Automan, a psychologically based model of a human driver

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Abstract

This paper describes the design of a generic autonomous agent for controlling vehicles in a driving simulator. The agent is based on recent developments in artificial intelligence, autonomous robotics and cognitive psychology, and is aimed at simulating realistic driving behavior. The agent is composed of four control systems. The Perception system controls visual attention and gaze direction. The Behavior System controls high level driving behavior. The Action system controls the actions required for low-level control of the car. The Emotion System implements the influence emotions have on human driving behavior. Furthermore, it contains three different types of memories. A declarative memory contains the knowledge that the agent has about the world. A procedural memory contains the rules and procedures required for driving. Finallly, a working memory is used for storing representations of the actual situation. These systems and memories are realized using a behavior based approach, in which the overall behavior of the agent is the result of interaction between small and simple behavioral patterns. Fuzzy logic is used to assure natural flow of information and to enable human-type reasoning.

1 Introduction

Research on human behavior has traditionally been performed in either laboratory settings or real world environments. While a laboratory setting provides explicit control over experimental conditions, it often lacks sufficient realism. This realism is present in real world situations, but these suffer from lack of controllability and from unexpected disturbances. Therefore, simulations are used, since they provide sufficient realism and ecological validity, while at the same time providing excellent control (Brookhuis, Bos, Mulder, & Veltman, 2000; DiFonzo, Hantula, & Bordia, 1998; Sauer, Wastell, & Hockey, 2000; Brehmer & Dorner, 1993). For this purpose, a variety simulators have been developed at the University of Groningen (Bos, Mulder, & Ouwekerk, 1999; Wolffelaar, 1996; Wolffelaar & Van Winsum, 1993), the first one being an advanced driving simulator. When building such a simulator, it is not only important to have an adequate model of the physical world. To create a realistic environment for the study of human behavior, adequate simulation of the behavior of other interacting (traffic) participants is also critical. The current simulator uses simple agents for simulating other traffic (Wolffelaar, 1996; Van Winsum, 1996). These agents are controlled by a small set of fixed rules. These rules enable the agents to function in the simulated traffic environment in a marginally acceptable manner. Because of their fixed rules, their behavior is highly straightforward and predictable. Drivers in the simulator inevitably get the impression that the other traffic participants are simple robots. Different kinds of traffic behavior and emotional influences, for example aggressive driving styles, or elderly people's driving styles, are very hard to simultate. Also, new traffic situations require the agents to be partly rewritten. For realistic agents in simulators, simple rules are not sufficient. (Tambe et al., 1995) shows, that the requirements for intelligent and autonomous agents in interactive simulations should be addressed by using a sophisticated cognitive model. They used the SOAR cognitive architecture (Laird, Newell, & Rosenbloom, 1987) to succesfully create realistic automated pilots for use in simulated air combat excercises (Hill, Chen, Gratch, Rosenbloom, & Tambe, 1997; Jones et al., 1999). The present paper describes a new cognitive model that can be used for simulating traffic participants. The goal of this model is to generate realistic driving behavior, incorporating emotional aspects, and creating a flexible, interactive agent. In the next section, the approach followed in designing such a model will be elaborated, and the theoretical and technical background needed for this approach will be discussed. Thereafter, the model and its subsystems will be described. Finally, the paper will be completed by a glimpse into the future.

2 Simulating behavior

2.1 Human driving behavior.

Over the years much research has been done on the question of how humans drive. (McKnight & Adams, 1970) performed a complete task analysis of a driving task. However, this analysis was aimed at behavior requirements (specifying how a driver should drive in theory) instead of being aimed at how a driver actually drives. Research indicates that it is useful to distinguish three task levels: strategical, tactical and a control level (Michon, Smiley, & Aasman, 1990; Cnossen, 2000). At the strategical level, plans are made about which route to take, what kind of transportation to use, etc. Decisions at this level are influenced by personal opinions, attitudes and circumstances. The tactical level describes how specific situations are handled; for example, how to cope with an intersection. At the control level all low-level control tasks are handled, such as steering, gear shifting, etc. Normally, tasks at this latter level will be handled automatically; in most cases, a driver is not conscious of how he shifts gears. The three levels influence each other, they interact; for instance, take the situation as depicted in figure 1. Driver A is confronted with a T-shaped intersection. He has to decide whether to select the left or the right road. This decision is made on the strategical level. Then, the driver has to make a turn, while attending to other traffic. This task is a tactical task; how it is performed is dependent on the traffic situation, and of course on the direction of the turn. If traffic permits, the actual turn is performed, which consists of braking, shifting gear, stearing and accelerating. These latter tasks are control level tasks, that are initiated from the tactical level.

