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T-ECHO: model of decision making to explain behaviour in experiments and simulations under time pressure

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Abstract

Objectives: To explain the mechanisms of decision making in sports. The 'Decision Field Theory' by Townsend and Busemeyer ((1995). Dynamic representation of decision-making. In R. F. Port & T. von Gelder (Eds.), *Mind as motion* (p. 101). Cambridge: MIT Press) was applied to a ball game situation.

Design/Method: A situation in basketball was simulated and used in two experiments. The simulation was realized using a local neural network (Behav. Brain Sci., 12 (1989) 435) and was based on a decision model T-ECHO (Tactical decision — Explanatory Coherence by Harmonic Optimization). Experiment 1 (*n*=53) tested decisions in a video-based laboratory decision task. Learning took place by watching video clips and was significantly better for implicit and explicit groups than for a control group. Experiment 2 (*n*=34) replicated the results by using incidental and intentional learning groups. Finally, comparisons between behaviour output of neural networks and participants' decision making were made.

Results: A good fit between simulation and participant behaviour was shown. Time pressure explained preference reversals from a dynamic viewpoint.

Conclusions: The use of simulations and decision experiments lead to a fruitful way to understand the mechanisms of decision making in ball games. © 2001 Published by Elsevier Science Ltd.

Keywords: Decision Making; Simulation; Time-pressure; Basketball

Introduction

To date, the model building of decision making in sport science has been primarily focused on the diagnostics of competition. Diagnostics of competition in games has concentrated on quali-

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tative or quantitative analyses of specific offence or defence behaviours (Perl, 1997). There have been few attempts to describe mechanisms of decision making (Alain & Sarrazin, 1990; Andreas, 1996Sarrazin, Alain, & Lacombe, 1986). However, in these attempts, it was not taken into account how these decisions are learnt. Although there are many established views on decision making, combined approaches, which integrate learning and decision making processes are lacking. The most favoured perspective for individual decision making behaviour is the cognitive approach (Tenenbaum & Bar-Eli, 1993). Because both environment and individuals in ball games are dynamic in nature, it seems appropriate to describe decision making from a dynamic perspective. A recent attempt to describe these highly cognitive processes in a dynamic fashion was developed by Busemeyer and Townsend (1993) and expanded by Townsend and Busemeyer (1995) in the Decision Field Theory (DFT). The DFT proposes three systems: the motor system, the decision system, and the valence system (see Fig. 1).

The left side of Fig. 1 M_{r1}–M_{r3} (goal approach motivation values) and M_{p1}–M_{p3} (goal avoidance motivation values) represents the motivational values of the consequences of different alternatives of actions. The various options are filtered through attention weights and therefore represent at time t the actual anticipated value of the actions. These parameters are vectors and are called V_1 and V_2. All alternative actions with their specific valence will be integrated in the decision system. The state of preference at t is calculated in the decision system P as the next input for the motor system, which carries out the option with the highest preference. One main assumption is the dynamic process of decision making which enables predictions about situational constraints, such as time pressure, or interactive constraints, like changing subjective expected utilities of options. For instance, the subjective expected utility in soccer to shoot at the goal may show intraindividual variance even if no situational factors change. The DFT assumes decision making through seven parameters to explain direction and strength of preference, accuracy trade-off, preference reversal, effects of position, approach-avoidance, and real time processing. The first two parameters are defined in the same way as the parameters in the subjectively expected utility models (SEU) by Kahneman and Tversky (1984). The main difference lies in the time parameters, which should be more important for decisions under time constraints. Because of their importance in sports,

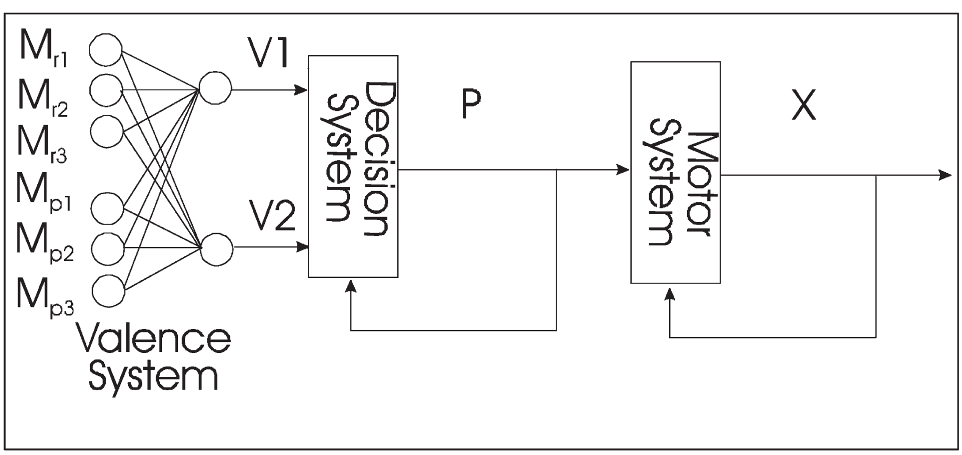

Fig. 1. Decision Field Theory by Busemeyer and Townsend (1993, p. 104 (modified)); see text for abbreviations).

they will be emphasized in more detail later. The parameter *preference reversal* describes the phenomena that humans change their preferred option in one decision process. This parameter will be chosen to demonstrate the strategy to model decision making from theoretical reconsideration to their implementation in computer simulations. To use the DFT as a starting point to model, we can use the valence, decision, and motor systems to describe the processes inside the person. Especially in a dynamically changing environment we need some ideas on how to describe the situation, as well as how the participant perceives the environment and what they perceive. Therefore a broader approach is used to describe all entities in the same logical framework. In order to do that, we have to choose a model procedure that allows us to describe cognitive processes and the environmental preconditions at different levels of explanation.

Modelling decision making

Opwis and Spada (1994) describe a three-step modelling procedure for cognitive processes including conceptualization, formalization, and implementation. The term conceptualization implies the development of taxonomies: defining objects, relationships between objects, operations on objects and relationships (Genesereth & Nillson, 1987). The first two problems to define objects and clarify their relation are easy to solve. In a defined game situation (e.g. basketball) the objects are the players, the ball, and the behavioural goals, etc. Objects, such as the playmaker (PM), have attributes that are described in mathematical sets, called tuples, for example {(PlayerPM, Ball_possession)…}. To define operations on objects and their relations appears more complicated. In cognitive modelling often logical axioms are used to describe presuppositions to formalize operations. Here, formalization, the second step of cognitive modelling, occurs through rules that permit general statements about hierarchies at different levels of abstraction. Chomsky (1980), for example uses grammar, which define a set of rules. Tactical rules in grammar are also used as a metaphor in decision making in sports (Bakker, Whiting, & Van der Burg, 1990). The third step, the implementation in expert systems, has been developed quite well for the diagnosis of competition. However, the simulation which combines learning and decision making processes has still to be modelled in sports.

