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Simulation of Cognitive Behaviour in Computer Games[1]

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1. INTRODUCTION

Two important research topics of the CEC MOHAWC project are analysis of cognitive performance in actual work context and experimental investigation of selected cognitive features by means of complex, simulated work domains, the so-called micro-worlds. Special efforts are made in the project to generalize in order secure cross-fertilization between the two lines of investigation. To support this latter effort, development of taxonomies for work analysis (Rasmussen et al. 1990) and for micro-worlds (Brehmer, 1990) is used to serve as a kind of intellectual interface.

A third important issue of the Mohawc project is an attempt to develop computer simulation models of cognitive functions in order to test the consistency of the models derived from the field studies and the experiments in micro-worlds.

The present paper presents for discussion one approach, among several possible, to the development of such simulation models. It is mainly concerned with the identification and modelling of cognitive strategies at the various levels of human functioning in order to understand the complex interaction of knowledge, rules and skills during a learning process.

The decision how to do something and then implement the decision in a synchronized series of precisely timed limb movements is an important ingredient of the work carried out by many kinds of professionals, from dressmakers to fighter-plane pilots. Since the early days of cybernetics and engineering bionics (see, for example, Moore and Speak, 1966), relatively little has been done to describe and understand how behavioral patterns not having root in conscious reasoning are acquired through learning by experience. It was the aim of the empirical study reported to get hints and derive hypotheses for generating an adaptive cognitive model of this kind of tasks. Consequently, the model should not only describes stable cognitive processes, but capture the changes during experience and skill acquisition.

It is our assumption that predicting the way a human agent will cope with work situations is basically done by first delimiting the mental strategies that *can* be used for what is needed and then examining the agent's prefer-

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ences and cognitive resources to identify the likely strategy he or she *will* use to get the work done. This means that in order to understand the possible mental strategies, one has to start with an analysis of the work domain at the various levels the human may interact with it. This kind of analysis has been carried out for domains such as process control, emergency management, library systems, etc., in terms of the means-end abstraction hierarchy (Rasmussen, 1986a). However, the complexity of constraints and possible strategies in such 'macro-worlds' makes it difficult to use them in well controlled laboratory experiments, aimed at testing and verifying modelling principles. Therefore we used a commercial video game called 'Gymnastics' that represents a 'micro-world' of highly limited alternatives for actions, where there is no difficulty in identifying the strategies players of the game can apply, assuming that subjects exhibit the same basic adaptive development in cognitive control, as one will find in more complex work domains.

2. THE APPROACH TO COGNITIVE SIMULATION MODELS.

One basic requirement for the simulation models in the present context is compatibility with the conceptual framework applied for work analysis and for experiments. This immediately point to models based on object-oriented simulation languages which are well suited to represent the causal scenarios and qualitative reasoning as found in description of work performance. The prototypical nature of causal representation create special problems with the representativeness of the behavioral trajectories generated by simulation; while the causal models represent types of behavioral patterns, simulation generates particulars. This topic has been discussed elsewhere (Rasmussen et al, 1990).

According to the point of view underlying the structure of the taxonomy for work analysis, human behavior in goal directed work can be represented as being adaptation guided by subjective performance criteria and preferences within an envelope of constraints defined by the work requirements and the cognitive resources of the individual. A matching approach in developing simulation models, therefore, is to take the starting point in a representation of the work-given constraints and to design an adaptive mechanism which is able to explore the boundaries of acceptable performance guided by different performance criteria which can be varied so as to match the type of behavior displayed by the model to that observed in corresponding experimental scenarios with human actors. In this way, a simulation model can be developed which is able to generate behavioral trajectories in a representation of the work domain. The point is that a model of a particular error-free human behavioral pattern is, in fact, only one of several possible operational implications of the constraints on performance posed by the work domain. Psychology enters the modeling first when meta-cognitive processes are included which represent self-evaluation of performance and the choice, according to subjective value criteria, among the various acceptable ways to cope with the requirements of the work domain.

There are, however, several issues to consider for the choice of simulation strategy. One will be whether simulation should be focused on well-adapted behavior in a familiar situation. In this case, the model will include several sets of production-rules, each representing the action rules of a particular coping strategy. Psychological traits will then only be represented in the subjective performance criteria guiding choice of strategy, in the cue-utilization heuristics and in the error mechanisms (see Rasmussen, 1986b). Another approach will be to include the learning phase when the actor discovers the rules of the trade and the cues guiding release of the action rules. We will discuss this in more detail below, but first we will consider the basis of simulation in terms of a separate representation of the work domain and of an adaptive control mechanisms operating in this domain to meet some specified goal.

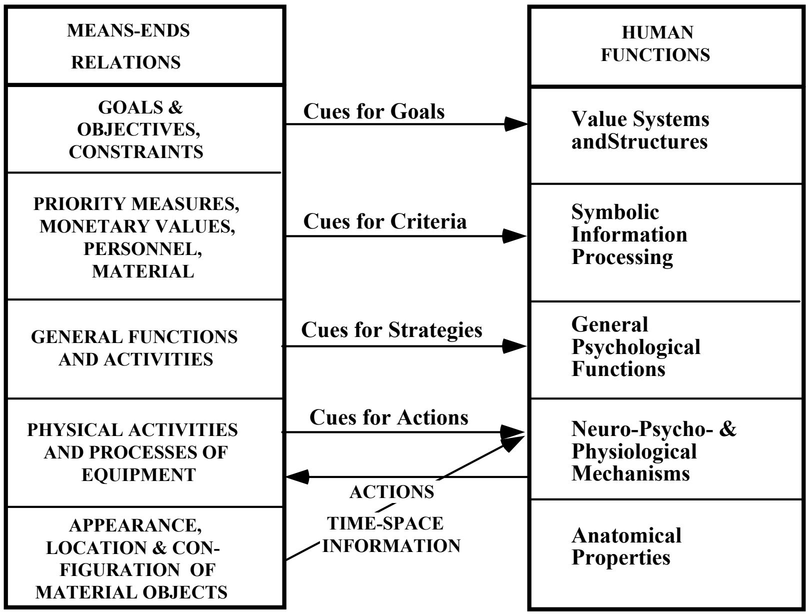

Figure 1. In a work situation or an experiment, an actor will read cues at different levels of abstraction, i.e., sample directly invariant high level features relevant for cognitive control. These cues influence action control at different levels.

2.1 The Field and the Actor

To test the consistency of a cognitive model we have to compare the performance of the model when interacting with a 'work domain' with the performance of subjects faced with the same domain. For the development of the simulation framework, consequently, it will be advantageous to chose a domain which can supply a reasonable amount of experimental data. For this reason the model development will be made with reference to computer games (Rasmussen, 1987).

The system to consider for experiments and the related simulation is illustrated by figure 1. An actor, i.e., a cognitive system which can be modeled at several levels of abstraction, is faced with a problem domain which, in the same way, can be considered as a multi-layered system of means-ends relations. For design of experiments with subjects operating in a simulated environment, it is important to consider which features of the domain behind the experimental cover-story are included in the simulation, and how the relationships to the actual simulation (computer system) environment are perceived by the subject. Similarly, choices are to be made with respect to the functions and mechanisms of the subject which are actually activated by the experiment and the related instruction. An example of this relationship is shown in figure 2 (for more detail, see Rasmussen et al., 1990).

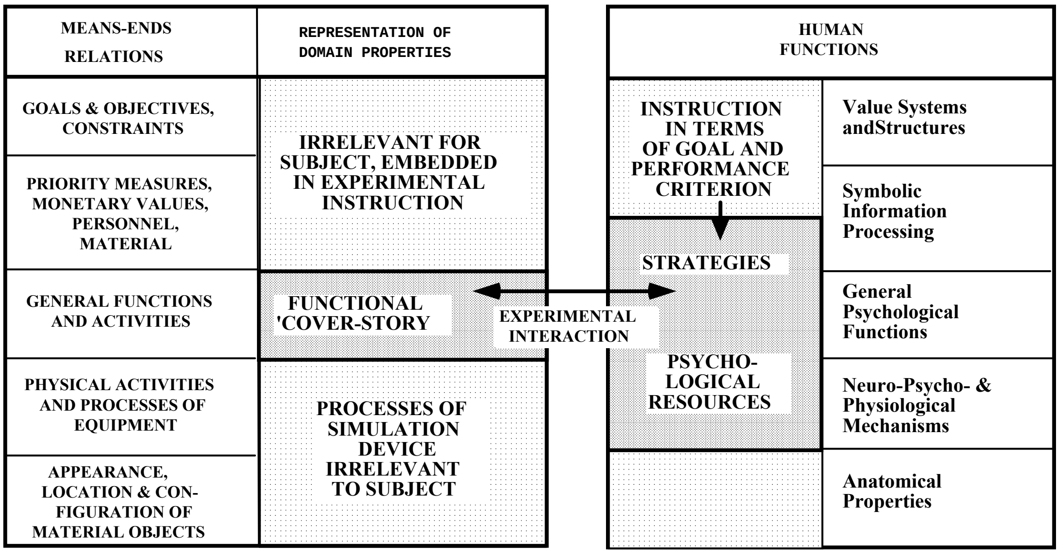

Figure 2. In the experimental setting shown, analysis is focused on identification of mental strategies brought to action by agents for particular task requirements, such as situation assessment, diagnosis, or planning. For such experiments, simulated tasks are frequently used in the laboratory, mimicking in a controlled way a task known from normal work context (electronic trouble shooting studied by means of computer generated networks of interrelated nodes, medical diagnosis cases presented in paper-and-pencil representation, etc.). In such experiments, the instruction is frequently phrased with reference to an actual task and professional subjects are used for the experiments.

