New Requirements for Modelling How Humans Succeed and Fail in Complex Traffic Scenarios

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Abstract. In this text aspects of human decision making in complex traffic environments are described and requirements for cognitive models that shall be used as virtual test pilots or test drivers for new assistance concepts are derived. Assistance systems are an accepted means to support humans in complex traffic environments. There is a growing consensus that cognitive models can be used to test systems from a human factors perspective. The text describes the current state of cognitive architectures and argues that though very relevant achievements have been realized some important characteristics of human decision making have so far been neglected: humans use environment and time dependent heuristics. An extension of the typical cognitive cycle prevalent in extant models is suggested.

Keywords: Human decision making, complexity, cognitive modelling, cognitive engineering.

1 Introduction

Every day we as humans are faced with complex scenarios in which we have to make decisions under time pressure. Most people know how to drive a car and most often we manage to reach our destination without being involved in an accident. Undeniably, traffic situations can be very complex. But we have learned to cope with critical situations and often we react intuitively without much thought. But, on the other side the high number of accidents that are attributed to human error [44] clearly shows the limitations of human behavior. One way to reduce the number of human errors is the introduction of assistance systems, like Flight Management Systems in aircraft and Adaptive Cruise Control in cars.

Air traffic environments like road traffic environments are inherently complex. Though pilots are highly trained professionals human error is also the main contributor in aircraft accidents [4]. Modern aircraft cockpits are already highly automated and assistance systems have in parts succeeded in reducing errors but new error types have emerged [13, 38, 39, 40, 47, 49]. As a consequence it has widely been accepted that automation systems must be developed from a human centred perspective putting the pilots or drivers in the center of all design decisions. Cognitive engineering [16, 7, 48] is a research field that "draws on the knowledge and techniques of cognitive psychology and related disciplines to provide the foundation for principle-driven

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design of person-machine systems" [48]. One line of research in this area deals with developing executable models of human behavior that can be used as virtual system testers in simulated environments to predict errors in early phases of design. But the question arises whether the current human models are capable of simulating crucial aspects of human decision making in complex traffic environments.

This text provides a short introduction in human modeling from the perspective of production system architectures (like ACT-R [3], SOAR [50] and CASCaS [25]) and shows how such models can be used in cognitive engineering approaches. Starting from a definition and two examples of complexity characteristics of human behavior will be elaborated based on results from research on Naturalistic Decision Making [22] and driver perception. The central message is that human decision making is based on heuristics that are chosen and applied based on features of the environment and on available time.

The environment and time dependent application of heuristics has so far been neglected in cognitive architectures. In order to capture these aspects human models should incorporate (1) meta-cognitive capabilities to choose an adequate heuristic for a given decision situation and (2) a decision cycle whose quality of results improves as deliberation time increases.

2 Examples of Complex Traffic Situations

In this section two examples of complex decision situations where humans might make erroneous decisions and where potentially assistance systems might provide support will be introduced. The crucial point is that before assistance systems are to be introduced we have to understand how humans make decisions in such scenarios and we have to be sure that with the new systems errors are really prevented and no new errors are introduced.

The first example describes an air traffic situation where pilots have to decide which airport to use (Fig. 1). An aircraft is flying towards its destination airport Frankfurt Main (EDDF). On their way the pilots receive the message that due to snow on the runway the destination airport is temporally closed. Further information is announced without specifying when. The options now for the pilots are either (1) to go ahead to the original airport (EDDF) and to hope that the runway will be cleared quickly, or (2) to divert to the alternate airport Frankfurt Hahn (EDFH) or (3) to request a holding pattern in order to wait for further information on the situation at EDDF. The goals are to avoid delays for the passengers and to maintain safety.

There are several aspects to be taken into account. If the pilots go ahead there might by the possibility that the runway will not be cleared quickly and that in the end they have to divert anyway. This would cause a delay because the aircraft will have to queue behind other aircraft that decided to divert earlier. If they divert a question to be answered is, if a delivery service will still be available which takes the passengers to the original destination, furthermore, if the duty time of the pilots will expire so that they will not be able to fly the aircraft back to the original airport. If they wait for further information there might be the chance that the pilots receive news that in the end the runway is re-opened. On the other hand, there is the chance that it will not be re-opened and a diversion is the only option left after some time of waiting. Will there still be enough fuel for this case?

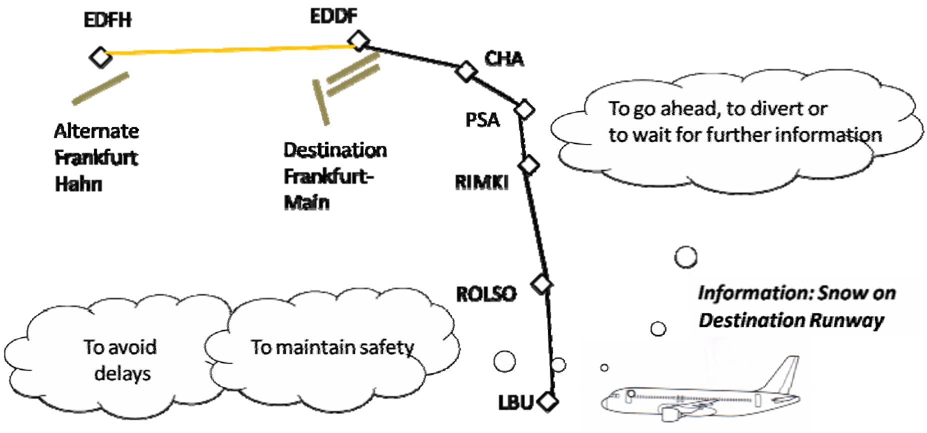

Fig. 1. Complex air traffic scenario

The second example describes a road traffic example in which a car driver has to decide either to stay behind a lead car or to overtake (Fig. 2). If (s)he intends to overtake then (s)he can either let the approaching car pass or not. For these decisions the speed of and distance to the approaching car as well as the lead car have to be assessed. Furthermore, the capabilities of the ego car have to be taken into account. Accident studies have shown that the problem in overtaking scenarios "stems from faulty choices of timing and speed for the overtaking maneuver, not a lack of vehicle control skills as such" [7].

