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Tactical pattern recognition in soccer games by means of special self-organizing maps ☆

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ABSTRACT

Increasing amounts of data are collected in sports due to technological progress. From a typical soccer game, for instance, the positions of the 22 players and the ball can be recorded 25 times per second, resulting in approximately 135.000 datasets. Without computational assistance it is almost impossible to extract relevant information from the complete data. This contribution introduces a hierarchical architecture of artificial neural networks to find tactical patterns in those positional data. The results from the classification using the hierarchical setup were compared to the results gained by an expert manually classifying the different categories. Short and long game initiations can be detected with relative high accuracy leading to the conclusion that the hierarchical architecture is capable of recognizing different tactical patterns and variations in these patterns. Remaining problems are discussed and ideas concerning further improvements of classification are indicated.

1. Introduction

Different computer-based approaches try to extract and analyze tactical patterns in sport games. Besides traditional statistical tools (cf. Hughes & Franks, 2009; Reilly, Cabri, & Araujo, 2005), neural network approaches from the area of computer science are discussed and evaluated in the field of

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team sport (Grunz, Memmert, & Perl, 2009; Jäger, Perl, & Schöllhorn, 2007; Memmert & Perl, 2006; Perl, Memmert, Bischof, & Gerharz, 2006; Pfeiffer & Perl, 2006). Considering the problem of recognizing different variations in tactical pattern several difficulties arise for all approaches.

This paper is concerned with a classification of short and long game initiations which are roughly defined at first. Both tactics start by winning the ball from the opposing team by the goalkeeper or a defense player. Next, the ball is passed to different team players. If each pass length exceeds approximately 30 m the complete tactical pattern is classified as a long game initiation, otherwise it is classified as a short game opening. The tactical pattern ends with losing the ball to the opposite team. It is a difficult task to formulate precise definitions. Involved players as well as the actions they choose may vary, leading to an enormous variety of observable patterns. Approaching the issue with a set of different rules to map all such variations to a representative type seems infeasible. Neither is it possible to formulate all required rules, nor to guarantee consistency between different sets of rules for different tactical patterns.

In order to improve classification we use artificial neural networks as a kind of machine learning approach, replacing the construction of such explicit rules by fuzzy similarity relations, which shows satisfying results in comparable approaches (Perl, 2002, 2004, 2008). In the following, we will first give a short introduction to the method of self-organizing maps (SOM), completed by some extensions of the standard SOM approach. Here, we will give a brief overview of the standard Kohonen's SOM. Then we will show the hierarchical architecture in more depth and take a closer look at the different levels. Therefore, we compare the results from our classification using the hierarchical setup to the results gained by an expert manually classifying the different categories.

1.1. The nature of SOM: Theoretical background and technical framework

A SOM consists of a set of artificial neurons which are normally arranged in a rectangular grid forming a two-dimensional map (for a review, see Kohonen (1995)). At the beginning, each neuron is initialized with a random vector whose dimension is equal to the dimension of the multidimensional input space. This vector is called the neuron's weight vector. To simplify the notation a neuron together with its corresponding weight vector will be referred to as a prototype. Before a network can be used for typification, it must learn the mapping. For this reason a training phase has to precede the testing or production phase. During training the net is fed with a set of samples, which are drawn at random from the input space. For each entered data sample the nearest prototypes are slightly moved towards the direction of the data. How far a prototype is moved depends on the similarity to the current data sample and the training step – i.e., when training starts the prototypes can be moved over larger distances while in the final phase a prototype should only make small movements. Similarity can be measured in different ways; we use the Euclidean distance to measure similarity. After training the map approximates a two-dimensional nonlinear manifold embedded in an usually high dimensional data space (Bishop, 2007).

1.2. Dynamically Controlled Network (DyCoN)

The standard Kohonen SOM suffers from one limitation which is relevant for our research. After the net has stabilized, it cannot be changed anymore. In particular the net cannot learn any new pattern or new variations in a pattern. Different approaches have been developed to solve this limitation (Perl, 2002, 2004). Dynamically Controlled Network (DyCoN; Perl, 2004) extends the standard SOM with an adaptive learning rate and distance. Using a Performance Potential (PerPot) Metamodel each neuron controls its own learning behavior enabling continuous learning (for a review, see Perl (2002); for practical implications, see Memmert and Perl (2009a)).

A SOM and derivations like DyCoN have the very important property that as far as possible similar inputs, e.g., variations of a pattern are mapped to the same neuron or to neighboring neurons (local conservation of topology). This is a rather abstract description and it can be better explained with an example.