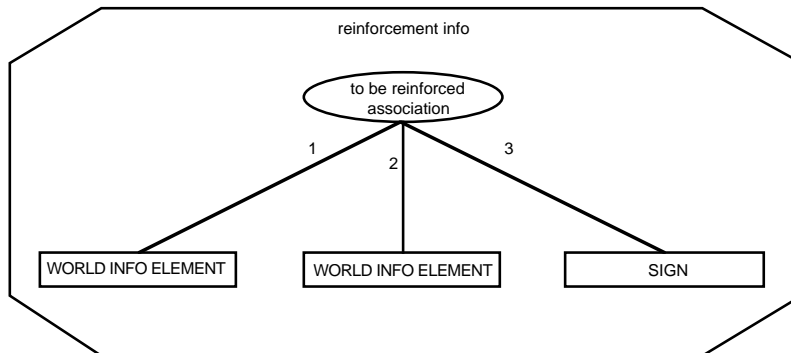


Figure 17 The information type reinforcement info

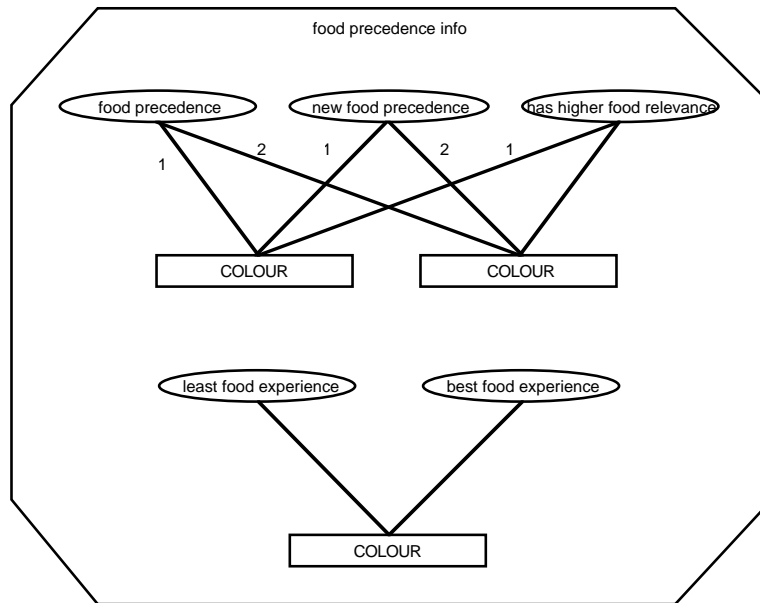


Figure 18 The information type food precedence info

Besides the information types introduced above, the domain information is extended by the sort COLOUR and the relation is_colour_at_position between COLOUR and POSITION. For more interesting experiments, also the number of positions was extended.

7.2.2 Knowledge

Knowledge used within observation management

The knowledge used within observation management is simple. For the goal find food, if it is unknown whether food is present at the own position, the observation to explore this position is always selected:

```

if      selected_goal(find_food)
and    belief(at_position(self, P1:POSITION), pos)
and    not belief(at_position(food, P1:POSITION), neg)
and    not belief(at_position(food, P1:POSITION), pos)
then   to_be_observed(at_position(food, P1:POSITION))

```

Knowledge used within action generation

The knowledge used within action generation is kept simple. For the goal find food

(1) if it is known that there is no food at the own position, all actions that are generated, are those of the form goto(P:POSITION) for the positions P:POSITION for which the agent has no belief on whether there is food present, and

(2) if it is known that food is present at the own position, the action eat is generated.

```

if      selected_goal(find_food)
and    belief(at_position(self, P1:POSITION), pos)
and    belief(at_position(food, P1:POSITION), neg)
and    not belief(at_position(food, P2:POSITION), neg)
and    not belief(at_position(food, P2:POSITION), pos)
then   possible_action_for_goal(goto(P2:POSITION), find_food)

```

```

if      selected_goal(get_food_inside)
and    belief(at_position(self, P:POSITION), pos)
and    belief(at_position(food, P:POSITION), pos)
then   possible_action_for_goal(eat, get_food_inside)

```

Knowledge used within action selection

For the action eat, the generated action is always selected:

```

if      selected_goal(find_food)
and    possible_action_for_goal(explore_position, find_food)
then   appropriate_action(explore_position)

if      selected_goal(get_food_inside)
and    possible_action_for_goal(eat, get_food_inside)
then   appropriate_action(eat)

```

For the other case the knowledge used within action selection is based on what the agent has experienced. From the colour relevancy ordering relations, within action selection action relevance ordering relations (relative for a given goal) are derived:

```

if      belief(is_colour_at_position(C1:COLOUR, P1:POSITION), pos)
and    belief(is_colour_at_position(C2:COLOUR, P2:POSITION), pos)
and    has_higher_food_relevance(C1:COLOUR, C2:COLOUR)
then   has_higher_relevance_for_goal(goto(P1:POSITION), goto(P2:POSITION), find_food))