3. THE GYMNASTICS S VIDEO GAME AS A WORK DOMAIN

Before the simulation model approach is discussed in detail, we will have a look at the Gymnast Girl Game and some of the most important result from the experiments.

Figure 3 shows a picture from the work scenario of the ‘Gymnastics’ game.

The timing skill needed in order to master the game reasonably well is quite extensive. First of all the player must learn to let the gymnast perform a good offset from the floor by pressing the joystick button approximately 400 ms after it was initially released. If the button is pressed too late (after 500 ms) or too early (before 200 ms), the gymnast will miss the springboard and come to a halt. The next thing to be learned is to straighten up the gymnast and land her on her feet by pulling the joystick back. This action, required after roughly 4000 ms, is timed by carefully watching the gymnast's terminal orbit and angle. The somersault maneuver presupposes that the player pushes the joystick forward before the gymnast has left the horse behind her. As long as the joystick is pushed forward, she remains in the full-tuck position required for fast rotation. However, her rotational speed will not be fast enough unless the player has made a preceding, precisely timed button press to push her off from the horse in the right moment. This moment occurs when the gymnast is in a nearly vertical position over the horse, approximately 1700 ms into the game, and it has a duration of about 100 ms only. Ability to comply with this timing demand is a prerequisite for becoming a performer of somersaults.

The Gymnastics game provides a real-time dynamic task, which may serve as a useful tool for studying learning of complex motor skills. The game has a high ecological validity and offers a good and instant visual feedback. Everything on the screen is almost exactly as most people have seen it in TV-transmissions of gymnastics. The player is, therefore, immediately attuned to the challenges of the situation. The interface has several well designed cue-action relations: the posture; speed and height of the gymnast at critical moments of the jumping clearly signal to the player that now he should interfere to initiate an action and he will immediately see the consequences of his actions. Furthermore, the spatial operations of the joystick has an isomorphic relation to actual body movements: "push button to jump"; "go left or right to twist"; "push button for pushing off the horse"; "move forward to curve the gymnast's body"; "pull back to make her upright when falling forwards"; etc. So the way the joystick must be operated to produce an action has an intuitive connection to real athletic striving.

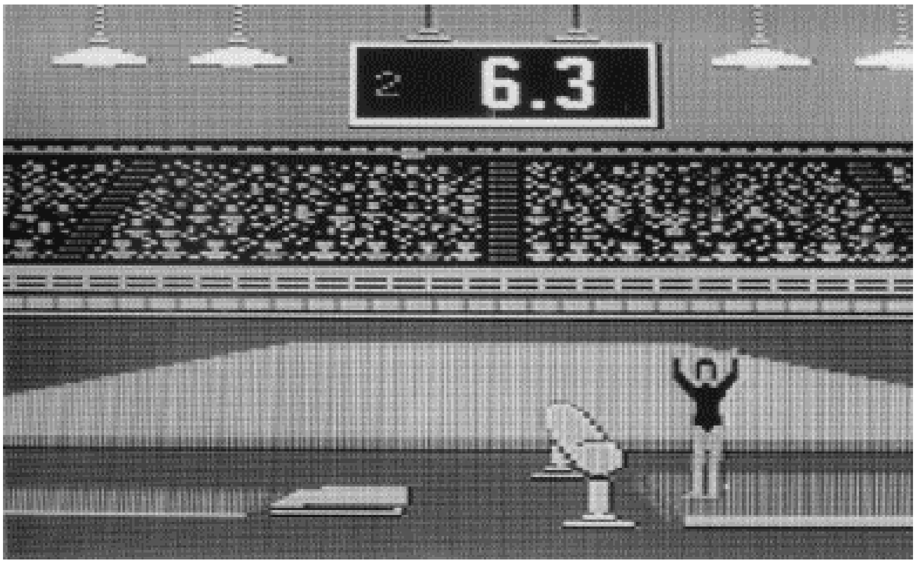

Figure 3: The game runs on a Commodore-64, and it presents the player with the task of getting a gymnast to make a graceful vault over a horse. Striving for a successful triple somersault in the Gymnastics game is the way to get a scoring of ten points, but great timing skill is then required to get the gymnast landed upright on her feet. If she falls, the reward obtained by performing a difficult maneuver is more than lost due to poor execution. By not attempting to make somersaults, the player reduces his risk of crash-landing the gymnast, but the maximum score can get is now reduced to eight points.

For all of these reasons, the naturalistic screen setting immediately makes it clear to new players what this game is about and the experimenter does not need to invent a "cover story." The common use of cover stories in cognitive experiments can be problematic for two reasons: (1) in order to make analogical reasoning in novel problem situations, the player must recall details from the cover story, which may be difficult to remember. (2) the cover story can be misinterpreted or under-specified from the very beginning and make the player form wrong analogies out of experimental control. (Brehmer, Leplat & Rasmussen, 1987)

3.1 Event Space of the Game

The computer automatically reacts to an attempted action dependent on the player's timing (note the narrow time constrains indicated on the time axis of figure 4) and gives the related visual feedback as output. In between those automatic decision nodes, the player has the opportunity to synchronize his action attempts. This is not to say, that the player consciously intends and plans an action on-line. Most often, the intensive visual attention demanded during the five seconds a vault lasts, forces the player to choose between the action alternatives before releasing the joystick button to let the gymnast go. This is in accordance with the generally accepted conception that skill-demanding acts are pre-selected subroutines that run off automatically, and that feedback from the environment while a skill is performed mostly serves synchronization and coordination purposes (Robb, 1972; Rasmussen, 1986; Colley and Beech, 1989).

By this way of representing the task, we are able to distinguish between two major problems to be solved during training from a control point of view: (1)the *synchronization* of actions with the behavior of the environment and (2) the *optimization* of actions to form a smooth and efficient pattern within the boundary of the task (Rasmussen, 1986).

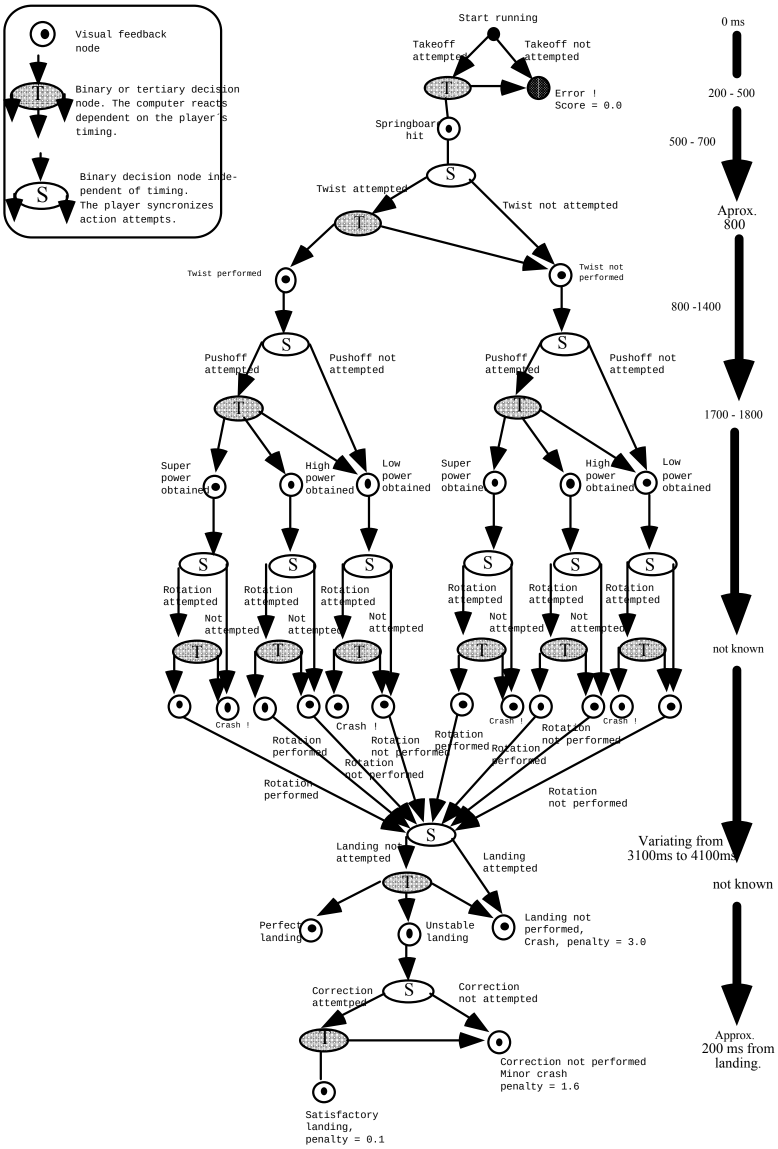

Figure 4: The event space of the “Gymnastics” video game. It is not a traditional flow chart description of the game rules because it contains two kinds of decision nodes, pertaining, respectively, to the player's and the computer's decisions. The diagram also contains nodes that indicate at what stages of the game the player receives a distinctive visual feed-back signal.