Conceptualization

In order to conceptualise tactical situations, ball game experts (German A-level coaches) formulated objects, relations, and operations, which were structured by the Belief–Desire–Intention model of Bratman (1987) called BDI-architecture. The use of the concepts ‘belief’, ‘desire’, and ‘intention’ in the BDI-architecture used for stimulation is different from their normal connotation in psychology. In simulation, belief, desire, and intention represent different neural nets with different function. Therefore, perception of environment (beliefs), goals and their valences developed by learning (desires), as well as the decision process with the connected motor outcome (intentions) can be modelled in the same architecture. Decisions in ball games are mainly structured by the given situation. This needs to be described in an additional assumption. Situations are clustered in classes of equivalence of invariant consequences of stimuli e.g.:

Objects: {beliefs, desires, intentions, classes of equivalence}
Relations: {⟨beliefs, desires⟩, ⟨desires, intentions⟩, ⟨desires, classes of equivalence⟩, ⟨beliefs, classes of equivalence⟩, ⟨classes of equivalence, intentions⟩, ⟨beliefs, intentions⟩}
Operations: {⟨beliefs_block/promote desires⟩, ⟨desires_block/promote beliefs⟩, ⟨classes of equivalence_block/promote desires⟩, ⟨classes of equivalence_block/promote beliefs⟩, ⟨beliefs_block/promote intentions⟩, ⟨desires_block/promote intentions⟩, ⟨intentions_block/promote beliefs⟩, ⟨intentions_block/promote desires⟩}

The set of objects is a sum of beliefs (movements of players), desires (if–then rules, which combine situations with goals), classes of equivalence (situations of attack and defence of different complexity), and intentions (possible decisions of players). Relations between objects have to be derived from theoretical assumptions of mechanisms. Firstly, it is assumed, that an interaction between beliefs and desires as well as an interaction between an integrated outcome of both and intentions exists. Secondly, knowledge can be acquired implicitly and explicitly. Operations are defined by either promoting or blocking influences through implicit and explicit learning experiences in classes of equivalence on the planned actions (Hoffmann, 1993). Fig. 2 illustrates these relations.

The model T-ECHO (Tactical decision — Explanatory Coherence of Harmonic Optimization) is based on the ECHO-model developed by Thagard (1989), which explains coherence in decision processes in a simulation by Optimization procedures. The specified version of ECHO (T-ECHO) describes in addition two independent ways of learning. Firstly, T-ECHO learns implicitly without goal-oriented knowledge through perception (belief → intention connection). The mechanism is borrowed from (implicit) perceptual processing (McLeod, 1998) in which a specific perceptual pattern is linked to a specific action. This perception–action coupling is implicit because it can be nonintentional and automatically learned (Frensch, 1998). In this manuscript it will be referred

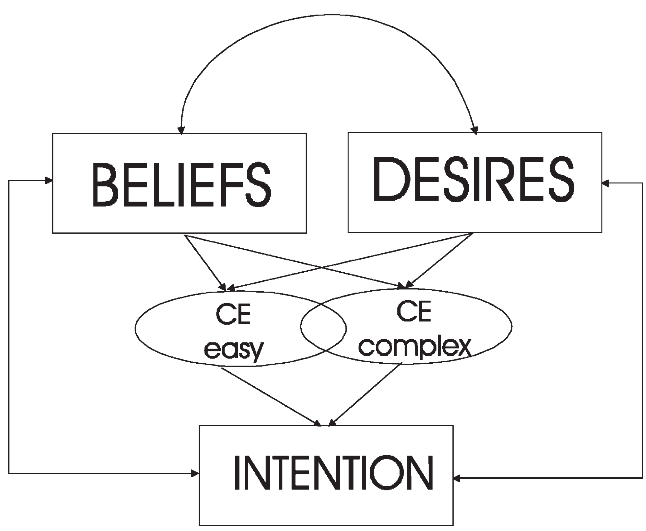

Fig. 2. Model T-ECHO (Tactical decisions — Explanatory Coherence of Harmonic Optimization) from BDI-architecture (CE=classes of equivalence).

to the explicit/implicit distinction rather than to a conscious/unconscious or declarative/procedural dichotomy because explicit and implicit processes are modelled equally well through the level of explanation in simulations and experiments. Secondly, T-ECHO displays effects of mental training without perception (belief → desire connection). This type of learning connects goals like scoring a basket in basketball with specific situations and gives additionally different options in a decision, which are represented by single valences in respect of the given situation. The main learning mechanism is described by if–then rules and the intention to explore and to use them. In a perceived situation options are generated by weighted internal or external goal settings to construct a set of if–then rules specific to classes of equivalence. Of course, the normal case is an interaction between these two procedures. Thus, in highly complex situations, implicit mechanisms of learning will cooperate with explicit instructions during the decision making process (Townsend & Busemeyer, 1995). Due to time pressure generalizations may be less possible. Furthermore it is assumed that the belief processes (mostly assumed to be faster) will overrule desire processes under time pressure.

Formalization

First of all, formalization needs a definition of the objects. The desires will be described by "context free grammars" (type 2, from the Chomsky-hierarchy). Grammars of this type contain four components G=(V,T,P,S): V is the set of variable symbols, T the set of terminal symbols, P the set of if–then rules, and S defines the starting symbol. Context-free grammars use rules B of $B \rightarrow w$ with $B \in V$. (w) is a word, which can consist of symbols between zero and infinity from $V \cup T$. To demonstrate the formalization process, an easy situation in basketball (*rotation of centre*) is described beginning with ball possession by the wing player (WR) on the right side, as follows:

G=({WR, Centre, Post, Playmaker, Defence_D1, Defence_D2, Defence_D3, Defence_D4, Defence_D5, attacks, attacks_not, no_reaction, takes_him, takes_over, sinks}, {basket,}, {p1, p2, p3, p4}, WR)

where p1: WR→ Defence_D2 no_attack basket, p2: WR→ Defence_D3 no-reaction post basket, p3: WR→ Defence_D3 takes_him defence_D1 no-reaction centre basket, p4: WR→ Defence_D3 takes_him defence D1 takes_over defence_D4 Defence_D5 sinks playmaker basket

Fig. 3 shows the graph for the rotation of a centre in basketball. The rule p1 for instance defines shooting at the basket. This easy if–then rule for the decision of the wing player on the right side (WR) depends on whether or not the direct defence player D2 does attack him in order for him to score with or without interference.

The beliefs are defined according to the desires. For perception, the movements of offensive and defensive players play the major role. In basketball, for example, the defensive players D2 move towards the offensive right wing player so that he is forced to return the ball to the playmaker. The possible actions (intentions) of WR are defined through either passing to other team members or shooting at the basket. Fig. 4 shows the situational rotation of a centre in basketball at time t, when the right wing player possesses the ball.