```

Using this total ordering of relevancy of actions the decision is made to ignore all actions for which at least two more relevant actions exist:

```

if      possible_action_for_goal(A1:ACTION, G:WORLD_INFO_ELEMENT)
and    possible_action_for_goal(A2:ACTION, G:WORLD_INFO_ELEMENT)
and    possible_action_for_goal(A3:ACTION, G:WORLD_INFO_ELEMENT)
and    has_higher_relevance_for_goal(A1:ACTION, A2:ACTION, G:WORLD_INFO_ELEMENT))
and    has_higher_relevance_for_goal(A2:ACTION, A3:ACTION, G:WORLD_INFO_ELEMENT))
then   ignored_action_for_goal(A3:ACTION, G:WORLD_INFO_ELEMENT)

```

Finally, all actions relevant for the selected goal, which were not ignored, are derived as appropriate:

```

if      selected_goal(G:WORLD_INFO_ELEMENT)
and    possible_action_for_goal(A:ACTION, G:WORLD_INFO_ELEMENT)
and    not ignored_action_for_goal(A:ACTION, G:WORLD_INFO_ELEMENT)
then   appropriate_action(A:ACTION)

```

From these appropriate actions only one is derived, at random.

The action selection approach discussed here is just one possible approach. Another, more simple approach would be to just take the highest action in the relevance ordering. However, this more simple decision model allows the agent less space for experimentation, and implies slower adaptation in certain circumstances. Also numerical approaches are possible; for an example, see Section 7.3 below.

Knowledge used within own adaptation

Within the component own adaptation the linear order of relevancy of colours for food is maintained and updated, on the basis of experiences. First experiences are evaluated: if there was food found at a position with a certain colour, a positive reinforcement has to be implemented for this colour, otherwise a negative reinforcement:

```
if      observation_result(at_position(food, P:POSITION), S:SIGN)
and    belief(is_colour_at_position(C:COLOUR, P:POSITION), pos)
then   to_be_reinforced_association(is_colour_at_position(C:COLOUR, P:POSITION),
                                   at_position(food, P:POSITION), S:SIGN)
```

The positive reinforcement is modelled by moving the colour upwards in the linear ordering one place, as long as it is not the highest colour. If it already was the highest colour, then nothing changes. If it was second highest, then it becomes the highest. The relation `food_precedence(C1:COLOUR, C2:COLOUR)` represents the immediate succession in the linear ordering.

```
if      to_be_reinforced_association(is_colour_at_position(C:COLOUR, P:POSITION),
                                   at_position(food, P:POSITION), pos)
and    food_precedence(C0:COLOUR, C1:COLOUR)
and    food_precedence(C1:COLOUR, C:COLOUR)
and    food_precedence(C:COLOUR, C2:COLOUR)
then   new_food_precedence(C0:COLOUR, C:COLOUR)
and    new_food_precedence(C:COLOUR, C1:COLOUR)
and    new_food_precedence(C1:COLOUR, C2:COLOUR)

if      to_be_reinforced_association(is_colour_at_position(C:COLOUR, P:POSITION),
                                   at_position(food, P:POSITION), pos)
and    best_food_experience(C0:COLOUR)
and    food_precedence(C0:COLOUR, C:COLOUR)
and    food_precedence(C:COLOUR, C1:COLOUR)
then   new_best_food_experience(C:COLOUR)
and    new_food_precedence(C:COLOUR, C0:COLOUR)
and    new_food_precedence(C0:COLOUR, C1:COLOUR)
```

If the colour was the lowest, the second lowest becomes the lowest:

```
if      to_be_reinforced_association(is_colour_at_position(C:COLOUR, P:POSITION),
                                   at_position(food, P:POSITION), pos)
and    least_food_experience(C:COLOUR)
and    food_precedence(C2:COLOUR, C:COLOUR)
and    food_precedence(C1:COLOUR, C2:COLOUR)
then   new_least_food_experience(C2:COLOUR)
and    new_food_precedence(C:COLOUR, C2:COLOUR)
and    new_food_precedence(C1:COLOUR, C:COLOUR)
```

For negative reinforcement, the opposite of the above takes place. The colour is moved downwards in the linear ordering, as long as it is not the lowest colour. If it already was the lowest colour, then nothing changes. If it was second lowest, then it becomes the lowest. If the colour was the highest, the second highest becomes the highest:

If the colour was the lowest, the second lowest becomes the lowest:

```

if      to_be_reinforced_association(is_colour_at_position(C:COLOUR, P:POSITION),
                                      at_position(food, P:POSITION), neg)
and    best_food_experience(C:COLOUR)
and    food_precedence(C:COLOUR, C1:COLOUR)
and    food_precedence(C1:COLOUR, C2:COLOUR)
then   new_least_food_experience(C1:COLOUR)
and    new_food_precedence(C1:COLOUR, C:COLOUR)
and    new_food_precedence(C:COLOUR, C2:COLOUR)

if      to_be_reinforced_association(is_colour_at_position(C:COLOUR, P:POSITION),
                                      at_position(food, P:POSITION), neg)
and    food_precedence(C1:COLOUR, C2:COLOUR)
and    food_precedence(C:COLOUR, C1:COLOUR)
and    food_precedence(C0:COLOUR, C:COLOUR)
then   new_food_precedence(C:COLOUR, C2:COLOUR)
and    new_food_precedence(C1:COLOUR, C:COLOUR)
and    new_food_precedence(C0:COLOUR, C1:COLOUR)

if      to_be_reinforced_association(is_colour_at_position(C:COLOUR, P:POSITION),
                                      at_position(food, P:POSITION), neg)
and    least_food_experience(C1:COLOUR)
and    food_precedence(C:COLOUR, C1:COLOUR)
and    food_precedence(C0:COLOUR, C:COLOUR)
then   new_least_food_experience(C:COLOUR)
and    new_food_precedence(C1:COLOUR, C:COLOUR)
and    new_food_precedence(C0:COLOUR, C1:COLOUR)

```

After updating the precedence relations by the new ones, by taking the transitive closure a total ordering is derived:

```

if      food_precedence(C1:COLOUR, C2:COLOUR)
then    has_higher_food_relevance(C1:COLOUR, C2:COLOUR)

if      food_precedence(C1:COLOUR, C2:COLOUR)
and    has_higher_food_relevance(C2:COLOUR, C3:COLOUR)
then    has_higher_food_relevance(C1:COLOUR, C3:COLOUR)

```

For more details of the behaviour of agent type E, see Appendix E.