3.2 A Means-End Analysis of the Gymnastics Game

The general work domain taxonomy in terms of a means-end hierarchy suggested by Rasmussen (1986), makes it possible to describe the various levels of tasks in the 'micro world' of the game (Table 1).

At the highest level of abstraction, the *intended functional effect* of the system upon it's environment is described. For the game designer, the goal is to create an interesting game, that people will buy. This is done by offering a system, that appeals to basic human feelings of joy involved in having fun, scoring points, competing with other players and learning the mastery of a graceful task.

At the level of *priority measures*, these goals are described in terms of the information processing embedded in the program as the games scoring rules. There are hints about some of these rules in the instruction manual, for instance "release the button to start your run."

Without experience its impossible to implement these abstract descriptions all at once, because the player lacks the necessary skills to get to the point where he e.g. would be able to get the girl in the air. At its best, the manual will serve as a catalyst for the discovery of new action possibilities during the skill acquisition and as an initial instruction for getting started. At its worst it will confuse and frustrate the player to be confronted with all those un-achievable action possibilities. So in practice, the player pays little or no attention to the rules as a whole, but takes the relevant rule into account when he has realized it's practical implications. For this reason, we provided the subjects in our experiment with a planned sequence of successive instructions, in order to hold the experimental control of the various sub goals to be pursued. Most of the effective rules are not described in the manuals, so the researcher must explore the taxonomy at this level through statistical analysis of recorded game data or software analyzes before he can give a full description as the one in figure 4.

Value systems and structures	Learn Have fun Score points Competition Task Mastery
Abstract function, priority measures	The "hidden" rules of the game, i.e. priority criteria.
General functions	Playing the game in terms of jump, rotate, land, etc.
Physiological functions	Joystick movement in terms of left, foreward, button press, etc.
Physical form	Hardware (Screen, stick, computer)

Table 1. A means-end description of the Gymnastics game as a work domain.

The level of *generalized function* is where the “hidden” scoring rules show up in the effect of the functions you choose. The language is that of a gymnastics performance. Operating the joystick is expressed in terms of "jump onto the springboard", "push off the horse", "make somersaults", etc. Performance is described numerically by a score and qualitatively by words such as "good offset", "unsuccessful landing", etc.

The level of *physical function* describes the interaction with the computer by joystick manipulation to control a stored program, whose main function is to move pixel patterns from one part of the screen to another. The player perceives a realistic screen animation with a moving object under his control. The control language is "left", "forward", "press button", etc.

The level of *physical form* describes the physical reality of the work domain, which in this case is the computer equipment. The player is only in active contact with the joystick and color monitor, and when he is attuned to the basic features of the equipment, the user need not concern himself with this level, as long as they do not cause problems at the level of physical function, (for instance when a warn down joystick becomes insensitive to button presses).

4. APPROACHES TO THE MODELING OF COGNITIVE TASK PERFORMANCE.

Several different levels of modeling the mechanisms of a human agent can be chosen. The right box in figure 5 shows how some of the typical concepts for modeling cognitive processes can be described within a means-end abstraction hierarchy. The selection is only illustrative and their origins are found in Anderson (1980), McClelland & Rummelthart (1987) and Rasmussen (1986).

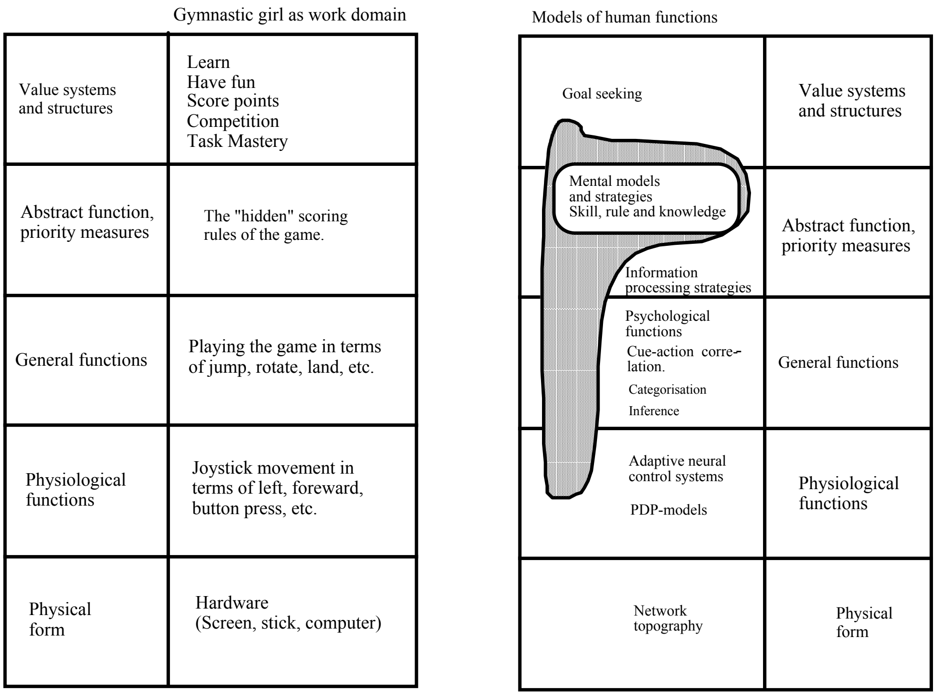

Figure 5: The human - work domain interaction in the Gymnastics game experiment.

Detailed descriptions of human information processing involved in a task like the Gymnastics game should take all the various task levels and the related forms of interaction into account, because of the possible decomposition and aggregating of information between the levels. (Rasmussen, 1986). This detailed description is particular needed if the modeling is based on single levels, in order to insure, that important information aggregated or decomposed from other levels, will be taken into account in the model.

In the present approach we have focused on modeling human behavior at the level of information processing strategies, with no emphasis on the architecture of the underlying neural or psychological mechanisms. Consequently, the cognitive system which is to be represented in a simulation model is of the nature as shown in figure 6 . This model can, in fact, be viewed as a hierarchically structured, self-organizing control system.

The bottom layer represents the adaptive, continuous control of movements. The next higher layer, the sequence controller which organizes elementary movement patterns into meaningful action sequences by means of cue-action correlations. Finally, the uppermost level takes care of plan formulation in unfamiliar situations by means of mental simulation supported by a mental model. One important feature which facilitates the development of a simulation model is, that during learning of rules and evolution of manual skill, new patterns of cognitive control are not necessarily generated by complex, cognitive transformation and compilation of higher level control structures. Instead, new effective control structures can be generated by empirical search and optimization while behavior is kept "on track" by higher level control. When new heuristics are identified and found acceptable, older, higher level control patterns may then degenerate. This point of view can be implemented in a cognitive model based on the kind search, test, and optimization mechanisms of a self-organizing control system which were widely studied during the 60s and which are now being taken up by the neural network and connectionist approaches.

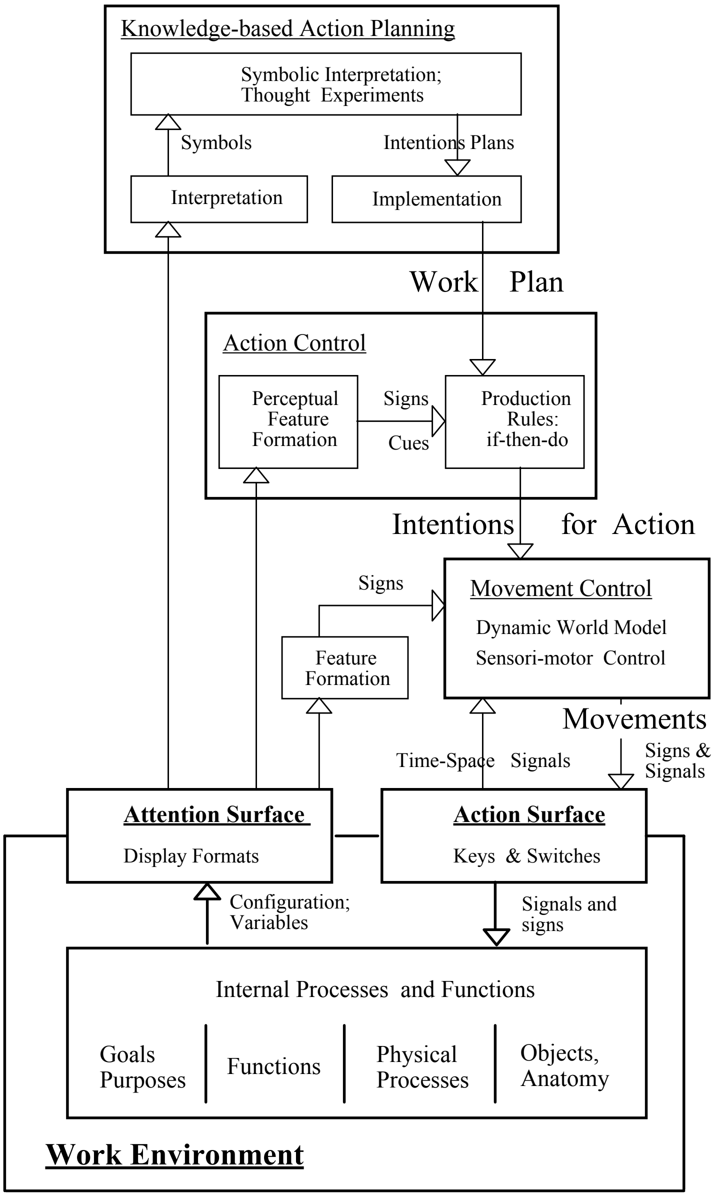

Figure 6 illustrates the different levels of cognitive control in a model in terms of a self-organizing, adaptive controller.