Although they influence each other, these three levels can be studied more or less independently. For instance, when studying human route planning it is not necessary to consider human manual skills. Conversely, a model of human vehicle steering should be able to describe human behavior at an intersection whithout considering why the driver wants to turn.

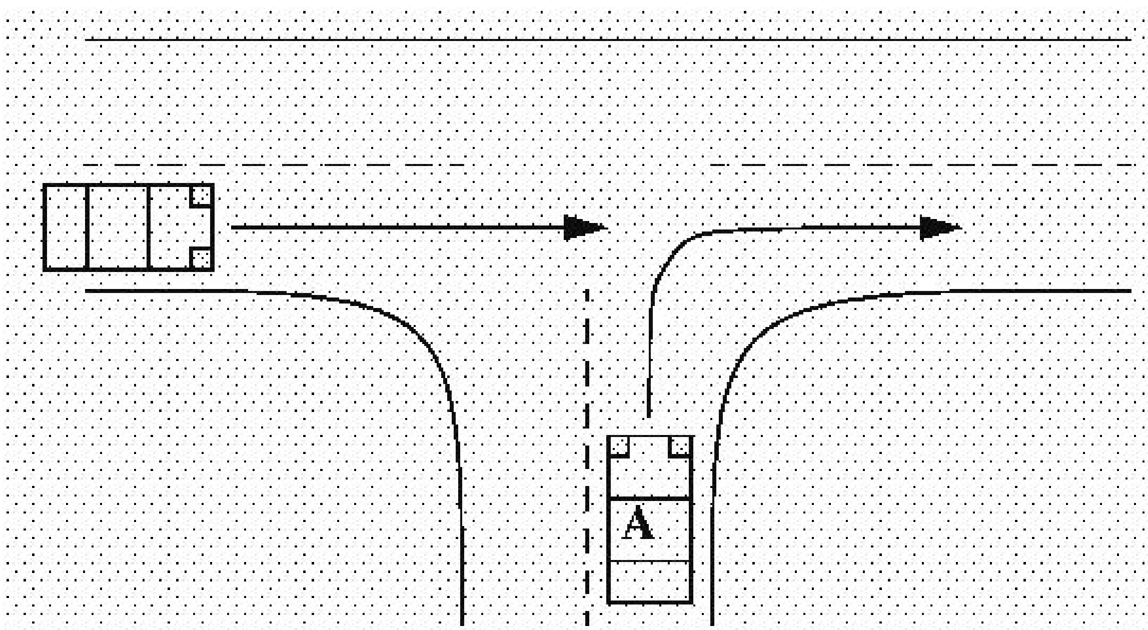

Figure 1: Approaching a T-shaped intersection. This situation involves tasks at the strategical (which road to take ?), tactical (wait for car from the right ?) and control (how much force to use on the brake pedal ?) level.