A space–time definition of the perceptual environment was selected, whereby the right wing player assesses only the distance of his directly opposed defender to decide if he should shoot at

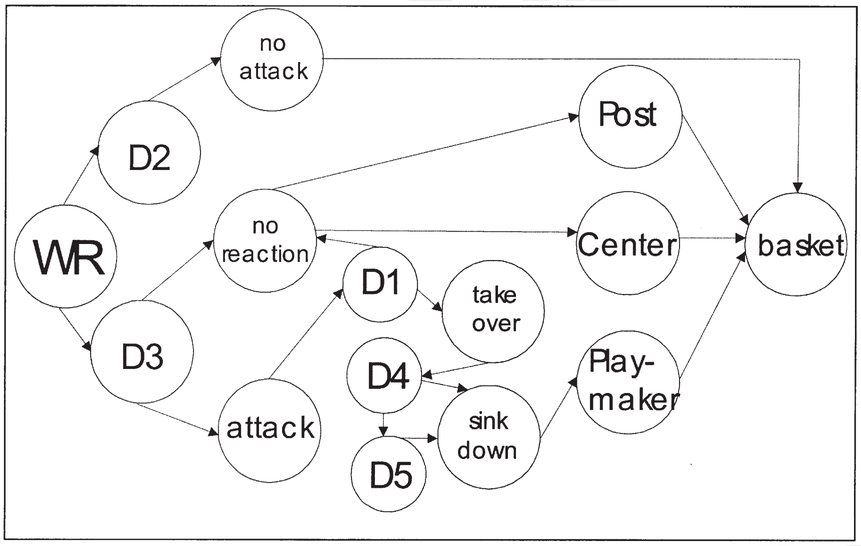

Fig. 3. Graph for the rotation of a centre in basketball.

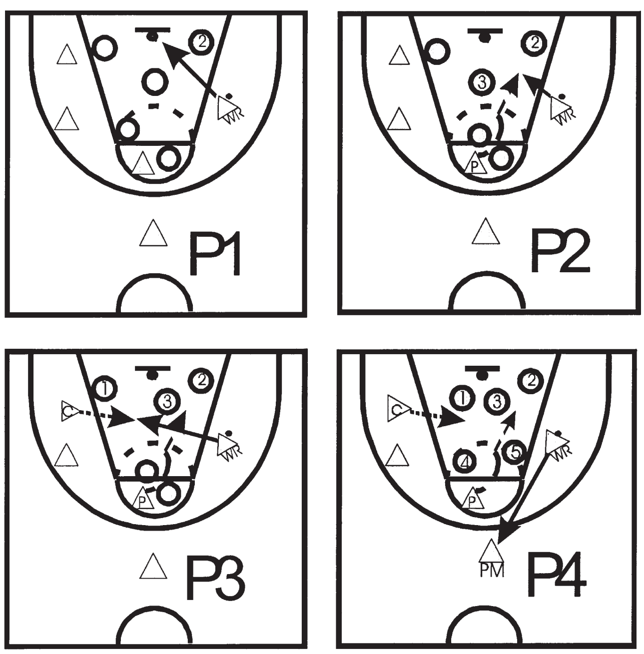

Fig. 4. Perceptual situation for rotation of centre in basketball, when right wing player (WR) possesses the ball; C=Centre, P=Post; PM=Playmaker, the number in circle refer to defence players in Table 1.

the basket or if he would be better passing to his teammates. The classes of equivalence are defined through one-to-one mapping of situations and goals in situations of varying complexity. Thus equivalence is claimed when in a perceived situation the same anticipated effects are associated. Complexity is determined by the cyclomatic number (McCabe, 1976) calculated in the graph (see Fig. 3). The cyclomatic number (vG) is calculated by $v(G)=e-n+p$ in Graph G with n vertices, e edges, and p connected components. In other words, more complexity occurs when fewer prior agreements in the offence are made and more freedom to decide is given (Ripoll, Kerlirzin, Stein, & Reine, 1995).

Implementation

The implementation was done in a local neural network, allowing to implement beliefs and desires in the same net architecture. The local neural network has symbolic knots (e.g. ball or defensive player D2), which are connected through promoting or blocking relations. For instance, the possible decisions exclude each other, because coherence was defined to search for one stable option with the highest activation. On the other hand, the defence player D2 promotes the decision to shoot to the basket in desire net (no attack) and belief net (far away). The desire net learns through a delta-rule, which changes weights depending on the distance between actual and expected outcome. The belief net uses a Hebb-algorithm, which calculates activation of every knot and every weight of a connection in considering a decay-parameter (Lange, 1992). This means that activation of knots at one time will enforce their connection and therefore increase the connection weights between them. Explanatory Coherence for Harmonic Optimization (ECHO; Thagard, 1989) is based on *parallel-constraint-satisfaction* which ensures a decision that enables the highest possible coherence (Thagard & Milgram, 1995). Coherence is reached if all the constraints in parallel are satisfied, for example when one option has been chosen. Activation is calculated after each iteration with the following algorithm:

$$a_j(t+1)=a_j(t)(1-\theta)+\{net_j\ (\max-a_j t))\text{if } \mathrm{net}_j>0 \text{ else } \mathrm{net}_j(a_j(t)-\min\}$$

a_j is the activity from knot j at time t. Learning is adjusted by the decay-parameter and optimised with net_j as the sum of $w_{ij}\ a_j\ (t)$. The decay-parameter describes the fact, that not all information is stored or used. Decay represents the construct of forgetting in simulations. To insert the assumptions in the local neural network the following sequence of steps is used.

Firstly, beliefs and desires are implemented in different neural networks. Each network contains specific knots with a starting activation between -1 and $+1$. Weights on the connections are used by changing a small portion around zero. The decay-parameter is set at 0.2. This average decay represents forgetting and is derived from empirical data of experiments in which rules for tactical decisions had to be learned (Roth & Raab, 1998). A fourteen (desire net) or thirteen (belief net) dimensional vector is used as a prompt for each rule (desires) or pattern of perception (beliefs) and then cross-multiplied in the matrix of knots with their starting activation (Fig. 5).

The definition of vectors depends upon the situation (rule-structured or perception-based) in which relevant knots in the desire net (see Table 1) and belief net (see Table 2) are more activated and irrelevant knots get low activated. Each vector has the same activity in total.

The implemented T-ECHO tries to reach coherence until a break down criterion occurs (chance from iteration $I_{(t)}$ to $I_{(t+1)}$<0.001), thus in the end, the system can give the output of all final