4.1 An Example of the Interaction between Skill- Rule- and Knowledge Based Cognitive Control.

Figure 7, which is a simplified version of fig.6, illustrates a possible interaction of the skill- rule- and knowledge-based control in a hypothetical problem situation from the Gymnastics game experiment. A medium-trained subject is trying to perform a double somersault. Suppose he masters the landing sequence for one rotation, but two rotations makes the girl crash land. He knows that in order to get an upright landing he needs to pull the joystick back a few hundred milliseconds before floor contact. But two somersaults do not give time enough to execute this sequence. He has also noticed, that a push-off from the horse just when the gymnast has passed a vertical position gives an additional jumping height. He then realizes that this additional high is a prerequisite for making a perfect triple somersault. The model describes how this functional reasoning takes form and how a useful strategy is implemented at the various levels of cognitive control.

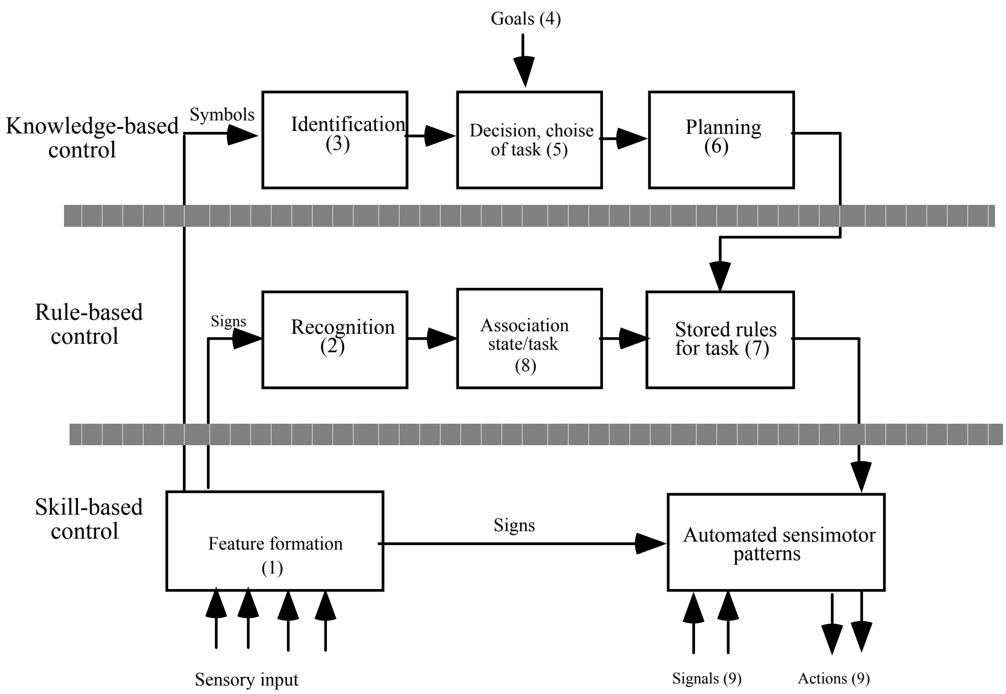

Figure 7: The dynamic interaction of skill-, rule-, and knowledge based control in an action problem from the Gymnastics game. The numbers refers to explanation given in the text.

As a sensory input, the visual feedback from the previous play □(1) is recognized as a crash-landing (2). Making a functional reasoning process, he identifies the reason for this: the girl did not get sufficient push-off power to perform a triple somersault if the timing constrains of the landing sequence has to be met (3). The overall goal (4) - to strive for maximum score - states that a triple somersault has to be performed. Consequently, he needs more time to make somersaults and uses the knowledge of the importance of the push-off timing for obtaining height, derived from his previous experiences. He then decides (5) to try to push her off just when she has passed a vertical hand stand. The plan (6) is then (in a very simplified version) to maintain the previous synchronization and timing, except for the push off timing, where he intends to play close attention to her position on the horse, in order to push her of at the right moment.

This plan is stored as a new rule for the synchronization of actions (7) in a control language like "If the girl has passed the vertical position then press button." At the next jump, this rule might wait in the synchronized sequence of actions plans to be activated when the sensory input gives a sign of a vertical position (8). But this cue-action strategy is not very likely to be effective, because the conscious rule-based control takes too long time to be executed successfully within the narrow time constrains.

Based on empirical observations from eye-mark recordings, we shall argue that the rule can be compiled through practice to a binary reaction task at the level of automated sensorimotor control, working as a signal-action loop (9). This is possible, because eye fixations in perception-action loops can control the alignment of objects in target positions (Gibson, 1979). Through this there is an activation of a low-level, unconscious action repertoire that formally can be described as: "look at places that demand timed operations, and execute planned operations when object enters central visual field." So, when the new plan gets compiled to a skill-based level, it might be in a form of:

1: Execute jump with previous synchronization and timing until a sign of the girl having contact with the horse arrives.

2: At arrival sign, look at target position and alert signal— action repertoire.

3: When object aligned in target position, press button.

4: Continue jump with previous synchronization and timing until the girl has landed successfully.

The control language of the process, as it might be tapped from e.g. verbal protocols, will be very restricted compared to the complexity of the actual process. The following examples are constructed with the inspiration from typical verbalizations during some of our experiments.

Identification:
".....it did not work, she did not get high enough ...."
Planning:
".... I will have to push her off when she is vertical...."
Stored rule for task:
".... now I really have to concentrate at the position on the horse"

And when the girl gets contact with the horse during the following jump:

"....Ready....." (Meaning: On the target position and alerting the signal-action-loop).

"Go !" (Meaning: The binary decision "to press" is taken by the signal-action loop).

Now when we have roughly delimited the type of mental strategies that can be used for interacting with the work domain of the Gymnastics game we will describe the experiments currently being conducted at our laboratory.

5. Experiments

We added code to the game program to log the joystick moves and the resulting updates of the program's various score counters. Detecting that the joystick was pushed forward is taken as an indication that the player attempted to make somersaults, and the rotation score tells whether or not he managed to perform the maneuver. In the extended version of the program, logging data from blocks of single games are written onto the Commodore's floppy disk. A game block consists of sixteen accomplished vaults plus the unsuccessful jumping attempts made by the player.

5.1 Unaided Learning by Doing

In an early pilot experiment, two subjects played more than 1500 plays each, without getting any instructions or cues to support the learning process (Westrenen, 1989). Summarizing the main results, the expected improvement in score and timing performance did not occur as strongly as one would expect from the power law of practice (see, e.g. Newell & Rosenbloom, 1981), although there were slow and small improvements. They happened throughout the experiment, and no point of significant improvement could be identified from various statistical analysis. The variance remained high, except for one of the subject's timing, which showed a constantly decreasing variance. These results indicate, that without instructions, performance tends to change randomly, reflecting an unstructured exploration of the event space in figure 4. Colley (1989) puts forward, that learning by doing might be used successfully with movements which requires balance and postural adjustment, for example learning to ride bicycles or to roller skate:

> "it is unlikely that this method would, on its own, be very successful for skills which have a procedural component, such as driving a car and learning a musical instrument," she says. (1989, p.181).

Our experiments certainly suggest, that this also is the case for even simple computer games as Gymnastics, where considerable procedural components are revealed by formal analyzes, c.f. figure 4. This might explain the vast communication often found in groups of children playing video games (Turkle, 1984) as the exchange of procedural knowledge necessary for task improvements.

5.2 Eye-Mark-Recordings

In a second experiment eye movements of 3 subjects playing the video game at succeeding levels of expertise were recorded to highlight the importance of the development of scanning strategies. These seem to be more static than the changing hand movement strategies, as they mainly reflect the pursuit of the object to be controlled. However, small changes in scanning strategies bear witness of the development of a dynamic task model as a discovery of crucial control and feedback points. Especially the occurrence of eye movement being ahead of the target movement reveals the formation of a mental task model. These asynchronous movements can be divided into three categories according to their functions in control terms. One category consists of fixations on feedback points for feed forward actions. By another category the players impose a forward period which supports the delicate timing of movement sequences by shortening the players' overall reaction time, compatible with the effect of the well known starting procedures in sport: "Ready - On your (in our case *eye*-) marks —Go!" (c. f. Robb, 1972). The last category of asynchronous movements consists of fixations that anticipate events in a monotonous sequence in which the player cannot interfere.