2.2 Modelling human behavior

Human behavior modelling is a diverse field, in which researchers engage with different objectives. Without engaging in an extensive review of the work being done, one can state that much research is centred around so-called *cognitive architectures* (Van Lehn, 1991). These are based on the assumption that human beings are capable of performing a wide variety of cognitive functions (from understanding language to playing chess) using the same basic underlying setup (the brain). If such a basic setup could be specified, one would have one system in which it would be possible to model various human cognitive processes. Cognitive architectures are attempts at specifying and implementing such structures. Well-known examples are ACT-R (Anderson & Lebiere, 1998), SOAR (Laird et al., 1987) and EPIC (Kieras & Meyer, 1995). However, especially in complex and dynamic tasks such as driving a motor vehicle, these architectures have some drawbacks (Banks & Stytz, 2000) (Meyer & Kieras, 2000). Situation assessment, decision making and planning are not part of the architectures, and must be manually modelled in each model. The architectures use production systems for their reasoning; these are sets of elaborate rules, and the logic to apply these rules. However, advanced reasoning techniques like fuzzy logic, bayesian and uncertainty reasoning are not incorporated in these production systems, which makes their applicability limited. Also, intentions and emotions are hard to model in these architectures. The goal and subgoal structure mostly used for control would be a candidate for this, but when intentions and emotions are considered behavior modifiers, this would not be the right way. Other problems are the granularity of the models and absence of perceptual/motor processes. Often, it is very hard to model on different levels; for instance, the strategical, tactical and operational levels from the previous section would be very hard to incorporate. Progress has been made with the incorporation of perceptual/motor processes in architectures, but the mechanisms used are far from ideal. Some other shortcomings exist as well, but they are not relevant for the subject of human driver behavior modelling (Banks & Stytz, 2000). Previous attempts at driver modelling in cognitive architectures (for example, Aasman, 1995) have suffered from these drawbacks. Alternatively, probabilistic models have been used for behavior modelling; for example (Oza, 1999). However, this is a very difficult approach if behavior is to be simulated for a wide variety of situations.

2.3 Autonomous Agents

An autonomous agent is an artificial 'creature' in a (virtual or real) world, that can act and react without direct interference from an outside controller; it is able, so to speak, make decisions for itself. In Autonomous Agent design, one usefull approach is called the *Behavior Based approach* (Brooks, 1991; Braitenberg, 1984; Steels, 1994; Steinhage & Bergener, 1997). The idea is, that to model intelligent behavior in a complex, dynamic environment, one can specify relatively independent modules that perform small parts of the behavior. Traditionally, one would make a central controller, that has access to all sensorial information and incorporates a decision mechanism to decide on the correct action. There are several problems with this approach. A central representation of the environment will probably be needed, that has to be updated when an action is performed or the environment changes. This representation has to contain all the information nec-cessary for the control structure to decide on an action as well. This is inherently complex (Dennett, 1987; McFarland, 1996). Also, the more complex the task of the agent and its environment gets, the more complex the control structure will be. For every possible situation, a process has to be designed to cope with that situation, and the central controller will need a mechanism to decide to start that proces. By contrast, in the behavior based approach the task of the agent is split up into small elementary *behaviors*.

These behaviors are directly coupled to only their relevant sensor inputs, and can be activated by these inputs. Also, behaviors can activate or inhibit one another. The overall behavior of the agent is determined by interaction between the elementary behaviors. By specifying relatively simple behaviors and their interactions complex behavior will emerge from the interaction of the smaller ones.

2.4 Fuzzy Logic.

To model human reasoning processes, one needs logic to specify rules. However, classical logic is not very well suited to model human reasoning in driving a vehicle. Classical logic needs precisely defined terms to function. However, human reasoning does not function with such terms. A car is perceived as driving fast, not as driving at 150.7 km/h. Rules that human beings use are *if the car in front of me is close and I'm driving fast then break*. The exact defintions of close and fast cannot be given. Classical logic will therefore fail for a driving task. Fuzzy logic however is designed to work with "vague" definitions (Ross, 1995; Kosko, 1992). With fuzzy logic, it is possible to use terms like fast, very close etc. without having to specify them exactly. The values of fuzzy variables are given by membership functions. These functions determine which values belong to the fuzzy terms; for instance, it may specify that speeds between 10 and 50 km/h are to be considered slow. A value can belong more or less to several terms ; 45 km/h is only a little slow, and is almost normal (see figure 2). This way, human reasoning processes can be modeled much better then by using classical logic.

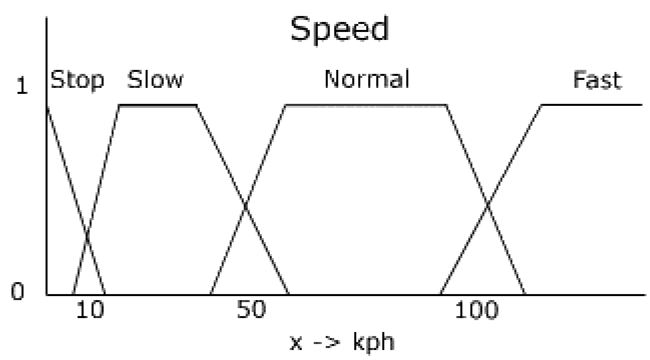

Figure 2: Fuzzy membership function for speed. As can be seen, the different values overlap. This makes it possible to work with not precisely defined terms. Membership functions can have all sorts of shapes. The function shown is simple and has proven to work very well in most cases.