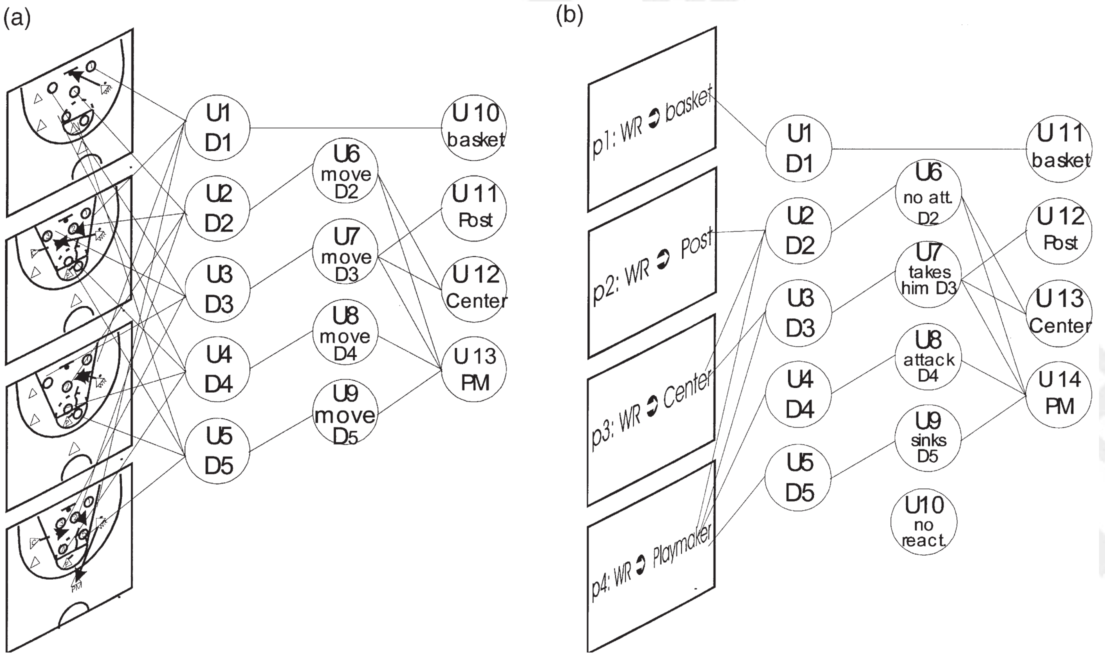

Fig. 5. Graph for the rotation of a centre in basketball belief-process (left) and desire-process (right).

Table 1
Input vectors for the desire net for all four possible decisions during the rotation of a centre in basketball. Rule 1 refers to situation P1 in Fig. 3, rule 2 to P2 and so forth. Players (WR, D1–D5) refer to Fig. 3 (no a. = no attack; no r. = no reaction; t. him = takes him; t. over = turn over). U11–U14 represent the decisions knots basket, post, centre, and playmaker respectively

	U1 D1	U2 D2	U3 D3	U4 D4 no a.	U5 D5 no r.	U6 D2 no a.	U7 D3 t. him	U8 D4 a.	U9 D5 sinks	U10 D3 no r.	U11–U14
Rule 1 basket	0.5	0.75	0.1	0.75	0.0	0.0	0.1	0.1	0.1	0.0	Mean 0.25
Rule 2 post	0.5	0.1	0.75	0.0	0.75	0.0	0.1	0.1	0.1	0.1	Mean 0.25
Rule 3 centre	0.5	0.1	0.7	0.0	0.5	0.0	0.5	0.1	0.1	0.0	Mean 0.25
Rule 4 playm.	0.5	0.1	0.2	0.0	0.0	0.3	0.3	0.3	0.3	0.3	Mean 0.25

activities. Obviously high activation of decision knots means that they have priority over the others that have low activation.

Secondly, the outcome of the decision knots from belief and desire networks deliver the new starting activation for the possible decisions (such as for the rotation of a centre, the shot to the basket or the pass to the centre, post, or playmaker). Now the decision knots from the desire and the belief net are combined in a common net including the final decision knots. Therefore, the

Table 2
Input vectors for the belief net for all four possible decisions during the rotation of a centre in basketball. Percept 1 refers to path WR to basket connections, Percept 2 refers to path WR to post connections in Fig. 4 and so forth. (perc. = percept). U10–U13 represent the decisions knots basket, post, centre, and playmaker respectively

	U1 D1	U2 D2	U3 D3	U4 D4	U5 D5	U6 D2 move	U7 D3 move	U8 D4 move	U9 D5 move	U10–U13
Perc. 1 basket	0.5	0.75	0.75	0.0	0.2	0.0	0.1	0.1	0.1	Mean 0.25
Perc. 2 post	0.2	0.0	0.5	0.5	0.2	0.3	0.3	0.2	0.3	Mean 0.25
Perc. 3 centre	0.5	0.25	0.0	0.3	0.25	0.3	0.3	0.3	0.3	Mean 0.25
Perc. 4 playm.	0.5	0.5	0.5	0.5	0.1	0.1	0.1	0.1	0.1	Mean 0.25

assumption is that knowledge and perception evolve their own preferences and then compete against each other for the final decision.

Results of simulation

The description of the results follows logically the implementation of beliefs, desires, and finally their combination. For each implementation T-ECHO calculates the given input vector on a pseudorandom activation matrix until coherence is reached. The number of iterations, the final activation of every knot is plotted, and the final matrix is presented in the programme (APL2, Brown, Parkin &, Polivka, 1989).

Modelling of beliefs

An average of 19.75 iterations allows T-ECHO to model the perception of the situation *rotation of the centre* in basketball represented in the belief net. The final activation of the decision knots can be plotted for each single percept (*P*). All percepts reach a satisfied coherence for the corresponding perceptions. The mean of the final activation was 0.70. *P1* (basket) and *P4* (playmaker) vector calculations receive approximately the same activation. For percept *P2* (post) and *P3* (centre) the anticipated decision was found to have the highest activation. Each percept is characterized by its individual output vector, which has a typical activation pattern. In Fig. 6 every percept contains 13 stripes, which represent the knots from left to right in Table 1. The last four stripes show the decision knots for *P1* to *P4*. The light grey colour of the first decision knot in *P1* (stripe number 10) shows higher activation than the competing decisions. Whereas in *P2* the second, in *P3* the third, and in *P4* the fourth decisions knot shows the highest activation, as expected.

Summarized, the percept *P1–P4* in Fig. 6 show the expected and hypothesized high final activation of the effects, which were predicted for this corresponding perception.

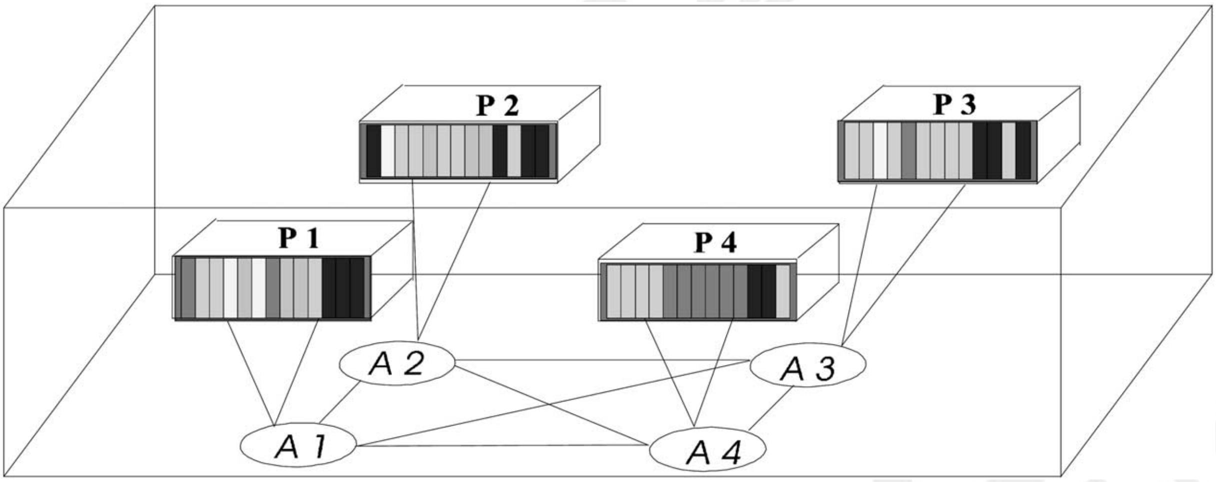

Fig. 6. Belief model for the rotation of a centre (light grey means high activation; P=percept, A=action/intention). Stripes from left to right represent knots in Table 2 (U1–U13). Last stripes 10–13 represent decision knots P1–P4 (basket, post, centre, playmaker).