Both examples will be used throughout the text to illustrate characteristics of human decision making in complex traffic scenarios.

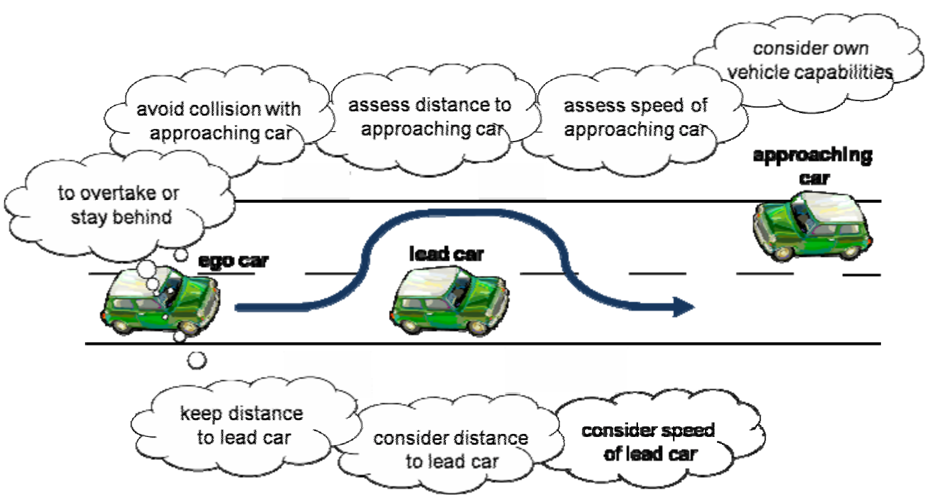

Fig. 2. Complex road traffic scenario

3 Cognitive Engineering

In the design of systems that support humans in complex environments, like the air and road traffic environment described above, characteristics of human behavior have to be understood and should be the basis for all design decisions. Such characteristics include potential human errors. In transportation human error is still the major contributing factor in accidents. One accepted solution to this problem is the introduction of assistance systems in aircraft and cars. Such systems have been introduced but still they need to be more intuitive and easy to use [38, 39].

During design and certification of assistance systems today, human error analysis is perceived as relevant in almost all stages: it has to be proven that human errors are effectively prevented and no new errors or unwanted long-term effects are induced. Nevertheless, the current practice is based on engineering judgment, operational feedback from similar cars or aircraft, and experiments with test users when a prototype is available. Considering the increasing complexity of the traffic environment and of modern assistance systems that are currently researched (e.g. 4D Flight Management Systems in aircraft and Forward Collision Warning in cars) methodological innovations are needed to cope with all possible interactions between human, system and environment. New methods have to be affordable and applicable in early design phases.

Cognitive Engineering is a research field that addresses this issue. Research focuses on methods, techniques and tools to develop intuitive, easy to use, easy to learn, and understandable assistance systems [31]. The field draws on knowledge of cognitive psychology [48] but stresses the point that design and users have to be investigated and understood in "in the wild" [33]. The term "cognition in the wild" has been introduced by Edwin Hutchins [20] and means that natural work environments should be preferred over artificial laboratory settings because human behavior is constrained on the one hand by generic cognitive processes and, equally important, on the other hand by characteristics of the environment. The objective of Cognitive Engineering is to make knowledge on human behavior that was acquired in the wild readily available to designers in order to enable designing usability into the system right from the beginning instead of adding it after the fact.

Our approach to Cognitive Engineering is based on cognitive models. In cooperation with other partners (e.g. the German Aerospace Center in Braunschweig, Germany) we perform empirical studies in cars and aircraft. Based on the data and derived knowledge about human behavior we develop cognitive models that are meant to be applied as virtual testers of interactive systems in cars or aircraft. These models are executable, which means that they can interact with other models or software to produce time-stamped action traces. In this way closed loop interaction can be simulated and emergent behavior including human errors can be predicted. The results of this model-based analysis should support the establishment of usability and safety requirements.

For the integration our model provides a dedicated interface to connect it to existing simulation platforms. The model is currently able to interact with a vehicle simulator and a cockpit simulator that are normally used for experiments with human subjects. The integration with these platforms has got the advantage that the model can interact with the same environment as human subjects. Thus, model data and human data produced in the very same scenarios can be compared for the purpose of model validation. The current status of our aircraft pilot crew model is presented in another article in this book [25].

4 Cognitive Models

The models that are most interesting for Cognitive Engineering are integrated cognitive models. Research on integrated models was proclaimed amongst others by Newell in the early seventies (see e.g. [30]). Newell argued in favor of a unified theory of cognition [29]. At that time and still today (and for a good reason) psychology is divided in several subfields like perception, memory, motivation and decision making in order to focus on clearly defined phenomena that can be investigated in a laboratory setting. The psychology of man is approached in a "divide and conquer" fashion in order to be able to design focused laboratory experiments revealing isolated phenomena of human cognition. Newell [29] suggested to combine the existing knowledge into an integrated model because most tasks, especially real world tasks, involve the interplay of all aspects of human cognition. The interaction with assistance systems involves directing attention to displays and other information sources and perceiving these cues to build up and maintain a mental model of the current situation as a basis for making decisions on how to operate the system in order to achieve current goals.

Integrated cognitive models can be built using cognitive architectures. Cognitive architectures are computational "hypotheses about those aspects of human cognition that are relatively constant over time and relatively independent of task" [36]. They allow to reuse empirically validated cognitive processes and thus they ease the task dependent development of a cognitive model. The architecture integrates mechanisms to explain or predict a set of cognitive phenomena that together contribute to the performance of a task.