7.3 An alternative numerical approach based on weight values

An alternative approach that can be built in the same agent model makes use of numerical weight values $w_E(a)$ for actions under given environmental circumstances E. As a special case, the weight values can be normalised to overall sum 1:

$$\sum_b w_E(b) = 1$$

Within the component action selection the selection can be made by making a random choice based on the probability distribution

$$w_E(a) / \sum_b w_E(b)$$

over the actions a (in the case the overall sum is 1, the denominator can be left out).

Within the component own adaptation, the update for a successful experience for action a can be done by (here λ is a factor between 0 and 1, for example 0.9):

$$\begin{aligned}1 - w'_E(a) &= \lambda (1 - w_E(a)) \\ w'_E(b) &= \lambda w_E(b) \quad \text{for } b \neq a\end{aligned}$$

The update for an unsuccessful experience for action a can be done by, for example:

$$\begin{aligned}w'_E(a) &= \lambda w_E(a) \\ 1 - w'_E(b) &= \lambda (1 - w_E(b)) \quad \text{for } b \neq a\end{aligned}$$

These formulae guarantee that, if the sum is 1 (in this, most simple, case the weights themselves can be used as a probability distribution) it will remain 1 after updates. For example, when $\lambda = 0.9$ and

$$\begin{aligned}w_E(a_1) &= 0.3 \\ w_E(a_2) &= 0.3 \\ w_E(a_3) &= 0.4\end{aligned}$$

then after a successful experience on a_1 , the update results in:

$$\begin{aligned}w_E(a_1) &= 0.37 \\ w_E(a_2) &= 0.27 \\ w_E(a_3) &= 0.36\end{aligned}$$

8 Overview of the Behaviour of the Different Agent Models

In this section the different types of behaviour of the agent models are presented and compared.

8.1 Global differences in behaviour

The following table the global differences in behaviour of the agent models are summarised.

	<i>agent A</i>	<i>agent B</i>	<i>agent C</i>	<i>agent D</i>	<i>agent E</i>
<i>situation 1</i> (<i>no food</i>)	do nothing	do nothing	look for food at random	look for food at positions without higher competitors	look for food at places with relevant colours
<i>situation 2</i> (<i>visible food</i>)	go to food	go to food	go to food	go to food at positions without higher competitors	go to food at positions with relevant colours
<i>situation 3</i> (<i>visible food</i> <i>made invisible</i>)	do nothing	go to food	go to food	go to food at positions without higher competitors	go to food at positions with relevant colours
<i>situation 4</i> (<i>invisible food</i>)	do nothing	do nothing	look for food at random	look for food at positions without higher competitors	look for food at places with relevant colours; learn from experience

The different variants of behaviour depicted in this table indeed satisfy the requirements expressed in Section 2.

8.2 More specific traces

In the Appendices A to E for each of the agent models a more detailed trace is shown. The information shown follows the graphical interface that has been made for demonstration purposes.

First, in Appendix A a behaviour trace of agent model A is presented for Situation 3. In this trace the rows represent states (states of the world and mental states of the animal), and all steps in the process are depicted as transitions from one of the rows to the next row; for example: observation (from row 0 to 1), an event in the world (appearance of the cup, from 1 to 2), observation (making the mental model of the world state up to date by removing the food and adding the cup, from 2 to 3), an event in the world (disappearance of the screen, from 3 to 4), observation (taking out the screen of the mental model, from 4 to 5). It is shown that at each time point, the animal only has an image of the current world situation, not of the past. Therefore the animal is not successful in reaching the food.

Next, in Appendix B behaviour of agent model B is shown for the same Situation 3. Also in this trace all steps in the process are depicted as transitions from one of the rows to the next row; for example: observation (from row 0 to 1), an event in the world (appearance of the cup, from 1 to 2), observation (this time the food remains in the mental model and the cup is added, from 2 to 3), action in the world (disappearance of the screen, from 3 to 4), observation (from 4 to 5), generating an action (the action go to p2, from 5 to 6), execution of the generated action (from 6 to 7). In this case the animal maintains beliefs about the world, and therefore still has the information about the position of the food, after the food was covered. It is shown that this animal is successful in reaching the food.

In Appendix C the behaviour of agent model C is shown for Situation 4. For shortness, in this trace a more condensed presentation is used. As in the previous traces changes of the world state are represented by a transition from one row to the next row. However, the observations following changes of the world state are depicted in the same row as the new world state occurs, and also the mental steps following the observations are depicted in this same row. It is shown how not only beliefs but also goals play a role in the determination of actions.