2.5 Vagueness

Of course, the fuzziness introduced by the membership functions can be manipulated. Is *normal* something between 50 and 110 km/h, or something between 60 and 140 km/h ? The smaller the range used in the membership functions is, the less vague or uncertain the property value is. This vagueness is used in the Automan model we introduce here; compare, for instance, what is perceived when someone takes a quick glance at the road from the left; the approaching car will be seen, but the driver will not be very well aware of its speed or distance. Also, other cars on the road may not be seen at all. However, with a long look, the speed, distance, even brand and colour of a car will be very precisely perceived.. The property values of the object representing the car will have a lower level of vagueness. For instance, suppose the speed of the car is normal. With the quick glance, the range of normal can be between 30 and 130 km/h. With a long look, this range can be decreased; normal can be more precisely defined as being between 40 and 60 km/h. Every fuzzy value has an intrinsic vagueness, and additionally, an actual vagueness. This actual vagueness will be adapted according to the situation.

3 The Automan Model.

Although a driving task can be described by three almost independent levels, the processes on these levels can be described in a similar way. The amount of force on a braking pedal required to attain a certain speed (a control task) can be determined by a set of rules, be they fuzzy or not. The decision to select and attain a certain speed (which is a tactical decision) is also governed by rules; for instance, if one wants to make a turn, one has to have a certain speed. Actually, one could say that the application of the control level rules is triggered by the outcome of the tactical level rules. The same argument holds of course for the strategical and tactical levels. On the strategical level, the driver has to decide whether he should turn left or right on this intersection. This is, of course, dependent on his final destination. Suppose the driver is traveling from Groningen to Utrecht, and a traffic sign says Utrecht is to the right. This process that can be described by a ruleset*: IF the final destination is to the right THEN turn right; IF the final destination is to the left THEN turn left.*

Because the driver has to turn right, a whole new set of rules is triggered. Of course, the driver first has to watch his speed: *IF I approach an intersection AND my speed is not slow THEN brake.* Then, the driver has to determine whether he can safely initiate his turn: *IF I am turning right AND a car from the left is near THEN stop. IF I am turning right AND I can't see whether a car from the left is near THEN slow down and keep looking. IF I am turning right AND there is no car near on the left THEN look to the right AND start turning*.

On the control level, initially Automan is braking to reduce its speed. Again this can be described as a ruleset. It is not so difficult to imagine rules that descibe these braking patterns. When, somewhat later, the driver is initiating his turn, another ruleset would be needed: *IF my speed is slow AND I am starting to turn right THEN steer right*. In this pattern, some more rules would be needed to control the turn, but the general idea will be clear.

By describing the three levels in the same way, using rulesets, it becomes possible to model a human driving behavior on all three levels. Actually, when one examines these rulesets closely, one can determine very specific sets of rules, that are applicable in specific situations, and need to be triggered by certain outcomes of other very specific rulesets. These rulesets are very well suited to be used in a behavior based design of a driver model. A ruleset can be seen as a behavior, as explained in section 2.3. In the context of cognitive modeling, the word behavior is used for a lot of things. Therefore, we will refer to the rulesets/behaviors we define for our model as *behavioral patterns.* In our example, there would be a strategical behavioral pattern, let's call it Drive_To_Utrecht. Furthermore, there would be two tactical patterns. The first one, Approach_Intersection, will be triggered by the perception of the intersection. The second one, Turn_Right_T_Intersection, will be triggered by the outcome of the Drive_To_Utrecht strategical pattern. Finally, operational behavioral patterns will be needed for slowing down and turning.

The driver model, called *Automan* (*Auto*mated Hu*man)*, is based on this concept. All tasks and subtasks involved in driving a car will be described as behavioral patterns. Automan's behavior is controlled by *active* behavioral patterns. A behavioral pattern can be made active either by some perception, or by another behavioral pattern. It can be at the strategical, tactical or control level. All active patterns are stored in *working memory*, together with all perceived objects (we will describe Automan's perception later on). Working memory is continously evaluated against rules in the *procedural memory*. In this memory, all rules necessary for the patterns are stored. These rules specify the patterns themselves, and when they have to be activated. Automan also has a *declarative memory*, in which its knowledge of the world is stored. In this memory, object definitions, which tell for example what a car looks like, are stored. Declarative memory is queried by the perceptual processes and reasoning systems for this knowledge when it is needed.