A lot of cognitive architectures have been suggested and some have been used to model human behavior in traffic. An overview of cognitive models is provided in [35, 23,18, 14]. The most prominent representatives are ACT-R [3] and SOAR [50]. ACT-R (Atomic Components of Thought-Rational) stems from the early HAM (Human Associative Memory) model [2], a model of the human memory. SOAR was motivated by the General Problem Solver [28] a model of human problem solving. These different traditions led to complementary strength and weaknesses. ACT-R has a sophisticated subsymbolic memory mechanism with subsymbolic learning mechanisms enabling simulation of remembering and forgetting. For SOAR, researchers only recently began to incorporate similar mechanisms [6, 32]. One outstanding feature of SOAR is its knowledge processing mechanism allowing to deal with problem solving situations where the model lacks knowledge to derive the next step. In such "impasses" SOAR applies task-independent default heuristics with predefined criteria to evaluate potential solutions. Solutions to impasses are added to the knowledge base by SOAR's universal learning mechanism (chunking).

Both architectures were extended by incorporating perceptual and motor modules of the EPIC architecture (ACT-R/PM [3]), EPIC-SOAR [5]) to be able to interact realistically with simulated environments. EPIC [27] is an architecture that focuses on detailed models of constraints of the human perceptual, and motor activity, knowledge processing is considered with less accuracy. ACT-R and SOAR neglected multi-tasking and thus were criticised for not being capable to model human behaviour in highly dynamic environments like car driving or flying an airplane. Aasman [1] used SOAR to investigate this criticism, by applying SOAR to model approaching and handling of intersections (SOAR-DRIVER). To incorporate multi-tasking, he modelled “highly intersection specific rules” for sequentially switching between tasks like eye-movements, adjust speed, adjust trajectory, attend, and navigate. Contrary to this task-specific approach, Salvucci [37] tried to develop a “general executive” for ACT-R/PM that models task-switching based on dynamic prioritization in a most generic form. His technique is based on timing requirements of goals (start time and delay) and task-independent heuristics for natural pre-emption-points in tasks. He tried to schedule tasks for car control, monitoring, and decision making in lane change manoeuvres.

Further cognitive architectures were motivated by the need to apply human models to the evaluation of human interaction with complex systems (MIDAS (Man-machine Integration Design and Analysis System) [8] and APEX (Architecture for Procedure Execution) [15]. These models focused on multi-tasking capabilities of humans from the very start of their development, but they neglected for example cognitive learning processes. MIDAS and APEX offer several tools for intuitively interpreting and analysing traces of human behaviour.

CASCaS (Cognitive Architecture for Safety Critical Task Simulation) is a cognitive architecture which is developed at the OFFIS Institute for Information Technology [24, 26]. It draws upon similar mechanisms like those in ACT-R and SOAR but extends the state of the art by integrating additional mechanisms to model the cognitive phenomena “learned carelessness”, selective attention and attention allocation.

Cognitive architectures provide mechanisms for simulating task independent cognitive processes. In order to simulate performance of a concrete task the architecture has to be complemented with task dependent knowledge. Task knowledge has to be

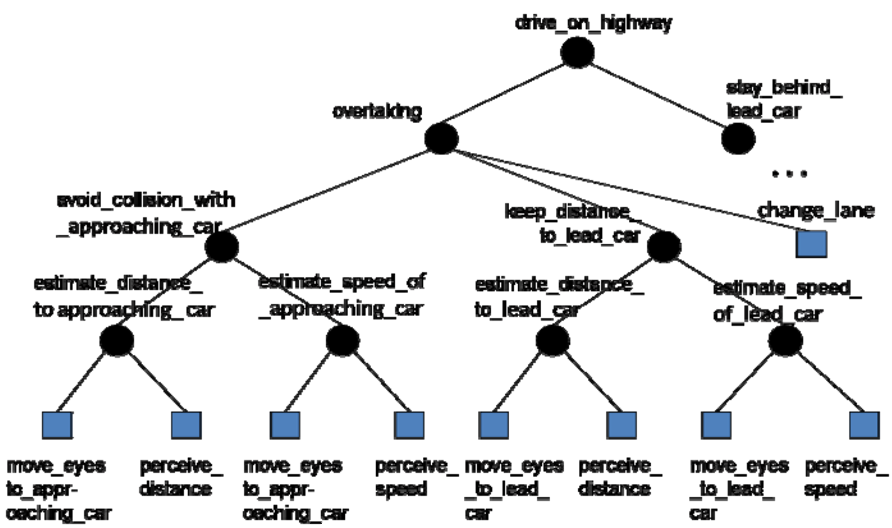

Fig. 3. Task tree for overtaking

modelled in formalisms prescribed by the architecture, e.g. in form of production rules (e.g. ACT-R, SOAR, CASCaS) or scripts (e.g. MIDAS). A common structure behind these formalisms is a hierarchy of goals and subgoals which can be represented as a task tree or task network. In Fig. 3 a task tree for the overtaking manoeuvre in the road traffic example from above is shown. In this tree a top level goal is iteratively decomposed into subgoals until at the bottom concrete driver actions are derived that have to be performed in order to fulfill a goal. The goals as well as actions can be partially ordered.

Every decomposition is either a conjunction or a disjunction. Conjunction means all paths have to be traversed during task performance. Paths may be partially ordered. Within the constraints of this order sequential, concurrent or interleaved traversal is possible. Disjunctions are annotated with conditions (not shown in Fig. 3) that define which paths are possible in a concrete situation. From these possibilities either one or several paths can be traversed. The choices that are not fully constrained by the task tree like sequential/concurrent/ interleaved and exclusive/ inclusive path traversal are defined by the cognitive architecture. In this way the architecture provides an operational semantics for the task tree which is based on a set of psychological phenomena.

Fig. 4 shows a simplified schema of a generic cognitive architecture. It consists of a memory component where the task knowledge is stored, a cognitive processor which retrieves knowledge from memory and derives actions, a percept component which directs attention to objects in the environment and retrieves associated data, and a motor component that manipulates the environment. The interaction of these components during the execution of task knowledge can be described in form of a cognitive cycle as illustrated in Fig. 5 in form of state automata. The cycle starts with the selection of a goal from a goal agenda - the goal agenda holds at any time the set of goals that have to be achieved. Next, new information is received from the percept or the memory components. Based on this data the next branch in the task tree can be chosen which then leads to motor actions (e.g. movements of eyes or hands), memory actions (storing new information) or new goals.