Appendix D describes behaviour of agent model D. It is shown that the agent is not going to a position as long as a higher competitor is present there, but as soon as this other animal leaves, it is visiting that position. Note that the short phrase ‘higher competitor at p2’ actually refers to a combination of two types of information: (1) another animal is at position p2, (2) this other animal is higher than me. The first type of information is about the world, whereas the second type of information is about other agents.

Appendix E shows adaptive behaviour based on reinforcement in Situation 4. In the initial relevance ordering of colours red-green-blue, red is the highest, then green, and blue is the lowest in relevance. If nothing is known about food at the positions p1, p2 and p3, then going to any of these positions is an option. The relevance ordering of actions is just copied from the relevance ordering of colours. From the highest two, one is selected at random: p3, with a red colour. From exploring this position a negative experience results. This leads to adaptation of the colour relevance ordering: red is pushed one position down, and green pops up to the first position. On the basis of this new ordering a decision is made about the next position to visit. Only the two candidates p1, p2 remain because it is known that at p3 no food is available. Position p1 is chosen (at random): with the green colour. Also here a negative experience results. This again leads to adaptation of the relevance ordering of colours: blue and green are interchanged. At last p2 is visited (with colour blue), which leads to a positive experience. Based on this experience the relevance ordering of colours is adapted: red and blue are interchanged. At this point the relevance ordering is blue-red-green. On the basis of this a next session is started.

9 Discussion

In this discussion first the relation to literature from Biology is discussed (Section 9.1), next a comparison is made to another multi-agent modelling method (Section 9.2), and finally (Section 9.3) a number of extensions are discussed.

9.1 Motivation and relation to literature from Biology

The biological literature on animal behaviour more and more involves simulation experiments as a source of knowledge and verification; e.g., see [3], [17], [23], [30], [36]. As an example, in [17], [30], [36] a commitment to game theory is made to obtain content of the models. An example of an approach based on an individual agent perspective is [23]. Often specific mathematical techniques are adopted and directly implemented in a programming language. In accordance with this the choice the animals’ behaviours are kept simple. This may be useful for the by itself interesting study of social patterns emerging from simple individual behaviours. But, since animals may also be able to show more complex patterns of behaviour, more complex modelling techniques may be required as well. Modelling more complex agent behaviours is less adequate using the usually adopted mathematical techniques. The literature on AI and Agent Technology offers more specific methods to design and implement (also more complex) intelligent agents and agent societies on a conceptual level. One of these methods is the compositional multi-agent system design method DESIRE (cf. [5]). In this paper it is shown how (depending on the complexity of the required

behaviour) different types of animal behaviour can be modelled and simulated at a conceptual level on the basis of DESIRE. Different (variants of) reusable compositional agent models were used to model the different required behaviours. It turned out that the modification of one model into a more complex model took much less effort than would have been the case in a direct programming approach. The advantage of this approach is that the models are designed at a high conceptual level, in terms of the processes, information and knowledge that is needed, and abstracting from implementation details. Nevertheless they can be executed by the DESIRE software environment. Due to the compositional nature of DESIRE it is easy to plug in components that incorporate mathematical techniques such as game-theoretic methods, connectionist methods or other adaptive algorithms. In this sense this compositional approach can be used as an extension to each of these approaches. Besides the simulation of animal behaviour discussed in this paper, a variety of other applications have been developed using DESIRE. Some recent multi-agent applications can be found in [4] (negotiation between agents), [7] (simulation of a society of agents), [11] (project coordination), [10] (distributed work flow and agenda scheduling), and [27] (agents in brokering processes).

Simulation of animal behaviour is an interesting type of application for multi-agent systems. Both areas can benefit from a more extensive study of this type of application. The area of multi-agent systems can benefit from the more detailed analyses and distinctions that have been made for different types of animal behaviour (see the Introduction). The study of animal behaviour can benefit from software tools for agent modelling at a conceptual level that support simulation. Moreover, formal techniques in the area of verification can be used to analyse and formalise behaviour properties of animals and their logical relations, as well as relationships between internal mental functioning and externally observable behaviours; e.g., [15], [26]. These formalisations can be a basis for the development of a (formalised) theory of animal behaviour.

9.2 Comparison to another multi-agent modelling framework

Another multi-agent modelling framework is Concurrent MetateM [20]. The comparison with DESIRE focuses on the structure of agents, inter-agent communication and meta-level reasoning; for more details, see [32].

In DESIRE, the knowledge structures that are used in the knowledge bases and for the input and output interfaces of components are defined in terms of information types, in which sort hierarchies can be defined. Signatures define sets of ground atoms. An assignment of truth values *true*, *false* or *unknown* to atoms is called an information state. Every primitive component has an internal information state, and all input and output interfaces have information states. Information states evolve over time. Atoms are persistent in the sense that an atom in a certain information state is assigned to the same truth value as in the previous information state, unless its truth value has changed because of updating an information link.

Concurrent METATEM does not have information types, there is no predefined set of atoms and there are no sorts. The input and output interface of an object consists only of the names of predicates. Two valued logic is used with a closed world assumption, thus an information state is defined by the set of atoms that are true. In a DESIRE specification of a multi-agent system, the agents are (usually) subcomponents of the top-level component that represents the whole (multi-agent) system, together with one or more components that represent the rest of the environment. A component that represents an agent can be a composed component: an agent task hierarchy is mapped into a hierarchy of components. All (sub-)components (and information links) have their own time scale. In a Concurrent METATEM model, agents are modelled as objects that have no

further structure: all its tasks are modelled with one set of rules. Every object has its own time-scale.