5.3 Group Experiment

This experiment was carried out with a school class made up of 13 girls and 10 boys, all of age 15 to 16. It was performed over a period of one week using two Commodore units placed in an empty class room. The idea behind the experiment was to train these teenager subjects collectively in acquiring the motor skill demanded to play the Gymnastics game well and to provide them with an opportunity to demonstrate their final skills in striving for score.

The training program was composed of four game sessions of increasing difficulty. In each session the subjects were requested to accomplish four game blocks, all to be performed as described in a short written instruction. The main purpose of the first two sessions was to let the subjects gain experience with the timing required to make a good takeoff from the springboard and to get the gymnast landed safely in an upright position. In the third session the subjects were faced with the more difficult task of learning to push off from the horse at the right moment. The last session consisted in trying to master double or triple somersaults without crash-landing the gymnast. Most of the subjects learned to perform the uncomplicated vaults exercised in sessions 1 and 2. There were quite a few who never managed the timing needed to make a powerful horse push; these subjects were consequently disabled from utilizing the subsequently implemented full-tuck position for fast rotation.

On the last day of the experiment, after the training program had been completed, the subjects were asked to produce four additional game blocks which they were encouraged to play according to their own individual preferences. Furthermore, they should regard the fourth block as a test game in which they should aim at getting the highest possible average scoring.

6. HINTS FOR COGNITIVE MODELING FROM THE EXPERIMENTAL RESULTS

In order give some hints for cognitive modeling some results from our experiments will be presented in addition to those already mentioned.

6.1 Features of Physiological Functions

Optimization:

Figure 8 shows the improvements in takeoff-time learning of a subject from the instructed group experiment within the first 86 trials. The time constrains of the task is indicated by the two thick vertical lines at 200 and 500 ms. In order make a good jump onto the springboard, the takeoff must be executed after 320 ms (dotted line), and maximum takeoff power is not obtained unless the offset from the floor is made after some 450 ms. The optimization of takeoff is quite rapid, from approximately 50 trials on sees a majority of takeoffs within the good range. Then, in a few attempt, the subject fails to takeoff before 500 ms (e.g. trials 49, 66, 77 and 82). This has a dramatic effect on takeoff-time in the following jump, which is hastened before the good range.

Some subjects in the experiment optimized their takeoff time by first decreasing it to avoid being too late in hitting the springboard. Then, as they became able to reduce the fluctuations in their timing, they gradually increased their takeoff times towards the optimum limit of about 450 ms.

Figure 8:The improvements in takeoff-time learning of subject 1 from the instructed group experiment.

In addition to the optimizations found in the motor skills, a typical perceptual optimization can bee seen in figure 9.

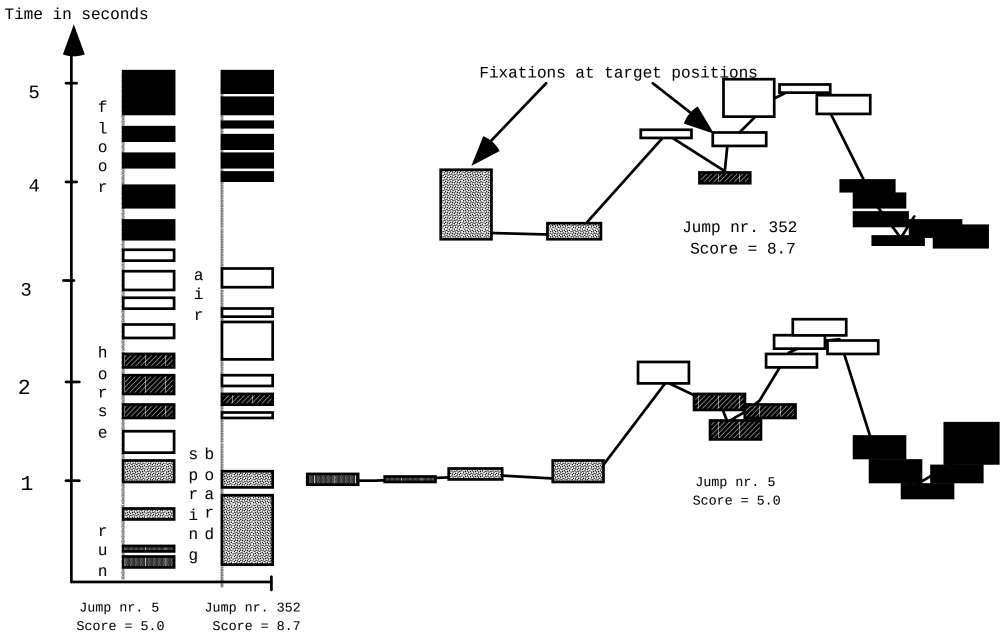

Figure 9: The bar graph shows the time sequence of fixations (at more than 100 ms) from two eye—mark-recordings of the same subject at a beginner level (trial number 5) and at a medium trained level (trial number 352).

While the first recording is characterized by many short fixations during the hole jump, the subject showed a tendency to cluster his fixations around the important control and feedback points when sufficiently trained. At the beginner level, he followed the girl with his eyes from the very start of her run towards the springboard, which can be seen on the right side of the figure, where the fixation-bars are imposed on the eye movements. At trial 352 he immediately looks at the point of offset and wait there until the signal-action loop is activated by the girl entering the central visual field, as described earlier. Then he gets a feedback on his offset by fixating at the place where the girl hits the springboard. The next important improvement in attention allocation is found in the (rather short) fixation at the girls legs, right above the horse. This fixation is used to support the timing of the push off by a precise judgment of her vertical position and it is not found at the beginner level.

Interference:

In order to investigate the interference between the various subtasks that had to be learned during the group experiment, we examined the frequency of successful takeoffs, twists, push-offs and landings through the whole experiment. First the subjects had to learn the mastery of takeoffs and landings, then the twists, then the push-offs and finally the rotations. An interference index (II) was constructed by looking for U-shaped learning curves in the data blocks for the performance at each of the days the subjects had to learn a new sub task. The focus on changes in each of the learning sessions was made in order to exclude the possible changes in performance between the days, due to the interruption of practice (causing a fall in performance), or due to the communication of procedural knowledge between the subjects outside the experimental setting, which might possibly have caused an increase in performance. The minimum decrease in a performance to be counted was set at 15 %, and this fall had to be followed by an increase of at least 15%. By summing up the relative decrease as the average length of the legs in the U-curves of successful attempts by the individual subjects, table 2 was constructed.

The table reveals several trends in the interference between the subtasks: first of all, it can be seen, that the takeoffs and push-offs are carried out by very robust competencies, which only shows a small sensitivity to the learning of other skills (155 II and 170 II, respectively) in comparison to twist and landing skills, which are fare more sensitive (465 II and 625 II, respectively).

Learning to push off had a minor influence on the frequency of successful landings (230 II), which is mainly due to the problems in controlling the additional height obtained by a push off. The learning of rotations caused problems in executing all of the previous learned competencies (785 II) but mostly on twists and landings. One could have supposed, that push-offs were more effected by rotations (which actually had an II = 170) than twists (which actually had an II = 320), since they are more close related in the action sequence than twists and landings are. But the results indicate, that interference is not only caused by closeness in the action sequence. When the same motor system is used for executing a time critical task, this may cause an interference phenomena, even though execution is separated by other motor operations. So, in our experiment, joystick operations has to be differentiated into button presses and limb movements of stick. A reasonable explanation of this phenomena in terms of the skill- rule and knowledge-paradigm might be, that when two rules call for the same action skill within a short time, they are likely to interfere with each other. Generally speaking, there must be a low-level distinction between the possible motor skills by which a task is accomplished, in order to make a valid model of how simultaneous rules can cause interference in the physiological functions being learned.

	Takeoff- & landing learning	Twist learning	Push off learning	Rotation learning	Interference sensitivity of operation
Fine Takeoff	-	N=2, M=45% **90**	N=2, M=27% **45**	N=1, M=20% **20**	**155**
Twist	-	-	N=4, M=36% **145**	N=9, M=36% **320**	**465**
Push off	-	-	-	N=7, M=24% **170**	**170**
Successful landing	-	N=3, M=40% **120**	N=8, M=29% **230**	N=10, M=28% **275**	**625**
Interference of subtask learning on operations	-	**210**	**420**	**785**	

Table 2: Interference matrix for subtasks in the Gymnastics game group experiment. N refers to the number of subjects scored for an U-curve in the various groups. M is the mean decrease of the scored U-curves.

6.2 The Inference of Rules and Selection of Possible Action Strategies

Considering the large amount of event experiences a subject gets by playing the game, it seems implausible that he will be able to remember them all. But on the other hand, he must remember some in order to make inference on new action rules. What are then the economical memory principles for experience selection?