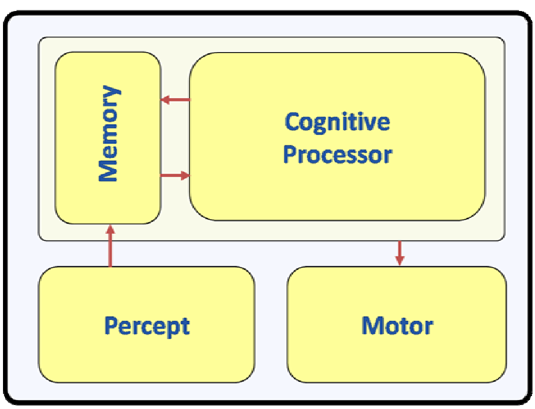

Fig. 4. Generic Cognitive Architecture

In order to illustrate the cognitive cycle the processing of a small (and simplified) part of the decision tree (Fig. 3) shall be explained. For this the task tree first shall be translated into production rules that are the central formalism in production system architectures like ACT-R, SOAR, and CASCaS (see Fig. 6). Let's assume the model's perceptual focus and attention is on the lead car. Fig. 6 illustrates four iterations of the cognitive cycle:

- *Cycle 1*: The currently selected goal is to drive on a highway. The speed of the lead is perceived from the percept component and the ego car speed is retrieved from the memory component. Since the lead car is slower than the ego car it derives a goal to overtake (by selecting rule 1, Fig. 6).
- *Cycle 2*: Overtaking is selected as the next goal and by applying rule 2 the action to move the eyes to the approaching car is derived (in this step no information has to be retrieved or perceived).
- *Cycle 3*: Next the current goal is kept and the action to move the attention to the approaching car is derived (by rule 3) which allows to perceive speed and distance information about the approaching car.
- *Cycle 4*: Again the current goal is kept, information about the approaching car is perceived from the percept component and information about the lead car is retrieved from memory. This information is evaluated and rule is 4 is applied to derive a motor action to change the lane.

This cycle is the basis for cognitive architectures like ACT-R, SOAR and CASCaS. The explicit distinction between moving the eyes and afterwards moving attention separately is a feature that has been introduced by ACT-R and again shows how the cognitive architecture provides a specific operational semantics for task knowledge. The distinction between movements of eye and attention is based on research in visual attention [45, 3] which shows two processes: pre-attentive processes allowing access to features of an object as color, size, motion, etc. and attentive processes allowing access to its identity and more detailed information, e.g. the type of car.

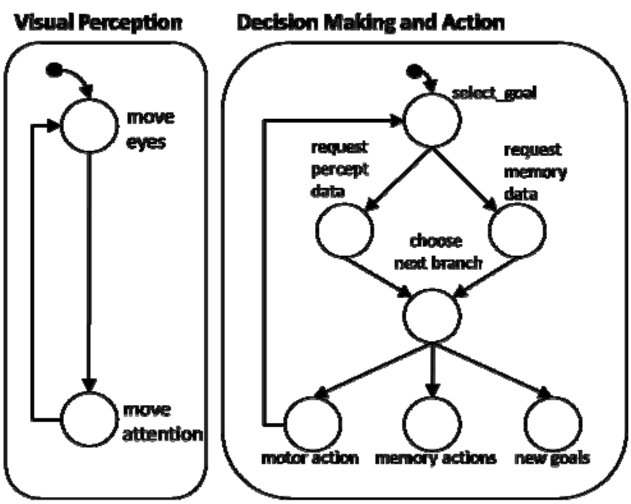

Fig. 5. Typical cognitive cycle

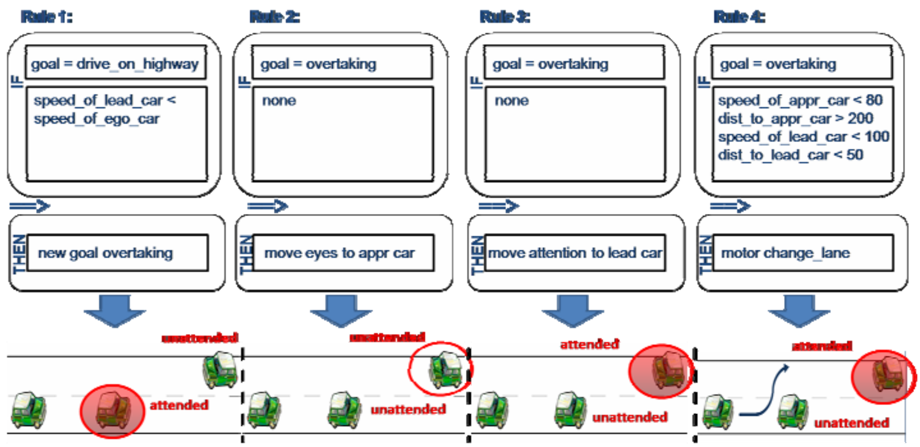

Fig. 6. Examples of rules for the overtaking manoeuvre

In the cognitive cycle described above decision making (if and when to overtake) is modelled as traversing a task tree or network with choice points. The question arises if this concept is adequate to simulate human behaviour in complex dynamic traffic environments. In this paper it is argued that the cognitive cycle has three important shortcomings: (1) processes of visual perception deliver data from the environment independent on the current situation, (2) there is no flexibility with regard to the decision strategy (traversing networks with choice points), and (3) the influence of time pressure is not considered.

These shortcomings simplify some very important characteristics of how humans cope with complexity. One major point is that humans use heuristics for vision and decision making to reduce complexity and to cope with limitations of the human cognitive system. The application of such heuristics is dependent on available time.

5 Decision Making in Complex Air Traffic Scenarios

In this section it will be described how pilots might make decisions in the air traffic scenario introduced above. Before doing so, the concept of complexity shall be further outlined in order to explicate the perspective underlying the decision procedures described below.

