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Modeling of decision making in ball games

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Keywords

Decision making, implicit learning, explicit learning, computer simulation, constraints satisfaction

Introduction

The emphasis on model building of decision making in sports science so far has primarily been focused on the diagnostics of competition. The goal of this article is to explain the mechanisms of how tested subjects learn to make tactical decisions implicitly (bottom-up) and explicitly (top-down). The theoretical support is based on the BDI-architecture (beliefs, desires, intentions; cf. Bratman, 1987). A tactical situation in Basketball was simulated where subjective perception contexts (beliefs), goals developed by learning (desires), and the outcome of the decision process (intentions) were modeled. The simulation was realized in a local neural network (ECHO; Thagard, 1989) and was specified by a decision model T-ECHO (Tactical decision – Explanatory coherence by harmonic optimization).

Modeling Decision Making/Method

Opwis & Spada (1994) describe a three-step modeling procedure for cognitive processes including conceptualization, formalization, and implementation. In a defined game situation (e.g. basketball) the objects are the players, the ball, and the goals, etc. Objects, such as the playmaker (PM), have attributes that are described in tuples {(PlayerPM,Ball_possession)...}. Formalization, the second step of cognitive modeling, occurs through rules that permit general statements about hierarchies of different levels of abstraction. The third step, the implementation describes two independent ways of learning. Firstly, T-ECHO learns implicitly without goal oriented knowledge through perception. Secondly, it displays effects of mental training without perception. Of course, the normal case is an interaction of these two procedures.

The implementation was done in a local neural network. The local neural network has symbolic knots (e.g. ball or defensive player x2), which are connected through promoting or blocking relations. They learn through a Hebb-algorithm, which calculates activation of every knot and every weight of a connection in considering a decay-parameter. ECHO (Explanatory

Coherence for Harmonic Optimization; Thagard, 1989) is based on ”parallel-constraint-satisfaction” which ensures a decision that enables the most possible coherence. Activation is calculated after each iteration with the following algorithm:

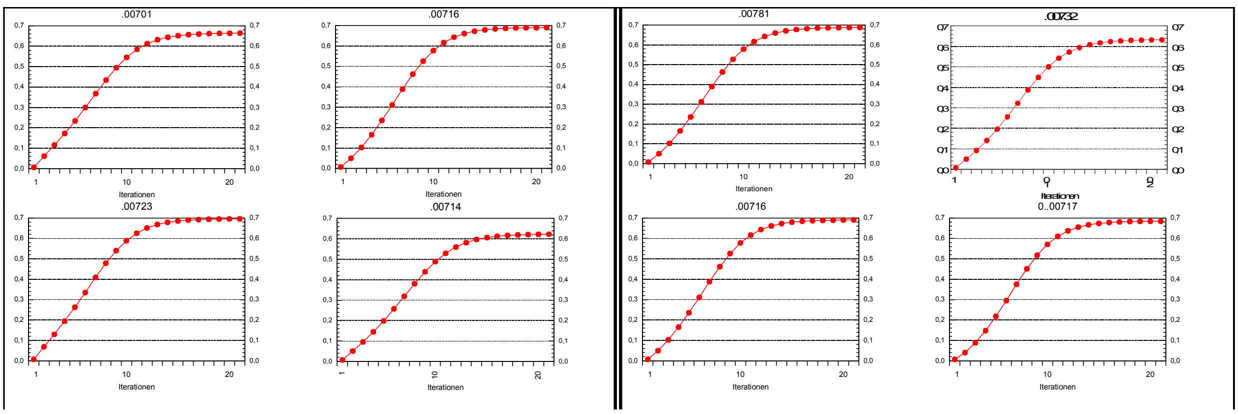
$$a_j(t+1) = a_j(t)(1-\theta\ ) + \begin{cases} net_j(\max - a_j(t) & \text{if } \mathrm{net}_j > 0 \text{ otherwise} \\ & \mathrm{net}_j(a_j - \min) \end{cases}$$

a_j is the activity from knot j at time t. Learning is adjusted by the decay-parameter θ and optimized with net_j as the sum of w_{ij} a_j (t). To install the assumptions in the local neural network the following sequence of steps is used: *First*, 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 change in a small portion around zero. The decay-parameter is set on 0.2 through an empiric diagnostic average decay from subjects in experiments who learn such rules for tactical decisions (c.f. Roth & Raab, 1998). A vector is used as a prompt for each rule (desires) or pattern of perception (beliefs) and then cross-multiplied in the matrix of weights. The definition of vectors depends upon the situation (rule-structured or perception-based) in which relevant knots get high activation and irrelevant knots get low activation. The implemented T-ECHO tries to reach coherence until a breaking down criterion (chance from Iteration $I_{(t)}$ to $I_{(t+1)}$ <0.001), thus at the end the system can give the output of all final activities. Obviously high activities of decision knots mean that they have a priority compared to the others who have low activities.