The communication between agents in DESIRE is defined by the information links between them: communication is based on point-to-point or broadcast message passing. Communication between agents in Concurrent METATEM is done by broadcast message passing. When an object sends a message, it can be received by all other objects. On top of this, both multi-cast and point-to-point message passing can be defined.

In DESIRE, meta-reasoning is modelled by using separate components for the object and the meta-level. For example, one component can reason about the reasoning process and information state of another component. Two types of interaction between object- and meta-level are distinguished: upward reflection (from object- to meta-level) and downward reflection (from meta- to object-level). The knowledge structures used for meta-level reasoning are defined in terms of information types, standard meta-information type can automatically be generated.

For meta-reasoning in Concurrent METATEM, the logic MML has been developed. In MML, the domain over which terms range has been extended to incorporate the names of object-level formulae. Execution of temporal formulae can be controlled by executing them by a meta-interpreter. These meta-facilities have not been implemented yet.

9.3 Possible extensions

In the approach presented here it was assumed that observations are always successful and lead to valid beliefs of the agent. Also the reasoning model within the agent is based on the assumption that information is perfect. Methods to treat *imperfection of information*, however, can also be included. For example, in [38] it is shown how an architecture for *default reasoning* can be modelled in a compositional manner. This generic reasoning model is available and can be reused in any agent model. Also a more complex generic model for nonmonotonic reasoning is available; cf. [19]. Another available generic reasoning model is the model for *reasoning about dynamic addition and retraction of assumptions* described in [24]. This model enables reasoning about the lack of information, and focuses the addition of information. Similarly generic reasoning models have been developed for reasoning with statements with a certain *degree of belief*. All these generic reasoning models can be included to scale up a given model to obtain more complex models.

DESIRE facilitates the process of modelling *tasks*; for example, see [9]. To limit the time and expertise as many elements as possible are reused (*generic task models*). Within DESIRE, generic task models and existing ontologies, are used for this purpose. Generic task models are used to structure the modelling process. On the basis of an (expert's) explanation of the tasks involved, a designer selects one or more generic task models and positions the task models in relation to the tasks at hand. This leads to discussions on the different ways to model the tasks, resulting in an initial conceptual model, often based on a generic task model.

Generic task models are generic in two senses: they may be generic with respect to the *task* at hand, and they are generic with respect to the *domain* of application. Often different levels of genericity with respect to a task may be distinguished. A refinement of a generic task model to a more specific task model is called a *specialisation*. A refinement of a generic task model to a specific domain of application is called an *instantiation*. Modelling focuses on both aspects of genericity, often starting with a very generic task model in the sense of the task at hand. This model may be modified or refined by specialisation and instantiation. Existing specialisations of a generic task model may be of use, as may existing generic knowledge structures. If such specialisations and/or knowledge structures do not exist, new specialisations and knowledge structures are developed. A task model as a whole can be included as a component in an agent

model, for example as in Figure 7. This supports easy extension of models by incorporating more complex tasks: scaling up a model with respect to task complexity.

Another possible extension of the research presented here is to use the wellknown BDI architecture to simulate animal behaviour. This BDI model (see [35], and its predecessor PRS [21]), is organised around the notions beliefs, desires, and intentions. How the generic agent model GAM depicted in Figure 7 can be refined to obtain a formally specified design model of the BDI-architecture, can be found in [6]. In short, the beliefs on the environment (the world and the other agents) are maintained within the components maintenance of world information and maintenance of agent information. The desires and intentions are represented within a refinement of component own process control, which in this case has a more complex, compositional structure, based on components belief determination, desire determination and intention and commitment determination. The latter component is composed of components goal determination and plan determination, which, in turn are composed of intended goal determination and committed goal determination, resp. intended plan determination and committed plan determination. For more details, see [6]. This BDI-model can be used to investigate questions relating mentalistic assumptions about animals to observed or simulated behaviour.

Yet other extensions of the research presented here can be found in the area of social simulation in societies consisting of simple animal-like agents. For example, in [14] experiments are reported with which social theories are tested by simulating interaction between different types of simple agents (i.e., agents with limited knowledge and capabilities). Four types of agents are distinguished on the basis of their social characteristics: social agents, parasite agents, solitary agents and selfish agents. The effect of an agent's social characteristic on interaction with other agents is measured by simulating agent behaviour in a situation in which 30 agents try to survive on a 15 * 15 grid in which 60 pieces of food are continually available in random positions. The experiments reported in [14] have been replicated and extended by reverse engineering based on the generic agent model GAM depicted in Figure 7. The refinement of the generic agent model to obtain the four types of agents was performed on the basis of the informal, textual descriptions provided by [14]. The only components within the generic agent model, applicable to these small agents, are the components own process control and world interaction management. The component own process control is composed of four components: own resource management, own characteristics, goal determination and plan determination. The component own resource management receives information about its current energy level and the resources it has consumed, with which it determines its new energy level. On the basis of information the component goal determination receives about its own social characteristics and its own energy level, it determines the goals the agent is to pursue: for example to find food, or to look for help. The component own characteristics receives information on the agent's energy level from the component own resource management. This information is used to determine the agent's next state (e.g., hungry, normal or in danger). The component plan determination receives information (1) from the component own characteristics, namely the agent's current state, (2) from the component goal determination, namely which goals are to be pursued and (3) from outside the component, namely the current state of the world. With this information the component plan determination determines which actions to take in the external world. The component world interaction management interprets information it receives from the external world, and transforms information about actions to be taken in the external world into specifications for actions which the external world can execute. Two components are defined to perform these tasks: the component observation information interpretation and the component action execution preparation. For more details, see [7].