Modelling of desires

The same procedure used for beliefs was also applied to desires. The differences in meaning and number of knots (see Table 2), as well as the start of activation, were adapted. The results are striking. First, four iterations less were used on average in the desire net than in the belief net for coherence. The clarity of well-structured rules could be responsible for faster coherence than the overlapping classes of perception. The second argument is that the total activation of the desire net is around 0.02 higher. To compare both nets the span for the matrix of chance and the decay parameter were held constant. The third most important argument is that the desire net could predict with more accuracy the postulated decisions. Only rule 3 (pass to the centre) received a smaller activation than the unexpected winner, the shot at the basket. In addition, and this is important for the interpretation, knowledge and perception favour slightly different decisions. Perception would suggest passing to the centre or to the playmaker, on the other hand, knowledge would favour shooting at the basket or pass to the playmaker.

Modelling of T-ECHO in total

The model T-ECHO combines the nets of beliefs and desires with the intentions. The final activation of the nets from beliefs and desires serves as a start activation for the decision knots in the total net. Therefore, model T-ECHO consists of three nets, of which each possesses the four decision knots (see Fig. 7).

After using the final activation from the single nets, it is still necessary to define the start activation of the intentions. We assume that all decisions are of equal value. Therefore, the probability for the four decisions is set at 0.25. This simplification is not a strong assumption because it just means that a basketball beginner would select each decision randomly. But it is also possible

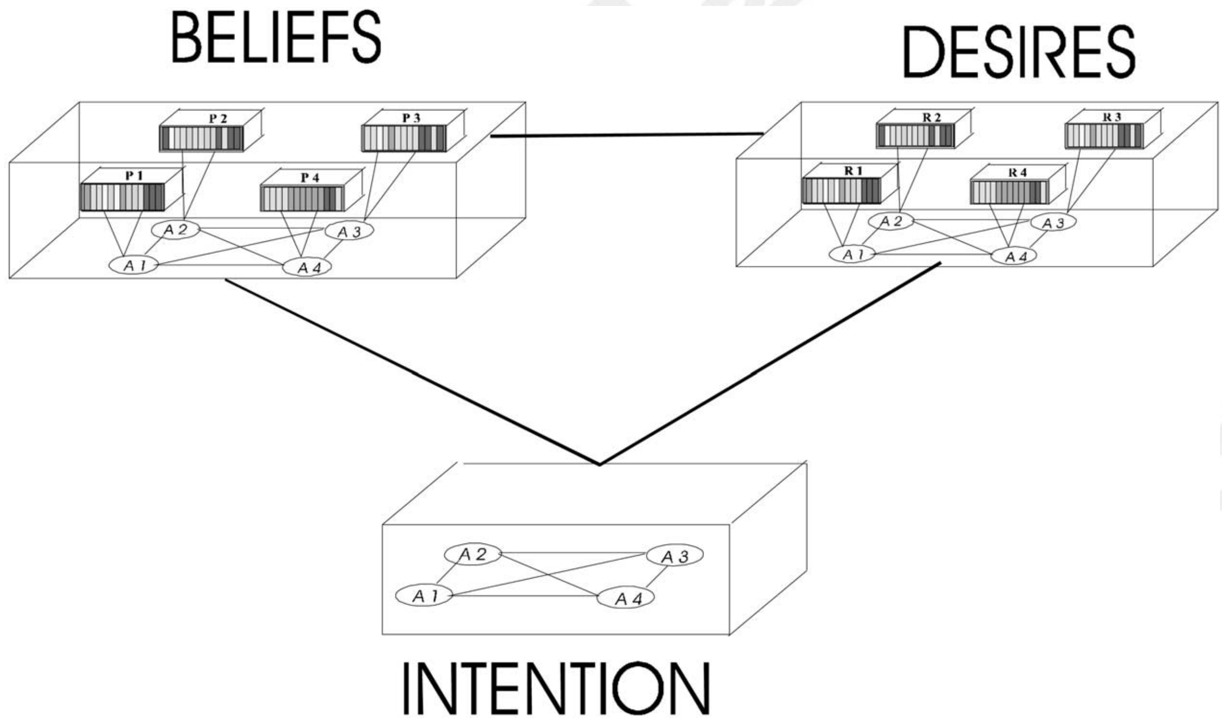

Fig. 7. Vector diagram for T-ECHO (percept P1–P4; rule R1–R4; action A1–A4).

to implement different weights at the start relating to other experiences or personal preferences (Fig. 8).

The simulation T-ECHO results in the highest activation for shooting at the basket (0.68) and passing to the playmaker (0.67). Passing to the centre (0.64) and passing to the post (0.57) show less activation. Hence, the first mentioned are given priority by the total net. Because the predictive power of this small difference in activation between options is not definitely clear, more evidence can be selected if order and relative distance between options can be found in decision experiments as well. To claim that these decisions are empirical data, which could be applied to human behaviour, makes it necessary to compare it with real life decisions.

Decision experiments

The same decision situation as in simulation was used in two experiments. Experiment 1 and 2 differ in this internal/external validity. Experiment 1 was conducted in a laboratory and Experiment 2 in the field to access how humans learn to decide in the modelled basketball situation.