Second, 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 center, the shot to the basket or the pass to the center, 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 assumption is that knowledge and perception evolve their own preference and then compete against each other for the final decision.

Results

The model T-ECHO combines the nets of beliefs and desires with the intentions (see fig. 1).



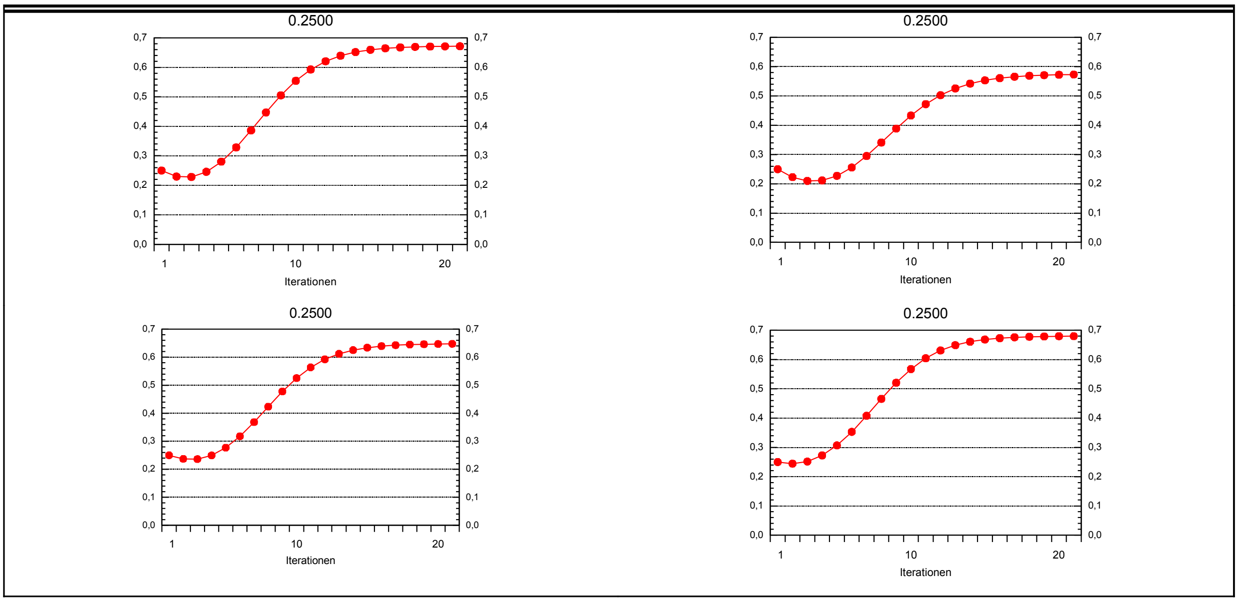


Figure 1: Activation of Decision Knots Model T-ECHO (upper left: percept 1 to 4; upper right: rules 1 to 4; down: Intentions basket, and pass to post, center, playmaker)

The final activation of the nets from beliefs and desires serve 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 figure 1). The simulation T-ECHO shows for shooting at the basket (0.68), passing to the playmaker (0.67) as the highest activations; passing to the center (0.64) and passing to the post (0.57) with less activation. Hence, the first mentioned are chosen by the total net by priority.

GENERAL DISCUSSION

While evaluating the realized modeling 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. However, the simulation shows the following critical points: First, T-ECHO is still static. A realistic dynamic modeling has to be implemented in real-time neural networks (GROSSBERG & GUTOWSKI, 1987). and also has to respect the dynamics within a decision (e.g. TOWNSEND & BUSEMEYER, 1995). Second, T-ECHO lacks other behavior relevant factors, e.g. emotions. Third, 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 in Robo-Cup (e.g. Burkhard, Hannebauer & Wendler, 1998). Finally, in order to explain different behavior of subjects in the same decision making situations, we must modify our models by testing hypotheses through simulations. Then experiments should be made, which could lead to a fruitful way to understand the decision making process in ball games.

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