The concept of complexity in this text is in line with the definitions given in the field of Naturalistic Decision Making (e.g. [34, 22]). Complexity is viewed as a subjective feature of problem situations. The same situation can be complex for one person but simple for another one. The level of complexity attributed to a situation is highly dependent on the level of experience a person has already acquired with similar situations. Due to experience people are able to apply very efficient decision making heuristics [51]. Nevertheless, it is possible to pinpoint some characteristics of situations that people perceive as complex: conflicting goals, huge number of interdependent variables, continuously evolving situation, time pressure (evolving situations require solution in real-time), criticality (life is at stake), uncertainty (e.g. because of ambiguous cues). Complexity often goes along with a mismatch of time needed and time given, which can lead to degraded performance. Based on this characterization complexity of a situation can be described by the following function:

$$complexity = f\,(\,problem\_features,\ known\_heuristics,\ applicable\_heuristics\,).$$

Classical decision theory (e.g. [21]) defines decision making as choosing the optimal option from an array of options by maximization of expected utility. In order to compute expected utility probabilities and a utility function are needed. Probabilities are needed to quantify uncertain information like uncertain dependencies. In the air traffic example it is uncertain if the runway will be cleared quickly. It depends e.g. on the current temperature, wind and level of snowfall. This uncertainty could be quantified by the conditional probability:

$$P\,(\,runway\_cleared\_quickly \mid temperature,\ wind,\ snowfall\,).$$

Further probabilistic considerations to be made are: If the pilots decide to wait will their duty time expire in case they have to divert later on? Will there still be enough fuel for a diversion? How long do they have to wait until further information will be available? If they decide to divert will the delivery service for the passengers still be available at time of arrival?

Utilities are needed in order to quantify for all possible situations the level of goal achievement. This has to be done for all goals and for all possible situations. In the air traffic scenario there are mainly two goals: to avoid delays and to maintain safety. The first utility could be defined as hours of delay using the following function:

$$U\!:\ delivery\_service\_still\_available \times expiring\_duty\_time \times diversion \times continue\_to\_original\_airport \times waiting \rightarrow hours\_of\_delay$$

Assuming that each variable is binary (and that the three decision variables are mutually exclusive) the foreseen hours of delay have to be given for 12 situations. Additionally the utility for maintaining safety has to be quantified. In summary, from the perspective of classical decision theory complexity can be defined by the function:

$$complexity = f\,(\,\#^{1}options,\ \#influence\_factors,\ \#probabilities,\ \#goals,\ \#utilities\,).$$

Classical decision theory was criticized by many researchers as inadequate to describe actual decision making of humans. E.g. Simon [42] stated that the „capacity of the human mind for formulating and solving complex problems is very small compared with the size of the problems whose solution is required for objectively rational behavior in the real world – or even for a reasonable approximation to such objective rationality". He coined the term "Bounded Rationality" [41]. Tversky and Kahnemann [46] described several decision heuristics people use in complex situations to cope with the limits of human decision making. Building on this seminal work the research field Naturalistic Decision Making investigates the way in which people actually make decisions in complex situations [22]. A main point brought up in this field is that proficient decision makers rarely compare among alternatives, instead they assess the nature of the situation and select an action appropriate to it by trading-off accuracy against cost of accuracy based on experience. Experience allows

[1] # meaning "number of".

people to exploit the structure of the environment to use "fast and frugal heuristics" [17]. People tend to reduce complexity by adapting behaviour to the environment. Gigerenzer introduced the term "Ecological Rationality"[2] which involves analyzing the structure of environments, tasks, and heuristics, and the match between them. By the use of structured interviews with decision makers several generic decision heuristics have been described [51]. Three of these are Elimination by Aspects, Assumption-Based Reasoning and Recognition-Primed Decision Making. In the sequel, it will be shown how pilots might use these heuristics to make a decision in the air traffic example.

Elimination by Aspects is a procedure that sequentially tests choice options against a number of attributes. The order in which attributes are tested is based on their importance. This heuristic can be applied if one of several options (in our example either to continue to the original airport, to divert to the alternative airport or to wait for further information) must be selected and if an importance ordering of attributes is available. Assuming the following order of attributes *snow_on_runway*, *enough_fuel*, *expiring_duty_time*, *delivery_service* a decision could be done in three steps. (1) There is currently snow on the runway, thus the original airport is ruled out. The remaining options are either to divert or to wait. (2) Because there is enough fuel for both decisions, the second attribute does not reduce the set of options. (3) If a diversion to the alternate is chosen the duty time will expire and there is no chance to fly the passengers to the final destination if the situation has cleared up. Consequently, a diversion is ruled out. Finally, there is only one option left which is to wait. Since a decision has been found the last attribute *delivery_service* is not considered because the strategy is non-compensatory. From the perspective of Elimination by Aspects complexity can be defined as:

$$complexity = f(\#options, \#known\_discriminating\_attributes).$$

The more options the more complex, but complexity is drastically reduced if discriminating attributes are available. The strategy does not necessarily use all attributes but focuses on the more important ones.

In Assumption-based Reasoning assumptions are generated for all unknown variables. For example, the pilots might assume that the runway will not be cleared quickly and that landing on the original airport will thus not be possible during the next hours. This would be a worst case assumption. Consequently, they would decide to divert. Roughly complexity for this heuristic depends on the number of assumptions that have to be made or on the number of unknown variables:

$$complexity = f(\#unknown\_variables).$$

Using Recognition-Primed Decision Making, the third heuristic, people try to recognize the actual situation by comparing it to similar situations experienced in the past. In this way expectations are generated and validated against the current situation. If expectations are met the same decision is taken. For example, the pilots recall a similar situation where there was snow on the original runway and further information were announced. In that situation the temperature was normal, wind was modest. The decision at that time was to wait for further information. Finally, the runway was

[2] Ecological Rationality and Naturalistic Decision Making are very similar but do not follow exactly the same research path. Differences are described in [43].

cleared quickly and the pilots could land. Based on this past situation, the pilots might verify expected attributes like the temperature and wind and if these fit with the past situation they could decide in the same way. The complexity might by defined by:

$$complexity = f\,(\,\#known\_similar\_situations,\ \#expectations\,).$$

From these three examples of decision procedures, the first conclusion for human decision making in complex scenarios shall be derived:

> *Humans use heuristic decision procedures to reduce the complexity of a situation. The use of heuristics depends on the given information and on the mental organization of knowledge.*

The human cognitive system and the structure of the environment in which that system operates must be considered jointly, not in isolation from one another. The success of heuristics depends on how well they fit with the structure of the environment. In Naturalistic Decision Making cognition is seen as the art of focusing on the relevant and deliberately ignoring the rest.