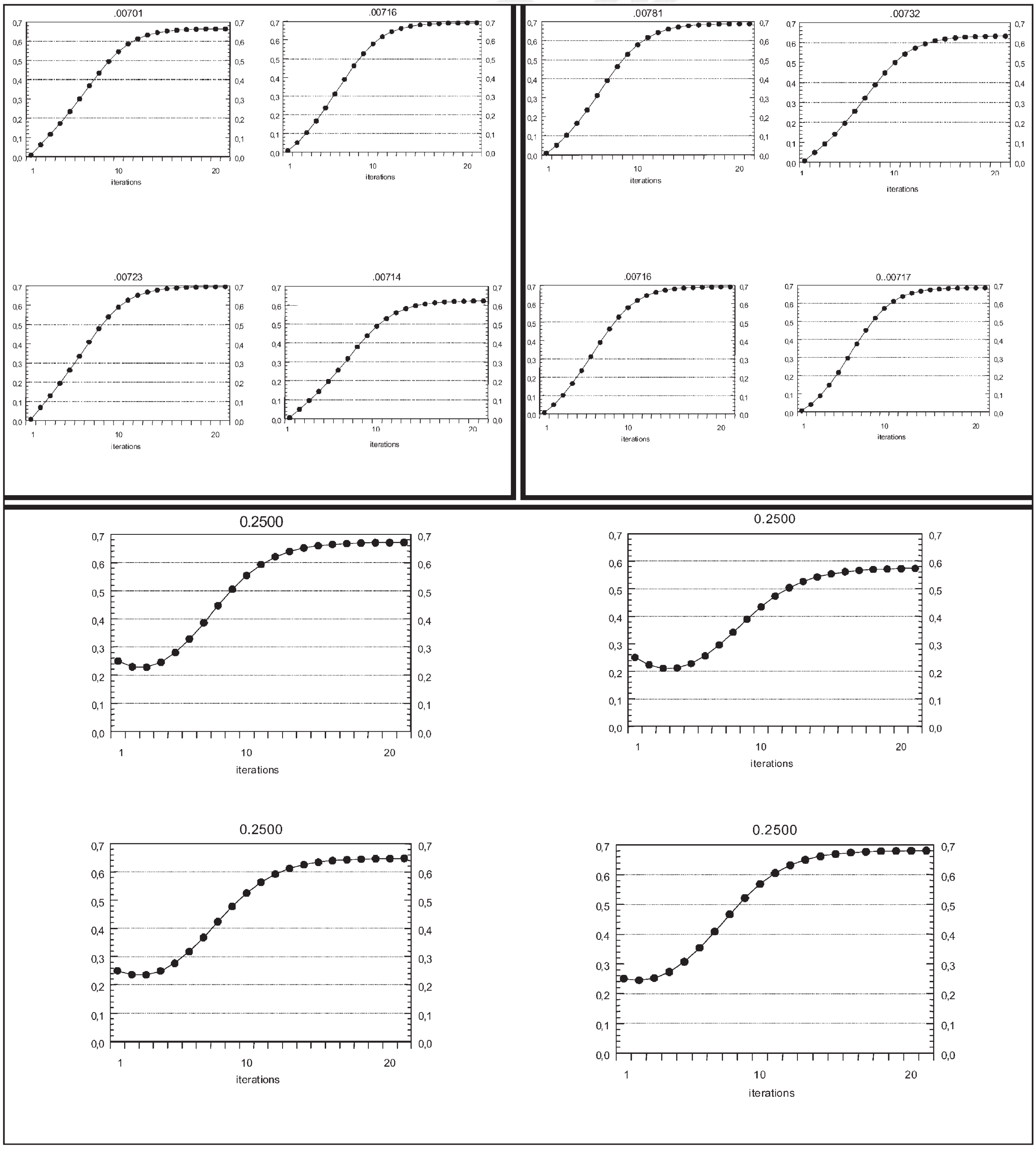

Fig. 8. Activation of decision knots model T-ECHO (upper left: percept 1–4; upper right: rules 1–4; down: intentions basket, and pass to post, centre, playmaker).

Experiment 1

Method

The purpose of this experiment was to explore the decision making of participants when they were forced to learn tactical decisions either implicitly or explicitly. Firstly, it was necessary to show that tactical decisions can be learned in both ways; secondly it was essential to show how these styles of learning affect decision making. Finally, it had to be shown which learning process will be more effective. A 3×2 MANOVA design was used. The participants were randomly assigned to three groups, the implicit group, the explicit group, and the control group. All treatment groups learned the situation 'rotation of the centre' in basketball through 200 self recorded video clips in four weeks by one session of 50 clips each week presented on a big video screen. The video clips were rated by experts and represented an equal amount of right and wrong decisions of the right wing player to shoot to the basket, pass to the post, pass to the centre or pass back to the playmaker. The explicit group was governed by the if–then rules, which define the clips. In the beginning of every session the if–then rules were ranked by complexity and presented via video scenes, verbal, and visual descriptions of the rules. On the other hand, the implicit learners received a cover story according to the paradigm of implicit learning of artificial grammars (Reber, 1967). They were told to take part in a psychological memory test and they had to memorize the decisions of the player with the red shirt (the right wing player). After 10 decisions they had to name the first or last five decisions in a partial recall test. The control group received no treatment and served as a baseline for the decision test.

Participants Male (n=27) and female (n=26) undergraduate students of the University of Heidelberg Department of Sport and Sport Science served as participants. They all were novices in basketball and received course credit for participation.

Apparatus After the treatment participants were tested in a video lab in a post test and a test of retention four weeks later. The test involved 51 scenes of a natural movement and perception situation of the rotation of the centre from the perspective of the right wing player. Every scene stopped when the right wing player possessed the ball. The participants were then asked to make a tactical decision about the further development of the attack. The participants had to make their decision and move as quickly as possible to one of the electronic mats on the floor in front of them. These represented the possible decisions of the marked player on the tape (see Fig. 9).

The chosen decision and the time between the stop of the scene and activation of the electronic mat in milliseconds were recorded by a specifically designed piece of software. After the test all participants were interviewed with open-ended questions and a questionnaire concerning their ability to verbalize the learned rules and to look for a detailed decision strategy (Wulf & Schmidt, 1997).

Results and discussion

Data were checked for assumptions for MANOVAs and corrected in the case of outliers. The α-level was set on 0.05. Only the results of the post test and the percentage of right decisions are presented, because it is considered that this is sufficient for the two main questions to be answered, that is, can tactical decisions be learned explicitly or implicitly, and does the type of

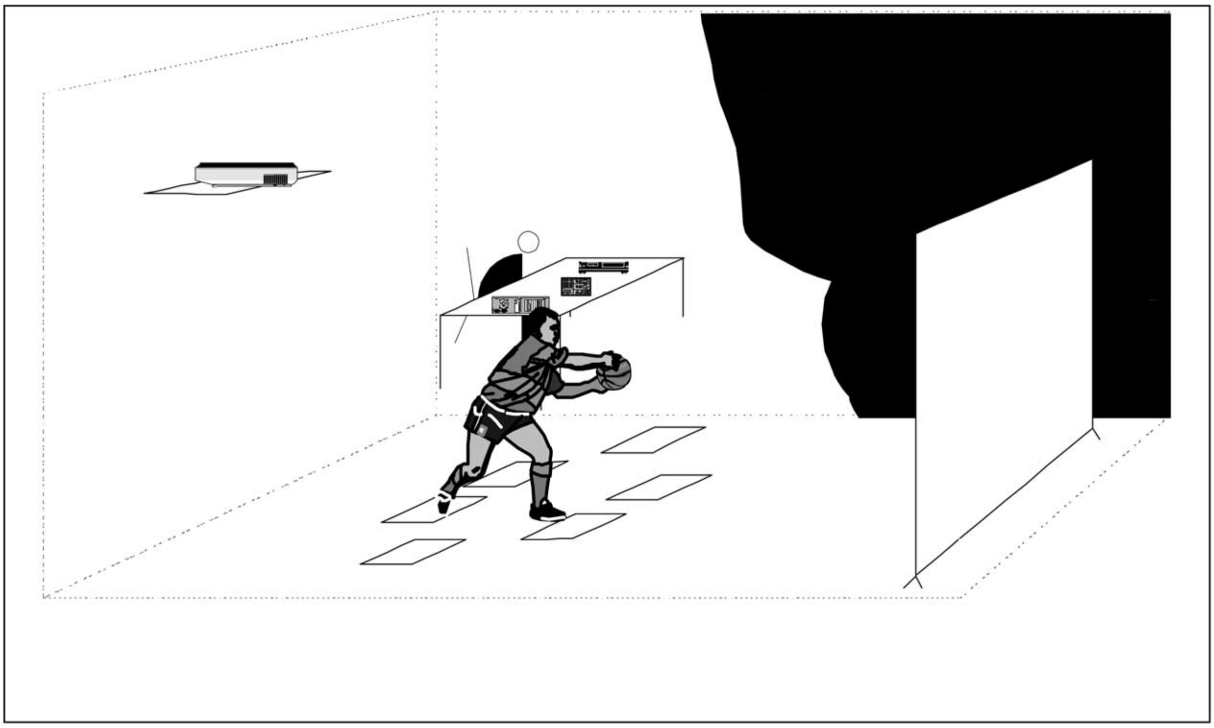

Fig. 9. Test of the tactical decision of the situation 'rotation of centre' in basketball.

learning result in different decisions being made? However, it is worth noting, that collinearity between dependent variables was r=0.32 and that the tests of retention showed similar results. Table 3 contains means and standard deviations of post and retention test results.