To simulate societies in which agents can behave in a deliberate normative manner, a model has been developed for a deliberate normative agent [13]. This type of agent has explicit mental representations of norms, which are interpreted operationally as (meta-)goals for its own behaviour. The deliberation also incorporates deciding about when to follow a norm and when to violate it. The model has been designed as a refinement of the generic agent model GAM in the following manner. Besides components for maintenance of world information and maintenance of agent information, also a component maintenance of society information is added. In this component the norms distinguished in the society are maintained. Society information is represented within this separate component for the ‘Society Model’ to make society norms more explicitly visible as distinct from personal norms of specific agents. Other components reused are agent interaction management, world interaction management and own process control. The latter component is refined into four sub-components: norm management, goal management, plan management, and strategy management. In the first of these components decisions on (personal) norm adoption are made. The adopted norms are operationalised within strategy management in terms of control of the goal management and plan management processes. For more details on the model, see [13]. In the near future social simulation experiments with these normative agents are planned. This example, and the one described in the previous paragraph shows how the models presented here scale up to more complex situations.

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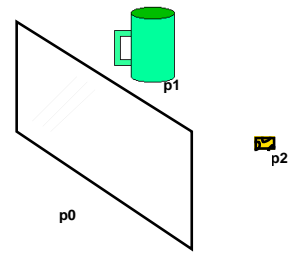
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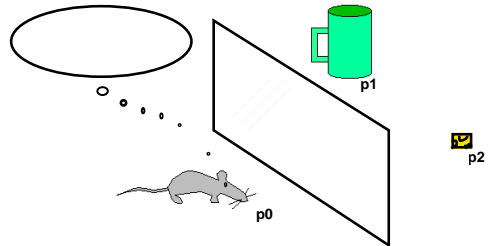
Appendix A Behaviour of Agent Model A in situation 3

	<i>world state</i>	<i>observation info of A</i>	<i>actions of A</i>
0	screen at p0 cup1 at p1 food at p2 no cup at p2 self at p0		
1	screen at p0 cup1 at p1 food at p2 no cup at p2 self at p0	screen at p0 cup1 at p1 food at p2 no cup at p2 self at p0	
2	screen at p0 cup1 at p1 food at p2 cup2 at p2 self at p0	screen at p0 cup1 at p1 food at p2 no cup at p2 self at p0	
3	screen at p0 cup1 at p1 food at p2 cup2 at p2 self at p0	screen at p0 cup1 at p1 cup2 at p2 self at p0	

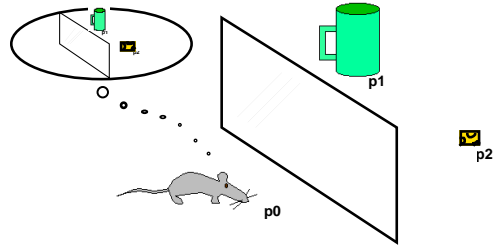
Trace A 3rd situation: 0



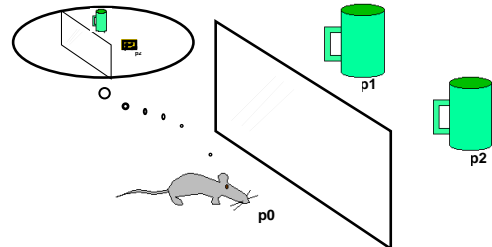
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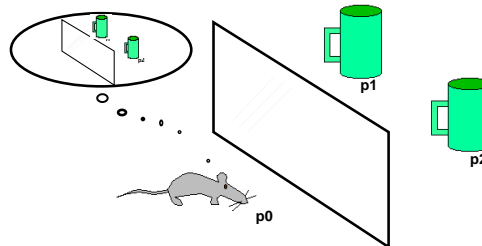
Trace A 3rd situation: 2



Trace A 3rd situation: 3

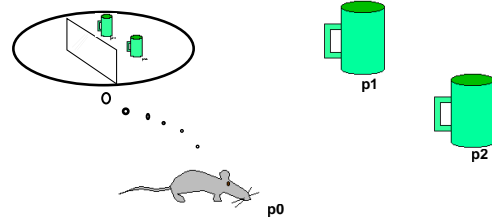


Trace A 3rd situation: 4

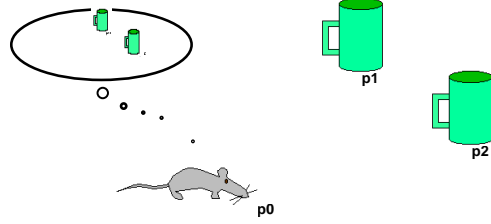


	<i>world state</i>	<i>observation info of A</i>	<i>actions of A</i>
4	no screen at p0 cup1 at p1 food at p2 cup2 at p2 self at p0	screen at p0 cup1 at p1 cup2 at p2 self at p0	
5	no screen at p0 cup1 at p1 food at p2 cup2 at p2 self at p0	no screen at p0 cup1 at p1 cup2 at p2 self at p0	