Apart from the three memory system, Automan consist of four executive systems: the *Behavior*, *Perception*, *Action*, and *Emotion* systems. All these systems are constructed using behavioral patterns, and all interact with Automan's memory systems in the same way. However, the functions performed and rules needed for these systems are so different, that it is conceptually convenient to distinguish them. In the following sections we will describe these systems in more detail.

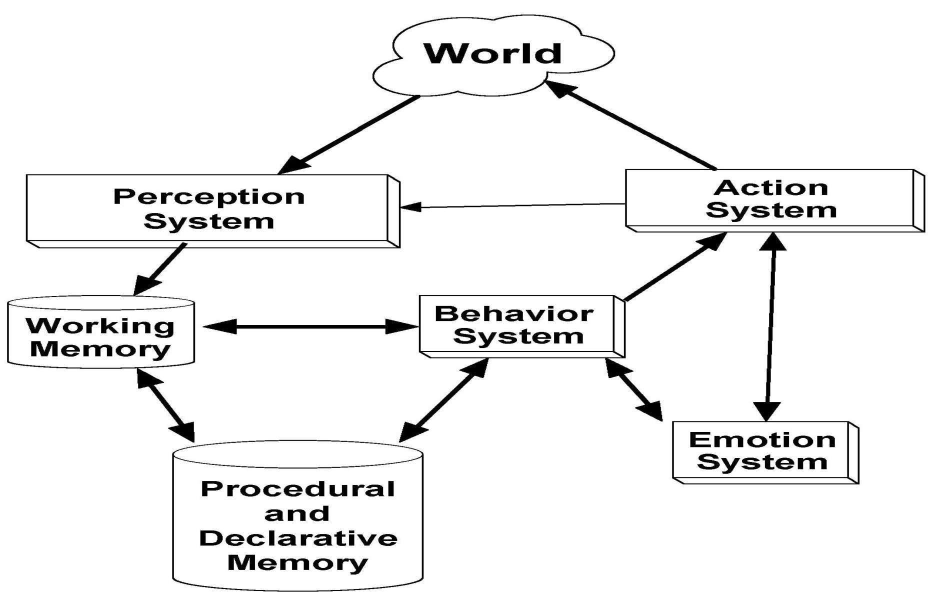

Figure 3: Automan's subsystems. The procedural and declarative memories have been drawn as one system, because they have the same communication channels with the other systems.

3.1 The Behavior System.

The behavior system takes care of activating the behavioral patterns associated with the tactical and strategical level. A behavioral pattern can be activated by a perception, which appears as an object in working memory, or by another behavioral pattern.

Behavioral patterns have a kind of hierarchical structure, representing the influence that the strategical, tactical and operational levels have on each other. This hierarchical structure manifests itself in the rules governing the activation of the patterns. For example, take the situation depicted in Figure 1: Automan is approaching a T-shaped intersection. The intersection will be perceived; this means, the perception system will create a new object in Working Memory. This object will trigger the activation of a behavioral pattern (we will call the pattern Approach_Intersection). This is a tactical pattern, and will contain rules that specify right of way, when to brake, etc. Also, this pattern on its turn can activate another pattern, which we call Check_Route. This is a strategical pattern, that will determine whether Automan will have to turn left or right. In our previous discussion of the example, we have introduced a pattern Drive_To_Utrecht; Check_Route and Drive_To_Utrecht together will activate another tactical behavioral pattern, Turn_Right_T_Intersection, that handles the actual turning.