The differences between groups were highly significant for decision quality ($F(2, 52)=11.92$; $p<0.001$) and decision time ($F(2, 52)=8.74$; $p<0.001$). A post-hoc analysis (Scheffé) also showed

Table 3
Descriptive results of post and retention test (experiment 1)

	Right decisions (%)		Time (ms)	
	M	SD	*M*	SD
Implicit group				
Post test	45	8.85	3430	371
Retention test	37.36	8.56	3465	431
Explicit group				
Post test	37.62	7.13	2786	487
Retention test	43.50	13.24	3028	357
Control group				
Post test	30.68	10.04	3078	509
Retention test	38.06	8.96	3180	633

that the difference was due to the main differences between control and treatment groups. Treatment groups had better decision quality compared to the control group. A detailed description of the decision behaviour in respect to the chosen options will be given during the comparison with the simulation data. So far it can be summarized that tactical decisions can be learned implicitly and explicitly which could be shown by the differences between treatment groups and control group. Also, on average the learners showed that their decision making quality was far higher than just chance. The remaining question is, are these learning and decision making processes similar to those in real settings? In order to answer this question a field experiment was conducted to replicate experiment 1 and to strive for more external validity.

Experiment 2

Due to the assumption that implicit and explicit processes are only the extreme poles of a continuum which cannot be reached easily in the field, a construct specification is necessary. Therefore, it was assumed that implicit processes are mostly used if no intention is present to learn the tactical structure. Thus, incidental learning situations were constructed which should primarily enhance implicit processes. On the other hand, the explicit processes were taught by coaches' instructions on the basis of basketball literature and expert groups.

Method

The same design as in experiment 1 was applied. Again, in a four-week period, with one session a week, 50 attacks (per session) were played with the rotation of the centre. The positions in the field were rotated after 5 attacks, so every participant had the same amount of attacks in each position. The explicit group was given the if–then rules visually on a blackboard at the beginning of every session. The coach also explained the if–then rules verbally. The implicit group, as in experiment 1, was instructed by a cover story to take part in a memory task in which it is useful to memorize the behaviour of the attackers. They were asked to memorize the first or second five decisions of the right wing player in a partial recall test. The control participants of experiment 1 were again used as a baseline for the tactical test also used in the prior experiment.

Participants

17 male and 17 female undergraduate students, who did not take part in the first experiment, served as participants. The students were participants of a beginners' basketball course in physical education. Students with active basketball experience were excluded. To control possible moderators groups were split into equal parts. Coaches were counterbalanced during treatment and both groups were given a cover story to hinder the possibility of transfer of useful information between the groups.

Results and discussion

The statistical preconditions of calculations were checked (see Experiment 1) and found to be satisfactory. The results focus on the quality of the decisions only. Because of no change in test situation between experiment 1 and 2, the same control group (n=15) was used as a baseline. Table 4 shows means and standard deviations of post test results.

As in experiment 1 significant differences could be found in the decision quality ($F(2, 48)$=8.74;

Table 4
Descriptive results of post and retention test (experiment 2)

	Right decisions (%)		Time (ms)	
	M	SD	*M*	SD
Implicit group				
Post test	44.05	10.79	3566	347
Retention test	54.04	13.21	3743	256
Explicit group				
Post test	45.1	12.36	3394	629
Retention test	54.91	13.86	3664	325
Control group				
Post test	30.68	10.04	3078	509
Retention test	38.06	8.96	3180	633

$p<0.001$) and decision time ($F(2, 48)=3.76$; $p<0.05$) although the expected effect size was reduced from experiment 1 ($\eta^2=0.33$) to experiment 2 ($\eta^2=0.28$) for decision quality. Post-hoc comparison (Scheffé) also clearly showed the difference between control group and treatment groups, which supports the pattern of results from experiment 1. In summary, again tactical decisions can be learned implicitly and explicitly. Both groups are superior to the control group and far superior to mere chance. Implicit groups showed better decision quality in post test results, which were not retained four weeks later, compared to the explicit groups. In addition, one explicit group (experiment 1) revealed faster responses than the implicit group. The practical consequences are discussed elsewhere (Raab, 2001).

Comparison of results of simulation and experiments

To compare the results of simulation and experiments, the activation in simulation and decision quality in video tests was transformed. Table 5 shows the total distribution and the proportionally correct decisions. The total number of decisions does not sum up to 100% because on average

Table 5
Proportional distribution of decisions (upper panel: participants; lower panel: simulation)

	Basket	Post	Center	Playmaker
Total of decisions of participants				
Exp. 1	0.31	0.24	0.23	0.19
Exp. 2	0.25	0.29	0.19	0.17
Right decisions of participants				
Exp. 1	0.77	0.77	0.71	0.66
Exp. 2	0.55	0.55	0.51	0.47
Simulation T-ECHO	0.68	0.57	0.64	0.67

7% made no decisions. Therefore, the correct decisions have to be related to 100%. The simulated data represent the final activation of decision knots of the total in T-ECHO.

Firstly, the results show that participants make more correct decisions in the lab training in comparison to the field training. Secondly, the decision behaviour in both experiments is nearly identical. Shots at the basket and passes to the post received priority. This behaviour is also consistent between different training groups, which are trained either more explicitly or implicitly (Roth & Raab, 1998). Thirdly, the most interesting difference between simulation and experiments was the pass to the playmaker in the simulation. This decision was almost ignored by the participants, who favoured trying to shoot at the basket and therefore risk more.

Are these results based on different amounts of perception and knowledge processes? There are at least two possible ways to look at the behaviour data of the participants. First, the distribution of the reaction times hint at the role which these different processes play in decision making situations. Therefore, it is assumed, that fast decisions are more likely to be generated by perception-based information whereas slow decisions are likely to be caused by knowledge-based processes. Second, the answers in the post experimental questionnaire about the verbalized rules and their attention strategies could be compared with the results of the single belief and desire neural nets. For the first strategy there was no structured distribution, which could explain different amounts of these processes. It is interesting, however, that in both experiments rules for shooting at the basket and passing to the playmaker were verbalized best, which is also true for the knowledge net in the T-ECHO simulation.