One intuitively good strategy would be to remember those actions that lead to an increase in performance. If the memory is biased for successful attempts, the inference on these will be more likely to provide new effective strategies. After the last session of the group experiment, where subjects had to compete for the highest average score, we asked them to estimate what average score they had obtained. 9 of the 23 subjects made a considerable overestimation while the rest came quite close to their actual score. This gives a total average estimation at 5.94 while the actually total average score was 5.22.

Instead of rejecting this result as an example of subjects being ostentatious, we analyzed the eye mark recordings of a subject playing 240 games to find further evidence of a success bias. He turned out to be very restricted in his attention to the obtained score shown after each jump. The average of the scores he paid attention to were 5.11 while the average of all 240 jumps was 4.00. This selective perception may be understood as another manifestation of a general cognitive principle of functional bias for success, if one accepts the widespread conception that mental models directs active looking, (See e.g. Stark & Ellis, 1981).

The subjects in the group experiment had to fill out a questionnaire after each training session, asking questions about the general functions of the program, like: where should the girl land on the springboard to make a good jump ? Overall, they made quite good inferences from their experiences, providing them with useful cue-action strategies. After the twist-learning session, the subjects where asked: "when is the right time to push the joystick to the right side or to the left side if you want the girl to make a twist?" The most effective strategy is to do this *before* the girl hits the springboard and keep it there while the girl is in the air, because this insures that the narrow timing constrains can be met within a longer executing time. Approximately half of the subjects thought that the best time was at the very takeoff or immediately after. One should have suspected this group to show a much lower performance than the group with the right conception. But this was not the case. It means, that the wrong cue-action rule did not govern action performance during the play, and must have been rationalized after the session when they had to give an answer to a question never considered before. Generally speaking, this indicates that some actions might be effectively learned without the support of a correct and conscious rule. In such cases, the subjects explanations of his cue-action strategies given in e.g. interviews or verbal protocols can be misleading. Therefore task analysis has to be supported with a careful examination of the actual task performance and an independent analysis of the domain constrains.

6.3 The Impact of Instructions

The effect of tutorial instructions can be seen as systematic changes in the attempted movement sequences of the subjects in the group experiment, in contrast to random changes in the two unaided learning series. When the subjects were told about the possibility of making e.g. the twist, almost all of them attempted to do so in a majority of the following jumps. Typically, only 50 % of the attempts succeeded in the beginning. By continuing to attempt the sub goal suggested by the instructions, most of the subjects were able to achieve a level of 100 % success within the same learning session for the easy tasks. The more difficult tasks like push off and rotation, were also attempted whit great enthusiasm in the beginning. But some of the subjects did not make any significant improvements and typically this lead to a decrease in the number of attempts. This points at an important effect of instructions, besides the direct cues it often gives: by knowing, that a task is possible, a new sub goal is implemented for a while, waiting to be achieved by the development of the necessary skills. If this does not happen within a reasonable time, the goal seems to diminish and the number of attempts decreases.

6.4 The Impact of the Action Goals

On the last day of the group experiment, after the training program had been completed, the subjects were asked to produce four additional game blocks which they were encouraged to play according to their own individual preferences. Furthermore, they should regard the fourth block as a test game in which they should aim at getting the highest possible average scoring. Hereby, we intended to change the specific goal of playing the game from "learning" to "demonstrating ability."

From the recordings of the joystick moves made by the subjects in this latter, highly goal-oriented task, it was possible to divide the subjects into three groups: (I) those who continually attempted to perform the somersault maneuver; (II) those who had a preference for this maneuver without intending to perform it continually, and (III) those who rarely or never tried to perform the maneuver. It is obvious to try to correlate this grouping according to playing style with the grouping that results from looking into the subjects' individual skill to actually obtain rotation scoring. The data recorded in training session 4, and in the three game blocks preceding the final testing block, suggest the following division of the subjects into three skill categories: (A) those who were highly or reasonably capable of producing well executed double and triple somersaults; (B) those who performed similarly except that they most often crash-landed the gymnast, and (C) those who were unable to get the push off power necessary for fast rotation.

The result of classifying the subjects according to playing style in the test game on the one hand and skill from training on the other is shown in Table 3 (girls) and Table 4 (boys).

Playing-style (I) represents great insistence to try to obtain a reward by attempting to perform a difficult task. Nine subjects exhibited this behavior. However, only four of the subjects possessed the skill needed to implement their ambition (group I-A). Two subjects consistently preferred the difficult task alternative without having the necessary competence to successfully execute the task (group I-B). There were, finally, three subjects who, despite the test situation, happily went on trying to perform a task they did not learn to manage in the preceding training program (group I-C). The ten subjects who resorted to playing-style II seem to have developed a fair understanding of the fact that it may be unprofitable to invariably stick to the most challenging way of coping with a task, even if one is a competent performer like the single subject in group II-A. Only four subjects did apparently decide, as suggested by their choice of playing style III, to completely renounce the potential reward from going for difficulty. These subjects (groups III-B and III-C) evidently realized that their skill in performing the somersault maneuver was poor and used this knowledge to select the less risky strategy for playing the test game. Note that group III-A is empty. Skilled players do not resort to trivial performance!

Learning Playing-Style Category	Contest Playing-Style Category		
	I	II	III
A	4	1	0
B	2	6	3
C	3	3	1

Table 3: Double classification of the 23 teenagers who participated in a gymnast game experiment. Due to the change of action goal, 4 subjects chose a more simple strategy (groups II-A and III-B) and 8 subjects tried to play a style they had not mastered before (groups I-B, I-C and II-C).

Though the experimental evidence presented above is very limited, we have a clear example of distinctively varying user preferences which are not directly related to actual personal competencies acquired through learning, but seem to be strongly conditioned by the context defined by a specific goal setting. The moment the context changes from a training situation to a task situation containing action alternatives, psychological and metacognitive mechanisms that were not active previously may become strongly behavior- controlling factors. This is an example of how process at the highest level of the means-end hierarchy, namely the goal-settings influences the choice of strategies.

7. Summary of Empirical Findings.

Table 4 lists the major empirical findings in our experiments so far. Structured within the means - end - hierarchy the findings relates to different levels of the skill learning process. The observations in our experiments have implications for the planning of simulation experiments, performed, for example, with a learning machine that has been programmed to adapt its behavior to an environment guided by training of the kind the teenagers were provided with in the Gymnastics game. Without building models of the mechanisms and phenomena reported into the learning machine, the latter will not permit reliable, predictive simulations of the way human beings utilize their skill and knowledge.

Value systems and structures	A specific goal setting within the same work domain has an over-all impact on decisions made by the subject.
Abstract function	Subgoals provided by instructions are taken into account in the subjects attempts, but if they are not reached within a reasonable time, their importance on performance tend to diminish.
General functions	Possible action strategies might be inferred and selected from experience by a functional bias for successes.
Physiological functions	Optimization during experience might be reactions to error signals and reduction of fluctuations. Negative interference might be found among simultaneous optima zations. Timing can be supported by anticipating eye movements on contro points.
Physical form	Not relevant

Table 4: The major empirical findings in our experiments.

8. Outline for a Cognitive Simulation Model

With the inspiration from the empirical results reported we will return to the theoretical considerations on cognitive simulation models presented in paragraph 2 and 4.

As mentioned earlier in this paper, we consider object-oriented simulated languages to be well suited for presenting the causal scenarios and qualitative reasoning. The basic idea is to let a model agent (MA) form an object, which is to explore the causal scenario (CS) of the Gymnastics game, represented by another object. Hereby, we establish a distinction between the agent and the domain in which the agent has to discover the various possibilities for synchronization and optimizations. These two objects will be implemented in two different processors, supplied with a third processor to take care of the graphical representations and other external functions.

The following descriptions of features of the MA and CS are highly tentative, and reflects the premature and vague status of ideas, currently being discussed at our laboratory.