Trace A 3rd situation: 5



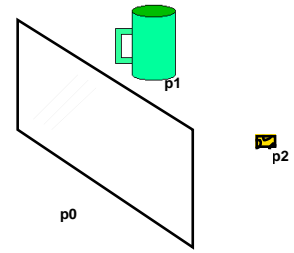
Trace A 3rd situation: 6



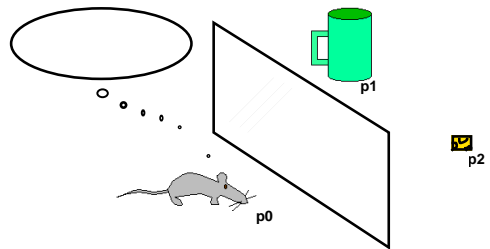
Appendix B Behaviour of Agent Model B in Situation 3

	<i>world state</i>	<i>beliefs B</i>	<i>actions B</i>
0	screen at p0 cup1 at p1 food at p2 no cup at p2		
1	screen at p0 cup1 at p1 food at p2 no cup at p2	screen at p0 cup1 at p1 food at p2 no cup at p2	
2	screen at p0 cup1 at p1 food at p2 cup2 at p2	screen at p0 cup1 at p1 food at p2 no cup at p2	
3	screen at p0 cup1 at p1 food at p2 cup2 at p2	screen at p0 cup1 at p1 food at p2 cup2 at p2	

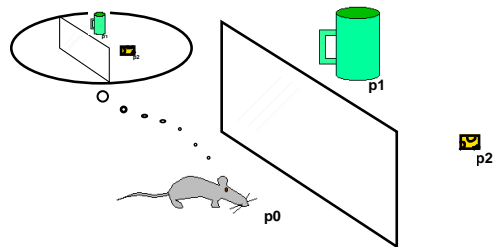
Trace B 3rd situation: 0



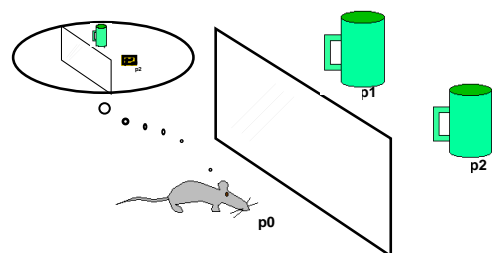
Trace B 3rd situation: 1



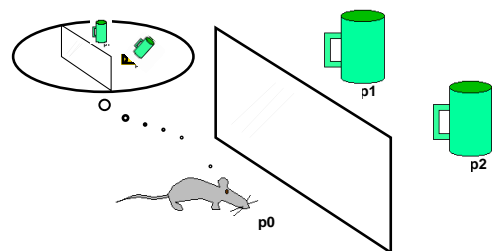
Trace B 3rd situation: 2



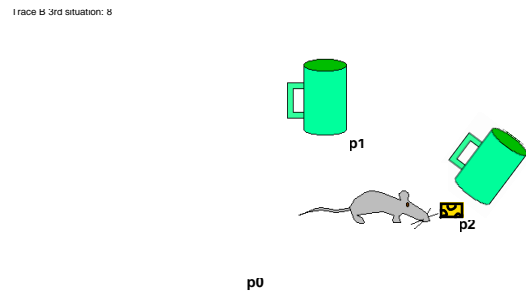
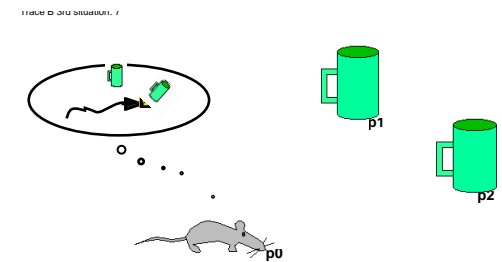
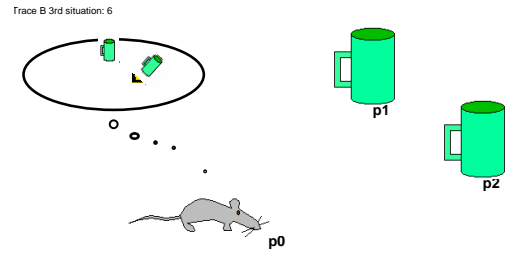
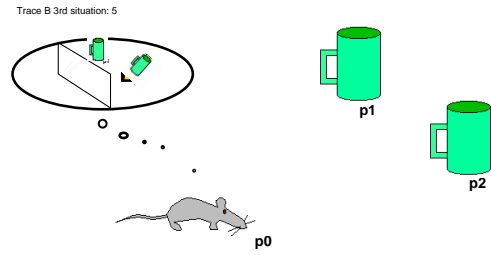
Trace B 3rd situation: 3



Trace B 3rd situation: 4



	<i>world state</i>	<i>beliefs B</i>	<i>actions B</i>
4	no screen at p0 cup1 at p1 food at p2 cup2 at p2	screen at p0 cup1 at p1 food at p2 cup2 at p2	
5	no screen at p0 cup1 at p1 food at p2 cup2 at p2	no screen at p0 cup1 at p1 food at p2 cup2 at p2	
6	no screen at p0 cup1 at p1 food at p2 cup2 at p2	no screen at p0 cup1 at p1 food at p2 cup2 at p2	go to p2
7	no screen at p0 cup1 at p1 food at p2 cup2 at p2 self at p2	no screen at p0 cup1 at p1 food at p2 cup2 at p2	go to p2