Expansion of model T-ECHO with time pressure

To expand the assumptions of T-ECHO we have to consider that decision making in sports mostly happens under changing time pressure constraints. Theoretical assumptions (Kuhl & Beckmann, 1983) and empirical evidence (Roth, 1993) were mostly guided mono-theoretically by subjective expected utility models (Kahneman & Tversky, 1984). Time pressure in these models cause different decision making strategies; thus easier strategies for instance are used in situations with higher time pressure (Ordónez & Benson, 1997). It is not explained how many different strategies we use, how our system chooses between these different strategies, and how we can predict the preference reversal outcome. So far, most attempts have been stage-models and domain specific for perceptual categorization (Lamberts, 1998, extended generalized context model) or the decision phase (Nosofsky & Palmeri, 1997, exemplar-based random walk model). A dynamic approach, on the other hand, explains accuracy of decisions differently, assuming preference reversal in a parallel fashion and by describing perception and decision in the same model. Busemeyer and Townsend (1993) implemented preference reversal in their DFT, which can also be used for multiattributed options by the expansion of Diederich (1997) in the multiattribute dynamic decision model (MDDM). In time pressure situations, according to Diederich's argument, the decision is made with the highest preference at the start of the process. This so-called *anchor point* from which the process starts explains, for instance, that we always have a preferred option, even if there is theoretically no time to process a decision. This anchor point also shows that the decision, which has been already made, may be the preferred one, although the situation slightly changed. But in terms of the model T-ECHO it belongs to different classes of equivalence. Because of the dynamic change of beliefs and desires in tactical decisions and the high time pressure situations, the expanded DFT is the preferred model to be used here. Therefore, it seems necessary to implement time pressure in T-ECHO to test preference reversals in understanding its influence on the decisions. So, given the same situation without time pressure humans may shoot at the basket but with time pressure they may pass the ball back to the playmaker. The argument presented here can be proven in T-ECHO if we accept some additional assumptions, for instance how time pressure may cause different effects in the belief and desire nets. Let us keep in mind that the formalized implicit processes of perception-action are fast. Let us also take into account that explicit processes formalized by comparisons of if–then rules take much more time, because they have to be retrieved from memory and are in one way or another computed by an algorithm. Time pressure may evolve preference reversals just by its different influence on belief and desire nets. In other words, because of the direct perception-action associations, these fast processes will control decision making under high time pressure conditions. In low time pressure situations, the 'more time' to generate options and to make comparisons throughout many attributes is at least possible and may therefore result in more accurate and different decisions. But how do we implement time pressure in T-ECHO? Time pressure in T-ECHO is implemented by telling the net to stop iterations by 5 (~25% of time) or 10 (~50% of time) iterations compared to the average amount of iterations to satisfy all constraints at 19.75 (belief) or 19.72 (desire). These manipulations increase time pressure even more than the one used in experimental settings (Roth, 1993). To compare the results of experiments and different simulations all parameters are held constant. The percentage of right decisions and the activation of the knots of the decision net were scaled from 0–100 to compare the results. Fig. 10 shows the results for different conditions of time constraints.

The comparison of different time pressure situations shows clearly that under conditions of very high time pressure, say 25% of time (left column of Fig. 10), the preference to pass the ball back to the playmaker is high, just like humans who cannot analyse the situation exactly and therefore choose a decision which is not risky. By time pressure of 50% (middle column of Fig. 10) the playmaker solution still has a high activation but to shoot at the basket is also taken into account. These preferences, compared to the non-time pressure situation (right column of Fig. 10), show the expected preference reversal. The highest activity for the playmaker solution, which was shown during time pressure, now becomes the lowest activity and therefore this option will not be chosen too often.

General discussion

While evaluating the modelling of T-ECHO, it can be observed that the three steps — conceptualization, formalization, and implementation — can project tactical processes of learning and decision making in ball games. The comparison between simulation and the empirical results still show the following critical points.

T-ECHO simulation of perception is oversimplified. Therefore, one could argue that simulation and experiments show differences in total. In future, space–time relations should be added by velocity of moving objects which are already implemented by real simulations, for example at the Robo-Cup (Burkhard, Hannebauer, &, Wendler, 1998).

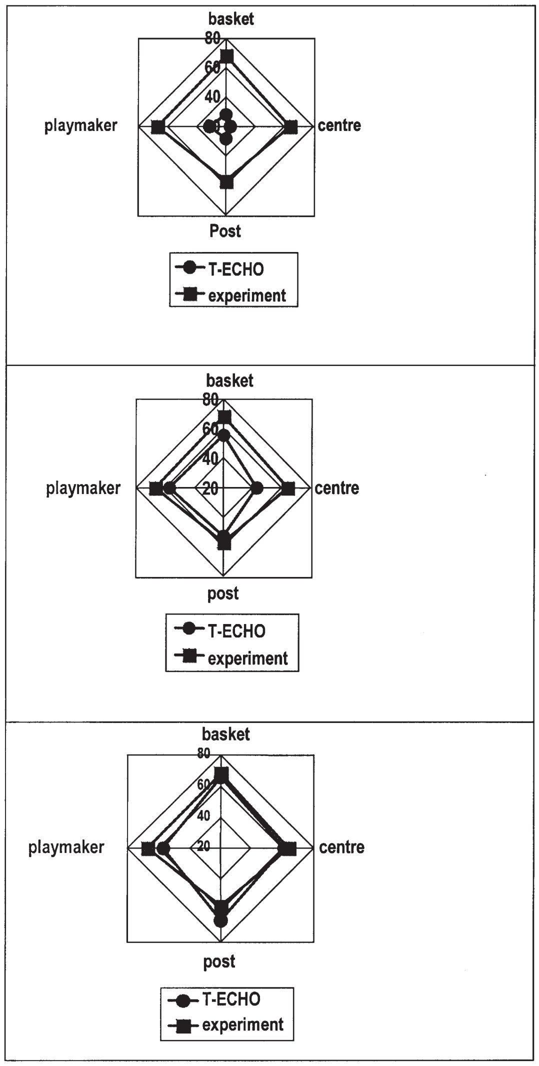

Fig. 10. Simulation of model T-ECHO vs. experimental data by time pressure (top: 5 iterations 25% time; middle: 10 iterations 50% time; down: no iteration stop 100% time).

Another important critique is, that T-ECHO is still static. A realistic dynamic modelling has to be implemented in real-time neural networks (Grossberg & Gutowski, 1987) and also has to respect the dynamics within a decision by more than the chosen parameters (Townsend & Busemeyer, 1995). In a first step, however, it could be shown that time pressure causes preference reversals with less assumptions than are used by subjective expected utility models.

The model T-ECHO lacks other behavioural relevant factors, such as emotions. Their integration has to deal with operations (conceptualization), knots (formalization), and start activations (implementation). One additional effect of a motivational factor from the experiments is that action oriented players prefer to shoot at the basket whereas state oriented players prefer to pass to the playmaker (Kuhl, 1986). To solve such problems, different starting activations should be used. Finally, in order to explain different behaviour of participants in the same decision making situations, we must modify our models by testing hypotheses through simulations. After that, decision experiments could be a fruitful way to understand the decision making processes in ball games.

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