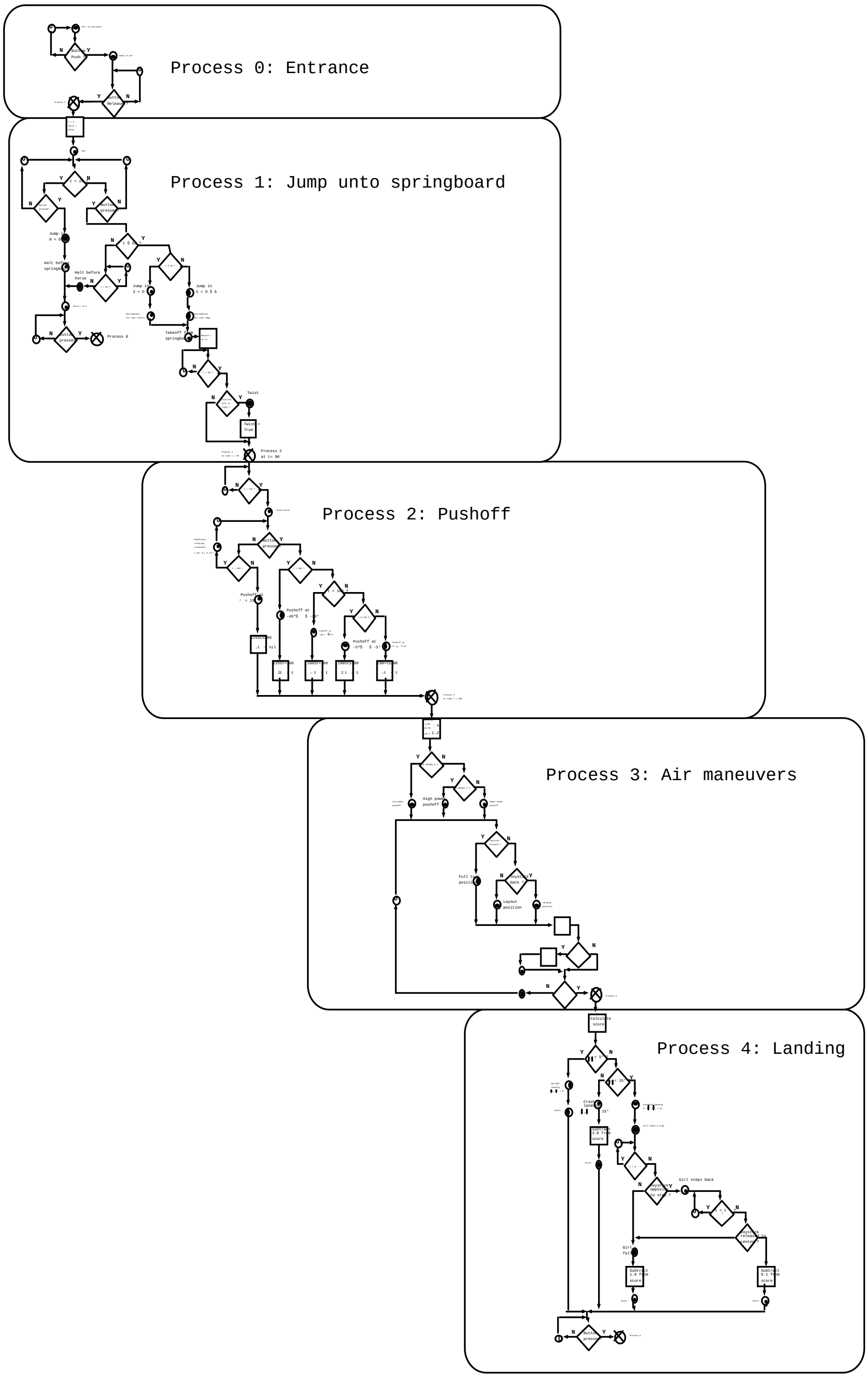

Figure 10: An overview of the timed causal scenario of the gymnastic game. (See appendix A for a detailed description).

8.1 The C□causal Scenario.

Figure 10, which is a timed process specification of the event-space in figure 4, gives a view of the causal scenario of the Gymnastic game to be implemented in the computer model. (See appendix A for a detail description of the individual process). The domain is highly clock-driven with time-slots found in each of the "Update timer" cycles . At certain points of time, the computer asks whether a particular action has been executed, and on basis of the answer, it provides distinctive visual feedback, which exclusively characterize each of the action possibilities. This means, that an exhaustive search of the event-tree can be based solely on the feedback provided.[1]

The clues included in the CS were selected with the support of the eye mark recordings. All of them do, at the various levels of expertise, attract the attention of the experimental subjects for a certain period, indicated by fixations (at more than 100 ms). Some of the cues remains attended during the hole training period, while others loses their attraction, as described in section 5.3 and 6.1 of this paper.

As it can be seen, the hole causal scenario can be well described as 5 sub-process, namely the entrance, the jump onto the springboard, the push off from the horse, the air maneuvers and the landing. The outcome of a sub-process are exported to the next sub-process as an updating of the values t_1 (takeoff time) and t_2 (push off time), which are included in the calculating of the girls air maneuvers and the final calculating of the score.

The modeling of the girls air maneuvers in process 3 calls for a simulation based on physical laws of the relation between achieved height, momentum, angular momentum and body angle. These laws are well defined and currently being implemented. The visual output of the air maneuver simulation is of a unique form, compared to the other well defined visual cues. We believe it to be an example off a compound, higher order invariant (Gibson, 1979), consisting of three sets of data, the height, the angular momentum and the body angle, which affords crash landing, unstable landing or perfect landing.

All though the causal scenario is not a 100% replica of the gymnastic game yet, we think it holds the fundamental causal relations and the approximate time constrains of the original game, which makes it a sufficient basis for the coming modeling attempts.

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[1] One basic problem in the simulation of a game player at the level of information processing strategies is the representation of the "direct perception" of cues releasing rules of action because these cues will be derived from global gestalts in the displayed patterns representing the state of affairs in snap-shots of the game scenario. The problem can be approached either by including a representation of a pattern classification and recognition mechanism in the simulation model. This will be necessary in a model simulating the subject in the fire-fighting game of Brehmer et al., (1990) and opens up the question of similarity matching discussed by Reason , (1990). In the fire-fighting game, action scenarios are related to types of forest fires which, in turn, are defined by complex spatio-temporal visual gestalts which are not related to simple display control signals . Another approach will be to start the model development from data collected from a game with a simple and direct mapping of the state of the display elements onto the cue-rule level. Such a simple mapping is found in the "gymnast game" in which cues for actions are related to well defined states of stable objects, i.e., to the state of the stable object "girl" in a "jump" across the stable object "horse".

8.2 Features of the Model Agent.

As functional *outputs*, the MA posses three types of movements (MO):

1) No action.
2) Button push and button release
3) Joystick movements in eight directions, and movement to the central position.

On the last two MO's there are some constrains, reflecting physiological constrains derived from analysis of the experimental results.

1) Synchronization time (SC).

Between each action, there is a certain amount of time, in which no actions can be carried out. The synchronization time represents the speed at which motor actions can be combined in the real world. As it's minimum the synchronization time has the shortest time the joystick can be moved from e.g.. south to north. This bar time will decrease towards minimum as a function of the number of times an action has been carried out.

2) Reaction time (RC).

In addition to the synchronization time there is a reaction time (RC). This will be defined as the time taken from the input of a visual feedback to the opening of the possibility to execute a movement. Like the SC, the RC will decrease towards a definite minimum as a function of the number of times the MA have gone through a particular cue-action correlation.

3) Stochastic variation (SV).

There is a stochastic variation on the time precision by which a planned action can be executed. This variation is decreased around the mean value of the time of successfully actions (that is: actions leading to the expected visual feedback).

Note, that the synchronization time described in 1) is subordinate to the stochastic variation - the bar time is first effectuated when an action has been executed.

4) Optimization mechanism (OM).

When the variation is reduced to a level where e.g. 90% of the trails falls within the successful range, the single action times will be driven forward by an increase of e.g. 5%. If this courses the action to fall outside the successful range, the next trail is hastened 5% before the former action time, as a reaction to the error signal, giving a decrease at 10% of the "punished" time of action. Then the action times are driven forward with smaller steps, e.g. 3%. When it gets an error signal, it jumps back with 6%, forward again with steps smaller steps (e.g. 2% increase) and so forth, until an optima have been achieved. This "rude" optimization mechanism is implemented in order to provide the MA with capabilities of "boundary seeking" of the kind found in our experiments, c.f. figure 8 in this paper.

Note, that the reduction of variability (3)) is independent of the optimization mechanism. (This mechanism might only be plausible for button presses and not for joystick movements).

8.3 Inference of Cue-Action Rules

With these constrains on its physiological output the MA is entering the causal scenario in order to get experiences by which it can derive the rules to govern its exploration of the scenario and apply different strategies and performance criteria. For the first experiments and related model developments, within this paradigm, we will focus on representation at the rule-based level. The skill-based level will, in computer games, very often be related to the basic interface manipulation skill, which (in particular with interfaces based on keyboards and command languages) will be conceptually foreign to the problem space of the game.

The cue-action rule sets is defined in a context given by the causal scenario (Appendix A) and the perception of this context will, in turn, depend on higher level cues. In consequence, the rule-based part of the model in figure 6 will have to extended in a way illustrated in figure 11 which stresses the fact that rules and cues will be developed corresponding to the different levels of means-ends relations of the problem space.

Figure 11 illustrates how the rule-based model operates at a higher level than the elements of the display-control surface of a game.

An important precondition for a satisfactory solution to the representativeness problem touched on in the introduction, it will be necessary to model how different strategies can be chosen for playing the game, which are related to different derivatives of the primary goal of the game. As a primary goal (1),we might e.g. want our model to perform in a contest situation like the teenagers in the experiment, deriving that the MA should aim at a high average score, or we might like it to be in a learning state, deriving (2) that it should seek many top-scoring cases irrespective of a low average. In addition, the choice of strategies will be influenced by different subjective performance criteria (e.g. fun of exploration, lack of commitment, etc.). In this case, parameters of the model can be identified for manipulation to generate a wide variety of trajectories which can be clustered around prototypical strategies. A MA with great fun of exploration should e.g. give high priority to an exhaustive search of the causal scenario and a low priority to scores obtained. Then it will be interesting to compare their performance with clusters obtained from different subjects and different phases of the experimental sessions. In this case, model parameters which correspond to features used for judgment according to subjective performance criteria can be identified.