6 Decision Making in Complex Road Traffic Scenarios

In this section it will be described how car drivers might make decisions in the road traffic scenario introduced above. The description starts, like above, from a normative perspective.

Normatively a car driver has to consider the following information in order to decide if it is safe to overtake or not [19]:

- The Distance Required to Overtake (DRO) as a function of distance to lead car, relative speed and ego vehicle capabilities,
- Time Required to Overtake (TRO) as a function of distance to lead car, relative speed and ego vehicle capabilities,
- Time To Collision with lead car (TTC_{Lead}) as a function of distance to lead car and relative speed,
- Time To Collision of approaching car with DRO (TTC_{DRO}) as a function of speed and distance between DRO and approaching car.

Overtaking is possible if $TRO < TTC_{DRO}$; the safety margin can be computed as $TTC_{DRO} - TRO$.

The problem is that this normative information is not always available. Instead, drivers use visual heuristics [12, 10]. Gray and Regan [19] investigated driver behavior in overtaking scenarios. They identified three strategies for initiating overtaking manoeuvres: (1) Some drivers initiated overtaking when TTC_{DRO} minus TRO exceeded a certain critical temporal margin, (2) others initiated overtaking when the actual distance to the approaching car was greater than a certain critical distance, (3) a thirdgroup of drivers used a dual strategy: they used the distance strategy if the rate of expansion was below recognition threshold and they used the temporal margin strategy if the rate of expansion was above recognition threshold. The rate of expansion is defined based on the angle ϕ which stands for the angular extend of an object measured in radians. The quotient $\delta\phi / \delta t$ is the rate of expansion. It is assumed that peoples' estimation of TTC can be described by the formula $\phi / (\delta\phi / \delta t)$. This formula is an example of an optical invariant which means that it is nearly perfectly correlated with the objective information that shall be measured [9]. Apart from such invariants people also use optical heuristics if invariant information is not available [9]. For example, the rate of expansion (motion information) becomes more impoverished as viewing distance increases. It is assumed that if motion information becomes available drivers use optical invariants like rate of expansion, otherwise drivers use visual heuristics like pictorial depth cues [9]. An example for pictorial depth cues is the size in field or relative size. The use of these cues can sometimes lead to misjudgments. In an experiment DeLucia and Tharanathan [10] found that subjects estimated a large distant object to arrive earlier than a near small object.

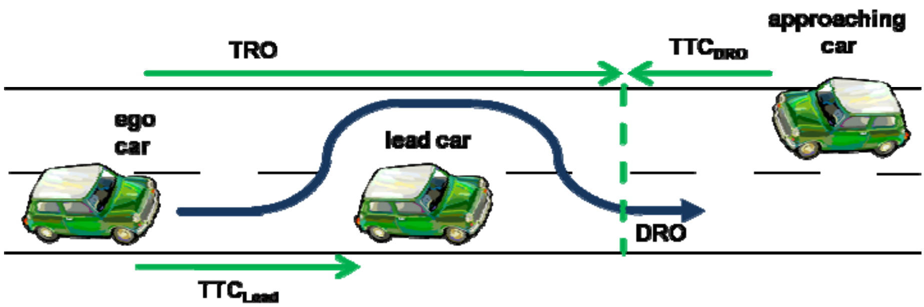

Fig. 7. Normative information for overtaking manoeuvre

Based on this investigation the second conclusion for human decision making in complex scenarios shall be derived:

> *People use visual heuristics to cope with limitations of the human vision system in highly dynamic environments. The use of these heuristics depends on information that is perceivable. If only distance information is available pictorial depth cues are used if motion information becomes available temporal information is used instead.*

Apart from distance to an object further parameters relevant for use of visual heuristics are motion in space, the nature of the current task [11] and visibility.

7 Extending the Typical Cognitive Cycle

Based on the two conclusions derived above two implications for cognitive modeling of human behavior in complex situations will be shown in this section. As a result extensions of the cognitive cycle introduced in Fig. 5 are suggested.

The first implication is that the cognitive cycle needs to be more flexible: The typical cognitive cycle models decision making as traversing a decision tree. In Section 5 it has been shown that people are very flexible in applying decision procedures. In order to model this behavior traversing a task tree should just be one of several other mechanisms for decision making. Additionally meta-cognitive capabilities to choose an adequate heuristic for a given decision situation based on environmental characteristics and available knowledge have to be added to the model. This extension is shown in Fig. 8 as a sub structure for the box decision making and action. There are sub boxes for different decision procedures which all could be further specified by state automata. On top of these a box for meta cognition is added which passes control to the decision procedures.

The second implication is that perception has to be modeled dependent on factors like distance to an object. Visual heuristics are applied in case that optical invariants are not available. This behavior has to be added to the percept component of the model. Based on physical parameter of the current situation it has to be assessed on which cues humans would most likely rely. This is modeled by including different perception mechanisms in the perception box (Fig. 8) that act as filters of incoming information extracting either invariants or different forms of visual heuristics.

A third implication is that the application of visual heuristics can change over time e.g. as the object gets closer motion information may become available. Also heuristic decision procedures can change over time. The quality of results can improve over time. For example, in cases when deliberation time is short the heuristic Elimination by Aspects may stop the process of checking attributes before the set of options has been reduced to one. In this case the choice from the remaining options may be done randomly. If more time is available the set may be further reduced and thus the quality of results can be improved.