3.2 The perception system

To drive a motor vehicle human drivers predominantly use visual perceptual information. Indeed, it has been argued that a large part of the driving task must be considered a visual task. We think this is somewhat exaggerated; not only other sources of information are used (e.g. sound, g-forces due to acceleration), but also a large part of the driving task is making decisions and controlling a vehicle. Nevertheless, visual perception remains an important aspect. Just like human beings, Automan has a restricted field of view. It has a small foveal field of view, in which objects are easily recognized (provided the objects are within sufficient range), and a much wider peripheral field of view, in which objects are only perceived under certain condtions; for example, if they are very conspicuous, or moving very fast. Eye- and head movements in traffic situations are closely related. Therefore, in determining the foveal and periphiral fields of view, we use Automan's *gaze direction*, not the direction of his eyes or head. (Land & Horwood, 1991) shows, that gaze direction is a good estimate of the visual field a driver pays attention to.

It is generally accepted that humans perceive one object at a time in traffic situations. Also, the more time spent looking at an object, the better it will be perceived (up to a certain optimal level, of course). To model the low level perceptual process in Automan a *Perceptual Filter* is included. This filter determines which object is currently being perceived. Mostly, this object will be in the foveal field of view. However, if a very conspicuous object is present in the peripheral field of view (e.g. because it is moving fast, is fairly big, or has salient colors) the perceptual filter will output that object.

If a person looks at an object, he not only perceives the object, but also object properties like speed, heading, colour, etc. However, several factors affect the quality of perception. Wheather conditions, time spent looking, and individual differences all have influence on what a person perceives, and how well he perceives it. For example, at first glance a car is viewed to be driving relatively fast. How fast? The person could say ‘between 20 en 80 kph.’ But after a longer look he may narrow it down to ‘about 50 kph’. Of course, there is a limit to how accurate a person can perceive properties of objects; ‘about 50 kph’ could be 45, but also 55 kph; it will be very difficult, if not impossible for a person to perceive speed even more accurate. We call this the *intrinsic vagueness of perception*.

We use the *vagueness* adaptations, explained in section 2.5, to model this perceptual feature. The perceptual filter modifies vagueness based on the time spent looking at a certain object. The more time is spent looking, the lower the vagueness. There is minimum perceptual time, that is needed to perceive objects and its properties at intrinsic vagueness. There is also a minimum perceptual time that is needed to perceive an object, with its properties at maximum vagueness (which would amount to not perceiving the properties at all, just the object). By varying the time neccessary to perceive an object properly, the perceptual function can reflect the efficiency of a human drivers perception. It is known, that experienced drivers can perceive a situation much faster then inexperienced or elderly drivers. This can be easily simulated in the model by increasing the perceptual time.

As explained, the output of the perceptual filter is dependent on the time spent looking at an object. This time, in turn, is governed by the *Visual Schemes.* A visual scheme is a behavioral pattern; its activation is based on the other active behavioral patterns. Drivers exhibit specific looking patterns in different situations; when overtaking a car, a person looks in a different manner than when taking a right turn. Visual schemes are used to model these patterns. They are activated by corresponding tactical or strategical behavioral patterns from the behavior system. Visual Schemes inhibit each others activation, so only one can be active at a time.