When the set of goals have been chosen and the derived strategies have been specified under the influence of performance criteria, a specific set of functions can be intended (3). The cues provided by the scenario will determine what kind of actions to carry out. Suppose, that the MA is confronted with the scenario for the very first time. What kind of cues does it provide for actions ?

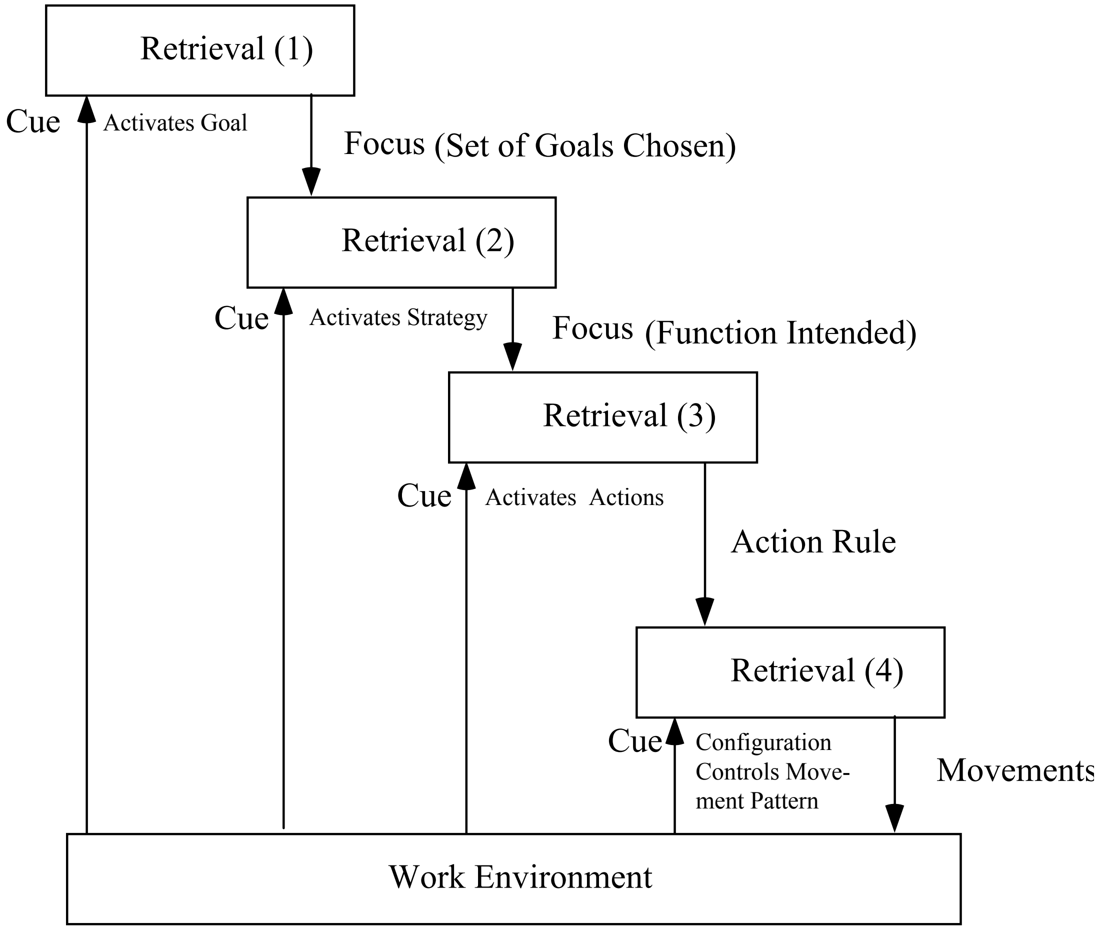

Figure 11 illustrates how the rule-based level of figure 6 is extended for development of a cognitive model which represents performance in a game which can activate different strategies and performance criteria in different stages of learning and with different individuals. The numbers refers to the examples given in the text.

We would claim, that the visual layout of the scene from the gymnastic hall (see figure 3) directly specifies a temporary action goal 'to get the girl over the horse'. Then the AM will be given some basic action rules, which we as human beings would have got either by analogical reasoning on our mental model of horse jumps or by a direct perception of the affordancies in the scenario. [2]

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[2] The horse height is a direct specification of some additional power needed in order to jump over the horse. This nessesity is given by the dimensionless ratio of the girls riser height , (which we would know approximatly by a proportionate scaling of the scenario), and the jumper´s leg length (Warren, 1984). This would lead us to seek for objects that

Example of an initial action rule:

if (run, jump, horse contact) in list of visual feedback

then temporary action goal achieved.

This kind of action rule specification is a great challenge as it forces us to be very precise in the construction of the rule set and in the inclusion of the naive physic rules needed for novel rule generation.

At the lowest level of rule-based reasoning (4) the relation between actual movements and achieved visual feedback will be established as a list of empirical cue(visual feedback) - action (movements in terms of time t and type (MO)) relations. This memory will have to be restricted if it is to be a plausible model of human capabilities. Some of the limitations are being captured by the physiological constrains of the MA´s output, e.g. the lack of precise knowledge of t due to its the stochastic variation . But the major limitations are still to be specified. We shall only briefly mention some of the limitations we are considering:

*A sequence of actions can gain status as a local movement chunk (LMC), which is a motor chunk, releasing the burden of the MA's restricted memory, because it can be executed by only one command to the synchronization controller. In the domain of the gymnastic girl, a LMC can be defined as being separated in time and/or by a shift between button actions and joystick movements.

Once a LMC has been established, it will only be able to unpack the LMC by tolerating some temporary disturbance in the timing of the action sequences - the MA's struggle against a growing habit. It will be necessary to unpack a LMC in order to implement a new action possibility that has been discovered, either by inference or by a novel visual feedback coming up as a result of a casual, stochastic driven action.

The formation of a LMC is an example on the evolution of a manual skill that are not generated by complex, cognitive transformation and compilation of higher level controls structures, c.f. the comments on figure 6 in this paper.

Hopefully this constrain will be able to produce some of the interference phenomena found in the experiments.

*The achieved score should not be remembered as list of specified actual scores. It's more likely that the mean score value achieved for different sets of LMC´s can be remembered.

*The MA will only have memory access to a certain amount of its latest trails, unless the movement can be either closely linked to the arrival of a visual feedback as a perception action loop working on display control signals or have been executed so often that it is embedded in a LMC.

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affords amplification of the girls kinetic energy, specifying that the running track and the springboard should be applied.

*Most of the visual feedback in the CS are pre-defined cues (e.g. "Jump in the distance of zero to tree centimeters from entrance" given in process 1), which in real world perception would have to bee detected as an distinctive cue. While some of these cues can be detected at the very first time they are seen (e.g. the twist in process 1), others are more subtle and might first bee discovered after several confrontations. This constrain can be dealt with in the administration of the MA's visual memory, operating with separate lists of "cues seen" and "cues detected". Each of the cues seen might then be given an individual value of their "visibility" which decides how many times one cue has to be seen before it will be written onto the "Cues detected" list, on basis of which, the MA may make inference to generate new action rules. The empirical eye mark recordings can support the assessment of the visibility of a certain cue.

8.4 The Interface to the Simulator.

In order to make the simulation process cognitive transparent for its potential users, we are considering different ways to visualize the performance and control structures of the MA, in addition to the representation of the causal domain. Similar, the optional inputs to the MA, e.g. different instructions provided, must be presented in a way which encourage free exploration and experiments with the simulators functions. As mentioned, we plan to let a third processor take care of all these communication functions.

One way to visualize the MA´s discovery of the event-space (fig. 4) would be to unfold the branches of the tree, when it gets experiences with the various synchronization possibilities. Starting with one big “black-box”, the first confrontations would e.g. unfold a visual feedback node for “stand in entrance”, “run”, “halt” etc. On this display of the MA´s current experiences, the user might:

* see how often a particular action has been carried out by the MA, e.g. the push-off frequency.

* click on a timing node to see the MA´s learning progress in e.g. takeoff-time learning, in a format like fig.8 in this paper.

* open a window showing the joystick movements in a time-position diagram of e.g. the latest 50 attempts in quick replay. This is very useful to get a picture of the developments in the MA’s movement patterns, on basic of which the LMC’s can be seen as invariants.

* click on pairs of timing nodes to see whether there is indications of interference between the optimization process.

The inspection of the MA´s rule-structure might be done from a window with a display like fig. 11 in this paper. By clicking at the various levels the relevant structures might be seen as a hierarchical tree. This rule structure will change considerably as the MA discovers new rules, and new goals or instructions might be given the MA by a direct manipulation of the rule structure. Instructions in the form of procedural knowledge could have the form of new action rules given at level 3 in a form like: *Achieve visual feedback (twist) at time (t = 90)* This instruction might light up a new, not yet achieved visual feedback node at the current event-space.

If the MA is put in a goal state of learning it will be prepared to take such orders. If it is in a goal state of competition, this instruction might lead to a conflict, as it courses a temporary decrease in the scoring. Conflicts between e.g. primary goals and performance criteria could be detected as deriving incompatible action rules by a rule consistency checking.

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