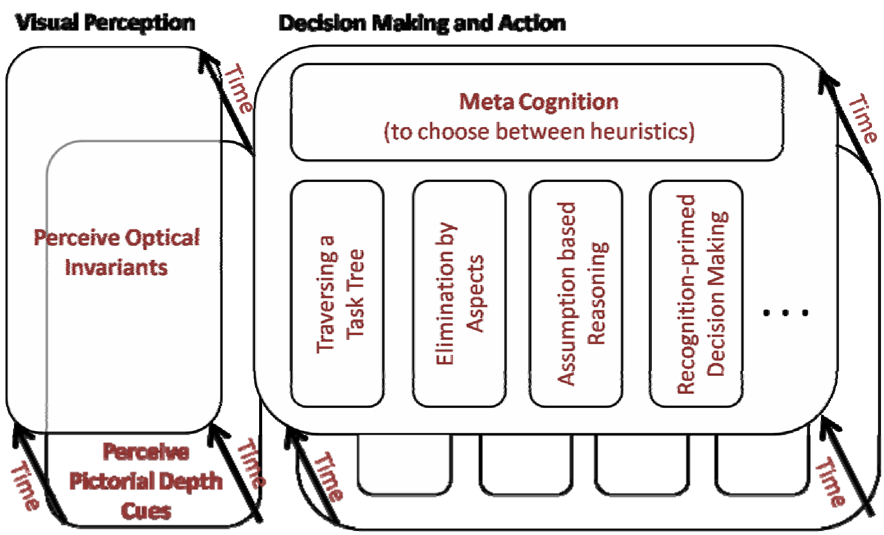

Fig. 8. Extended Cognitive Cycle

As a consequence time should be added as a new dimension to the cognitive cycle (Fig. 8). This new dimension may have two effects:

(1) as time passes the current heuristic could be stopped (e.g. relying on optical depth cues) and another heuristic may be started (e.g. relying on optical invariants),
(2) as time passes the current heuristic may deliver improved results.

8 Summary

In this text the typical cognitive cycle prevalent in cognitive architectures has been illustrated. Human decision making has been described based on two examples from the Aeronautics and Automotive domain. Based on research from Naturalistic Decision Making and visual perception of drivers important characteristics of human behaviour in complex traffic environments have been described. From these characteristics new requirements for cognitive modeling have been derived. The requirements have been introduced in from of extensions of the typical cognitive cycle of cognitive architectures. The text addressed the application of cognitive models as virtual testers of assistance systems in cars and aircraft.

References

1. Aasman, J.: Modelling Driver Behaviour in Soar. KPN Research, Leidschendam (1995)
2. Anderson, J.R., Bower, G.: Human associative memory. Winston & Sons, Washington (1973)
3. Anderson, J.R., Bothell, D., Byrne, M.D., Douglass, S., Lebiere, C., Qin, Y.: An integrated theory of the mind. Psychological Review 111(4), 1036–1060 (2004)
4. Boeing Airplane Safety: Statistical Summary of Commercial Jet Aircraft Accidents: Worldwide Operations, 1959-2005. Boeing Commercial Airplane, Seattle, WA (2006)
5. Chong, R.S., Laird, J.E.: Identifying dual-task executive process knowledge using EPIC-Soar. In: Proceedings of the Nineteenth Annual Conference of the Cognitive Science Society. Lawrence Erlbaum Associates, Hillsdale (1997)
6. Chong, R.: The addition of an activation and decay mechanism to the Soar architecture. In: Proceedings of the 5th International Conference on Cognitive Modeling (2003)
7. Clarke, D.D., Ward, P.J., Jones, J.: Overtaking road accidents: Differences in manoeuvre as a function of driver age. Accident Analysis and Prevention 30, 455–467 (1998)
8. Corker, K.M.: Cognitive models and control: Human and system dynamics in advanced airspace operations. In: Sarter, N., Amalberti, R. (eds.) Cognitive Engineering in the Aviation Domain, pp. 13–42. Lawrence Erlbaum Associates, Mahwah (2000)
9. Cutting, J.E., Wang, R.F., Fluckiger, M., Baumberger, B.: Human heading judgments and object-based motion information. Vision Res. 39, 1079–1105 (1999)
10. DeLucia, P.R., Tharanathan, A.: Effects of optic flow and discrete warnings on deceleration detection during car-following. In: Proceedings of the Human Factors and Ergonomics Society 49th Annual Meeting, pp. 1673–1676. Human Factors and Ergonomics Society, Santa Monica (2005)
11. DeLucia, P.R.: Critical Roles for Distance, Task, and Motion in Space Perception: Initial Conceptual Framework and Practical Implications. Human Factors 50(5), 811–820 (2008)
12. DeLucia, P.R.: Pictorial and motion-based information for depth judgements. Journal of Experimental Psychology: Human Perception and Performance 17, 738–748 (1991)
13. Dornheim, M.A.: Dramatic Incidents Highlight Mode Problems in Cockpits. In: Aviation Week & Space Technology, January 30 (1995)
14. Forsythe, C., Bernard, M.L., Goldsmith, T.E.: Human Cognitive Models in Systems Design. Lawrence Erlbaum Associates, Mahwah (2005)
15. Freed, M.A., Remington, R.W.: Making human-machine system simulation a practical engineering tool: An apex overview. In: Proceedings of the International Conference on Cognitive Modelling (2000)