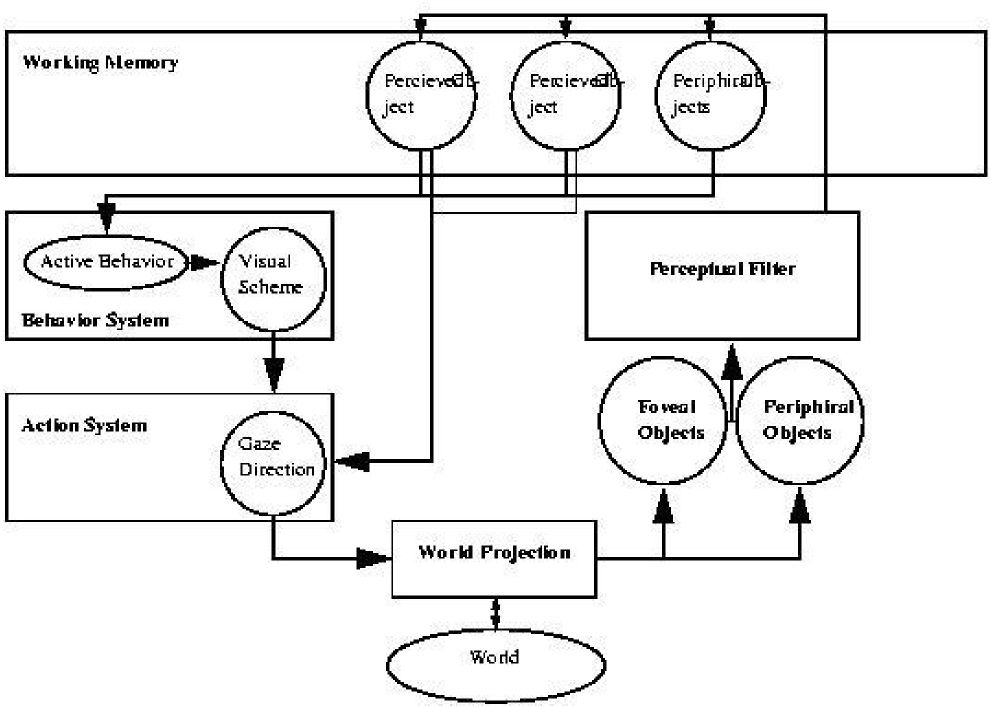

Figure 4: Automan's perception system. The world projection is the interface between the world and Automan, and determines what can be physically seen. The perceptual filter

determines what is perceived from the things that can be seen.

A visual scheme develops priorities for various gaze directions, and rules to update these priorities. The gaze direction of Automan will be set to the direction with the highest priority in the active visual scheme. The rules consult working memory for perceived objects in the various directions. If, in a certain direction, a sufficient number of objects are perceived recently enough, the priority of that direction will be decreased. Another direction will now develop highest priority, and the gaze direction will be shifted. How many objects suffice to change priority depends on the visual scheme; sometimes, only one object is enough (for example, a traffic sign), but sometimes a complete picture of the situation is needed.

Take our T-shaped intersection example: the Navigate _T_Intersection behavioral pattern has just become active. This behavioral pattern will have a visual scheme associated with it, let's call it Check_T_Intersection, that specifies where the driver has to look. Naturally, in the first place it is important to know whether the road from the left has right of way, or whether a stop sign is present. The priority for looking to the right side of the road will thus be highest. As soon as a traffic sign is perceived (or no traffic sign is perceived of course), the priority of this direction will be decreased, and the priorities of the directions of the two roads are increased. The directions for the road that is most important in the situation (right-of-way or not) will develop the highest priority. This priority will be decreased again, after a more or less complete picture of the direction is perceived. [1]

3.3 The Action System

The action system of Automan consists of operational behavioral patterns. These patterns consist of simple rules to control the vehicle. For example, the Steer_Right behavior would be part of the action system, and contains rules to control the turn; how much force to apply to the wheel, how much to compensate, etc. These rules will be similar to standard control systems, that have been used succesfully in human vehicle control modelling; fuzzy logic is very suited for making such control systems. This operational level Steer_Right behavioral pattern will be activated by the tactical Turn_Right_T_Intersection behavioral pattern, when the road is clear to make the turn.

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3.4 The Emotion System

One major influence on human decision making is emotion. A good example of an emotion influencing behavior is that of aggression. Aggressive drivers tend to keep short distances to other vehicles, tend to overtake more, tend to force their place in traffic onto other participants, and so on. Some people are predisposed to aggressive behavior; aggression is a kind of personality trait for them. Their driving behavior will be aggressive, regardless of the traffic situation. Other people might be aggressive because of events that came to pass just prior to their participation in traffic. However, a large part of aggression in traffic comes from the traffic itself. People get frustrated about traffic jams, slow drivers, traffic lights, and so on.

.In Automan, emotions are controlled by success of behavioral patterns. They are also

[1] It is not enough to perceive only one car; it might be another car is overtaking, for instance.

implemented as behavioral patterns, whose activation is determined by the succes of specific other behavioral patterns. If Automan is driving behind a slower car, but cannot overtake this car, the overtaking behavior will be active relatively long. This will steadily increase the activation of the frustration pattern. In turn, emotions influence activation of other behavioral patterns. Suppose, in the intersection example, Automan is very frustrated; he might be late for his presentation in Utrecht. The Turn behavior will be more easily activated, and the Slow_Down behavior will be harder to activate. Therefore, Automan will likely try to make the turn just before the approaching car, instead of slowing down.