Appendix C Behaviour of Agent Model C in Situation 4

	<i>world state</i>	<i>beliefs C</i>	<i>goals C</i>	<i>actions and observations C</i>
0	screen at p0 cups at p1, p2 food at p2 self at p0			
1	no screen at p0 cups at p1, p2 food at p2 self at p0	no screen at p0 cups at p1, p2 self at p0	be fed find food	go to p1
2	no screen at p0 cups at p1, p2 food at p2 self at p1	no screen at p0 cups at p1, p2 self at p1	be fed find food	to be observed food at p1
3	no screen at p0 cups at p1, p2 food at p2 self at p1	no screen at p0 cups at p1, p2 self at p1 no food at p1	be fed find food	go to p2
4	no screen at p0 cups at p1, p2 food at p2 self at p2	no screen at p0 cups at p1, p2 self at p2 no food at p1	be fed find food	to be observed food at p2
5	no screen at p0 cups at p1, p2 food at p2 self at p2	no screen at p0 cups at p1, p2 self at p2 no food at p1 food at p2	be fed get food inside	eat
6	no screen at p0 cups at p1, p2 no food at p2 self at p2	no screen at p0 cups at p1, p2 self at p2 no food at p1 no food at p2	be fed find food	

Appendix D Behaviour of Agent Model D in Situation 4

	<i>world state</i>	<i>beliefs D</i>	<i>goals D</i>	<i>actions and observations D</i>
0	screen at p0 cups at p1, p2 food at p2 higher competitor at p2 self at p0			
1	no screen at p0 cups at p1, p2 food at p2 higher competitor at p2 self at p0	no screen at p0 cups at p1, p2 self at p0 higher competitor at p2	be fed find food	go to p1
2	no screen at p0 cups at p1, p2 food at p2 higher competitor at p2 self at p1	no screen at p0 cups at p1, p2 self at p1 higher competitor at p2	be fed find food	to be observed food at p1
3	no screen at p0 cups at p1, p2 food at p2 higher competitor at p2 self at p1	no screen at p0 cups at p1, p2 self at p1 no food at p1 higher competitor at p2	be fed find food	
4	no screen at p0 cups at p1, p2 food at p2 no higher competitor at p2 self at p2	no screen at p0 cups at p1, p2 self at p1 no food at p1 no higher competitor at p2	be fed find food	go to p2
5	no screen at p0 cups at p1, p2 food at p2 no higher competitor at p2 self at p2	no screen at p0 cups at p1, p2 self at p2 no food at p1 no higher competitor at p2	be fed find food	to be observed food at p2
6	no screen at p0 cups at p1, p2 food at p2 no higher competitor at p2 self at p2	no screen at p0 cups at p1, p2 self at p2 no food at p1 food at p2 no higher competitor at p2	be fed get food inside	eat
7	no screen at p0 cups at p1, p2 no food at p2 no higher competitor at p2 self at p2	no screen at p0 cups at p1, p2 self at p2 no food at p1 no food at p2 no higher competitor at p2	be fed find food	

Appendix E Behaviour of Agent Model E in Situation 4

	<i>world state</i>	<i>beliefs E</i>	<i>experience E</i>	<i>goals E</i>	<i>actions and observations E</i>
0	cups at p1, p2, p3 green at p1 blue at p2 red at p3 food at p2 self at p0		food relevance: red-green-blue	be fed find food	
1	cups at p1, p2, p3 green at p1 blue at p2 red at p3 food at p2 self at p0	cups at p1, p2, p3 green at p1 blue at p2 red at p3 self at p0	food relevance: red-green-blue	be fed find food	relevancy of actions: go to p3 go to p1 go to p2 selected: go to p1
2	cups at p1, p2, p3 green at p1 blue at p2 red at p3 food at p2 self at p1	cups at p1, p2, p3 green at p1 blue at p2 red at p3 self at p1	food relevance: red-green-blue	be fed find food	to be observed food at p1
3	cups at p1, p2, p3 green at p1 blue at p2 red at p3 food at p2 self at p1	cups at p1, p2, p3 green at p1 blue at p2 red at p3 self at p1 no food at p1	food relevance: red-blue-green	be fed find food	relevancy of actions: go to p3 go to p2 selected: go to p2
4	cups at p1, p2, p3 green at p1 blue at p2 red at p3 food at p2 self at p2	cups at p1, p2, p3 green at p1 blue at p2 red at p3 self at p2 no food at p3	food relevance: red-blue-green	be fed find food	to be observed food at p2
5	cups at p1, p2, p3 green at p1 blue at p2 red at p3 food at p2 self at p2	cups at p1, p2, p3 green at p1 blue at p2 red at p3 self at p2 no food at p1 food at p2	food relevance: blue-red-green	be fed get food inside	relevancy of actions: eat selected: eat
6	cups at p1, p2, p3 green at p1 blue at p2 red at p3 no food at p2 self at p2	cups at p1, p2, p3 green at p1 blue at p2 red at p3 self at p2 no food at p1, p2	food relevance: blue-red-green	be fed find food	relevancy of actions: go to p3 selected: go to p3