16. Gersh, J.R., McKneely, J.A., Remington, R.W.: Cognitive engineering: Understanding human interaction with complex systems. Johns Hopkins APL Technical Digest 26(4) (2005)
17. Gigerenzer, G., Todd, P.M.: The ABC Research Group: Simple heuristics that make us smart. Oxford University Press, New York (1999)
18. Gluck, K., Pew, R.: Modeling Human Behavior with Integrated Cognitive Architectures: Comparison, Evaluation, and Validation. Lawrence Erlbaum Associates, Mahwah (2005)
19. Gray, R., Regan, D.M.: Perceptual Processes Used by Drivers During Overtaking in a Driving Simulator. Human Factors 47(2), 394–417 (2005)
20. Hutchins, E.: Cognition in the Wild. MIT Press, Cambridge (1995)
21. Keeny, R.L., Raiffa, H.: Decisions with Multiple Objectives: Preferences and Value Trade-Offs. Wiley & Sons, New York (1976)
22. Klein, G.: Naturalistic Decision Making. Human Factors 50(3), 456–460 (2008)
23. Leiden, K., Laughery, K.R., Keller, J., French, J., Warwick, W., Wood, S.D.: A review of human performance models for the prediction of human error. Technical report, NASA, System-Wide Accident Prevention Program, Ames Research Center (2001)
24. Lüdtke, A., Möbus, C.: A cognitive pilot model to predict learned carelessness for system design. In: Pritchett, A., Jackson, A. (eds.) Proceedings of the International Conference on Human-Computer Interaction in Aeronautics (HCI-Aero), 29.09.-01.10 (2004)
25. Lüdtke, A., Osterloh, J.-P., Mioch, T., Rister, F., Looije, R.: Cognitive Modelling of Pilot Errors and Error Recovery in Flight Management Tasks. In: Palanque, P., Vanderdonckt, J., Winckler, M. (eds.) HESSD 2009. LNCS, vol. 5962, pp. 54–67. Springer, Heidelberg (2010)
26. Lüdtke, A., Osterloh, J.-P.: Simulating Perceptive Processes of Pilots to Support System Design. In: Gross, T., Gulliksen, J., Kotzé, P., Oestreicher, L., Palanque, P., Prates, R.O., Winckler, M. (eds.) INTERACT 2009, Part I. LNCS, vol. 5726, pp. 471–484. Springer, Heidelberg (2009)
27. Meyer, D.E., Kieras, D.E.: A computational theory of executive cognitive processes and multipletask performance: Part 1. basic mechanisms. Psychological Review 104, 3–65 (1997)
28. Newell, A., Simon, H.A.: GPS, a program that simulates human thought. In: Feigenbaum, E., Feldmann, J. (eds.) Computers and Thought (1961)
29. Newell, A.: Unified Theories of Cognition. Harvard University Press (1994); Reprint edition
30. Newell, A.: You can't play 20 questions with nature and win: projective comments on the papers of this symposium. In: Chase, W.G. (ed.) Visual Information Processing. Academic Press, New York (1973)
31. Norman, D.A.: Steps Toward a Cognitive Engineering: Design Rules Based on Analyses of Human Error. In: Nichols, J.A., Schneider, M.L. (eds.) Proceedings of the SIGCHI conference on Human factors in computing systems, pp. 378–382. ACM Press, New York (1982)
32. Nuxoll, A., Laird, J., James, M.: Comprehensive working memory activation in Soar. In: International Conference on Cognitive Modeling (2004)
33. Olson, J.R., Olson, G.M.: The Growth of Cognitive Modeling in Human-Computer Interaction since GOMS. In: Human-Computer Interaction, vol. 5, pp. 221–265. Lawrence Erlbaum Associates, Inc., Mahwah (1990)
34. Orasanu, J., Connolly, T.: The reinvention of decision making. In: Klein, G.A., Orasanu, J., Calderwood, R., Zsambok, C.E. (eds.) Decision Making in Action: Models and Methods, pp. 3–21. Ablex Publishing Corporation, NJ (1993)

35. Pew, R., Mavor, A.S.: Modeling Human and Organizational Behavior. National Academy Press, Washington (1998)
36. Ritter, F.E., Young, R.M.: Embodied models as simulated users: Introduction to this special issue on using cognitive models to improve interface design. International Journal of Human-Computer Studies 55, 1–14 (2001)
37. Salvucci, D.: A multitasking general executive for compound continuous tasks. Cognitive Science 29, 457–492 (2005)
38. Sarter, N.B., Woods, D.D.: How in the World did we get into that Mode? Mode error and awareness in supervisory control. Human Factors 37(1), 5–19 (1995)
39. Sarter, N.B., Woods, D.D.: Strong, Silent and Out of the Loop: Properties of Advanced (Cockpit) Automation and their Impact on Human-Automation Interaction, Cognitive Systems Engineering Laboratory Report, CSEL 95-TR-01, The Ohio State University, Columbus OH (1995)
40. Sarter, N.B., Woods, D.D., Billings, C.: Automation Surprises. In: Salvendy, G. (ed.) Handbook of Human Factors/Ergonomics, 2nd edn. Wiley, New York (1997)
41. Simon, H.A.: A Behavioral Model of Rational Choice. In: Models of Man, Social and Rational: Mathematical Essays on Rational Human Behavior in a Social Setting. Wiley, New York (1957)
42. Simon, H.A.: Administrative Behavior. A Study of Decision-Making Processes in Administrative Organization, 3rd edn. The Free Press, Collier Macmillan Publishers, London (1976)
43. Todd, P.M., Gigerenzer, G.: Putting Naturalistic Decisions Making into the Adaptive Toolbox. Journal of Behavioral Decision Making 14, 353–384 (2001)
44. Treat, J.R., Tumbas, N.S., McDonald, S.T., Shinar, D., Hume, R.D., Mayer, R.E., Stanisfer, R.L., Castillan, N.J.: Tri-level study of the causes of traffic accidents. Report No. DOT-HS-034-3-535-77, Indiana University (1977)
45. Treisman, A.M., Gelade, G.: A feature-integration theory of attention. Cognitive Psychology 12, 97–136 (1980)
46. Tversky, A., Kahneman, D.: Judgment under uncertainty: Heuristics and biases. Science 185, 1124–1131 (1974)
47. Wiener, E.L.: Human Factors of Advanced Technology ("Glass Cockpit") Transport Aircraft. NASA Contractor Report No. 177528. Moffett Field, CA: NASA Ames Research Center (1989)
48. Woods, D.D., Roth, E.M.: Cognitive Engineering: Human Problem Solving with Tools. Human Factors 30(4), 415–430 (1988)
49. Woods, D.D., Johannesen, L.J., Cook, R.I., Sarter, N.B.: Behind Human Error: Cognitive Systems, Computers, and Hindsight. Wright Patterson Air Force Base, Dayton, OH: CSERIAC (1994)
50. Wray, R., Jones, R.: An introduction to Soar as an agent architecture. In: Sun, R. (ed.) Cognition and Multi-agent Interaction, pp. 53–78. Cambridge University Press, Cambridge (2005)
51. Zsambok, C.E., Beach, L.R., Klein, G.: A Literature Review of Analytical and Naturalistic Decision Making. Technical Report Klein Associates Inc., 582 E. Dayton-Yellow Springs Road, Fairborn, OH 45324-3987 (1992) http://www.au.af.mil/au/awc/awcgate/navy/klein_natur_decision.pdf