It is also possible to model people with a predisposition for aggresion, or with aggresion induced by recent events, in Automan. Some emotional behavioral patterns can have a very high initial activation, to reflect the emotional state of the driver.

3.5 Evaluation and updating objects

Properties of objects are initially set by the perception system, like distance from the intersection, speed, etc. These objects will stay in working memory and can still be needed by the behavior system. However, the world is a dynamic system. Especially in driving, the environment is continously changing, either because of the actions of the driver itself, or because of the presence and actions of other traffic participants. Thus, the reliability of the perceptual objects in working memory will degrade over time. A car that was seen a couple of seconds ago can have a totally different speed and heading.

Therefore, properties of objects in Working Memory are continously updated. Dependent on the property, this update consists of either estimating new values, deleting the object from working memory, or activate a certain visual scheme to perceive the object and its properties again. In the example where Automan is approaching the intersection, suppose he is looking to the right. However, the active tactical behavioral pattern (suppose it is Turn_Right_T_Intersection) needs information about traffic from the left to decide whether to start the turn or stop and wait. Working memory will update the properties of the object representing the car from the left, by using its last known speed and distance and the time the car was last seen. Of course, the uncertainty of these values (their '*vagueness*') increases when they are calculated this way. If this vagueness becomes too large, the perceptual system will be engaged to guide Automan's gaze direction to the left.

3.6 Activation of behavioral patterns

Behavioral patterns are activated by other behavioral patterns or by perceived objects. Also, an active behavioral pattern can influence its own activation. This has an effect which is widely know in psychology: humans will stick to their current decision, although more appropriate decisions have arisen. Automan has for example decided to start to turn right. It then notices the car from the left. If Automan had seen it in time, he may not have started the turn. But he did start it, so the Steer_Right operational behavioral pattern is still active. It will remain active, even when the Negotiate_Intersection behavioral pattern starts activating the Brake pattern. Dependent on the situation, this can result in a collision. Another example to clarify this: if a person is driving behind a slow vehicle, the person will determine whether he can overtake. If the lane is free, he may decide to start overtaking. While in the process of overtaking, suddenly a car approaches from the other side. If this situation occurred before he started overtaking he may not have started the routine. But he did, so he may try to ‘go for it’ and keep overtaking.

Naturally, this process is also influenced by the emotion system.

4 Conclusions and Fut ure Directions

This paper shows an example of using sophisticated techniques in modelling the task of operating a motor vehicle in a simulated environment. Until now, the Automan project has not escaped the design phase. To actually implement the model, some additional parts would be needed; a design has been made of a cognitive architecture, incorporating these parts (Heemskerk, Quispel & Warris, 1999).

Although initially designed for simulating traffic participants in a traffic simulator, Automan’s use can be much broader. When the model is well developed and validated, it can also be used for testing new traffic situations and road configurations. This kind of research can not be done in real life, of course, and using a simulator with test subjects is a time-consuming process. It would be convenient to use cognitive models for this purpose. Research into modelling traffic jams can also be done, by using large sets of Automen. This would make it possible to investigate whether certain styles of driving, or certain legal measures, are really effective in combating traffic jams. Research into the use of new equipment in cars, for example navigation systems or mobile phones, can be greatly facilitated using an Automan model. Furthermore, parts of Automan can be used in research into specific aspects of driving. All three levels in Automan are modelled on a level that sufficiently fine-grained for its overall behavior to be realistic, but of course this modelling could be done in more detail, if a specific aspect of driving is under investigation. When research is to be performed in these aspects, Automan can be used as a background architecture. The processes can then be modelled while taking the whole driving task into account.

Alternatively, it would be very interesting to see whether the concepts developed and the approach followed in designing Automan could be used for modelling other tasks. Nowadays, a growing need exists for adequate user models. The approach followed here would be very usefull in a lot of domains, especially in dynamic, demanding task environments. Take, for example, an ambulance dispatcher simulation. Such a simulation models the task of an ambulance dispatcher, that has to deploy and coordinate all ambulances in a certain region. This simulation could greatly benefit from realistic ambulance agents, that can react autonomously to obstacles or unexpected situations, and can communicate with the dispatcher. This enables the use of sophisticated scenarios, in which multiple complicated accidents can be used. Alternatively, one could use the approach in this paper to model the ambulance dispatcher itself. .

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