Human Movement Science 31 (2012) 267–270

Contents lists available at SciVerse ScienceDirect

Human Movement Science

journal homepage: www.elsevier.com/locate/humov

Guest editorial

Special issue: Network approaches in complex environments

With the enormous improvement of data acquisition during the last 10 years or so, the rather serious problem arises how to transform all those data to useful information. Moreover, without analyzing the data one does not know if it contains any useful information at all. Therefore, new and, if possible, automatic devices are needed which are able to accomplish this transformation from data to useful information. Artificial neural networks have proved to be able to do so. As experience from the last decade shows, such networks can successfully be used in sports in case of process analyses where 'process' mainly means motion, game, or training. It has to be pointed out that the development of net-based analysis in sports cannot completely be understood from dealing with only one of those fields of application. A lot of correspondences and connections between those different approaches helped to find appropriate solutions in cases that first looked quite different and eventually turned out to be quite similar.

The first approaches we are aware of started in the early 2000s with lower level phase analyses of games. Discussions with biomechanics then showed that, reduced to sequences of data, movements are rather similar to games, resulting in fruitful approaches of net-based motion analysis. One main result from this research was that the reduction from the process as a whole to its phases or components may be extremely helpful for understanding and comparing motions. Currently, net-based phase-analysis is used successfully for high level tactic analyses in games.

In the context of this background, the special issue is introduced with some remarks on history and technical aspects of net-based process analysis, followed by a brief characterization of the main working areas and closed by a short introduction to the actual contributions to this special issue.

Process analysis: Quantitative vs. qualitative aspects

Analysis of complex natural processes can be done either quantitatively or qualitatively. In brief, quantitative analysis calculates characteristic values, distributions or structural relations. It can be easily done using appropriate packages but normally neglects process dynamics and component interactions. Qualitative analysis, in contrast, tries to identify types of interaction, time dependent dynamics, key activities, and striking features. Normally, appropriate analysis features have to be developed specifically and the results are mostly not general but exemplary ones.

Combination of quantitative and qualitative aspects by means of natural learning simulation

Of course, there is no decision whether qualitative or quantitative analysis is the better choice. As almost always in cases like this, the truth lies in between: Statistics, frequencies, and quantitative structures are as important as time-dependent interactions and striking features. Both paradigms,

0167-9457/$ - see front matter
http://dx.doi.org/10.1016/j.humov.2012.04.001

quantitative and qualitative, have been combined successfully in neural networks – an approach motivated by the way natural brains work. The main idea is that of learning by observing and thereby connecting the quantitative aspect of frequency with the qualitative aspect of meaning.

Soft computing

Nowadays, artificial neural networks, evolutionary algorithms, and fuzzy modeling form the area of "soft computing" constitute concepts and methods that have proven to be very helpful in solving complex problems with still surprisingly high precision in surprisingly short calculation time. In particular, motion and game analysis deal with complex processes that are characterized by statistical numbers as well as by behavioral phenomena, and are thus specifically qualified for net-based analyses. During the last years, there have been many successful applications of neural networks to motion analysis.

Artificial neural networks: Basic intentions

Originally, artificial neural networks were thought to simulate biologic neuron structures and their learning behavior. Meanwhile, not in the least influenced by the huge difference of neuron numbers in artificial and biological networks, the approach has been reduced to a technical and/or mathematical concept of pure information handling.

Nevertheless, there are some remarkable similarities between artificial and biological learning (see, e.g., Perl & Weber, 2004), which in particular in the case of DyCoN (Dynamically Controlled Network, see Perl, 2002, 2004; Memmert & Perl, 2009a, 2009b), help to optimize training processes. One aspect that is of technical as well as of physiological interest is that of reducing the amount and precision of information, which makes the handling, classification and recognition of data patterns much easier.

Artificial neural networks: Types and approaches

There are essentially two approaches, both called 'artificial neural network', which mathematically have the same roots, but are quite different methodically as well as in practical application: A first approach, which is often used synonymously with 'neural networks', is that of back-propagation and/or feed forward networks (FFN). Here, the generally unknown input–output-relation of a function or process is learned by means of a set of representative samples. This approach can be mainly used for simulative calculation of relations in case of controlling dynamics of the function or if process is unknown.

A second approach, which mainly deals with automatic clustering and type recognition of complex data, is that of self-organizing maps (SOM) or Kohonen feature maps (KFM). Again, a set of representative samples is necessary for the network training. However, the aim is to recognize similarities between the input data and organize them into clusters of similar data, which is done by the network on its own. After training, a net can recognize the corresponding cluster – i.e., the 'type' – of data to be characterized. There are three main fields of application for artificial neural networks in sport: motion analysis, game analysis and multiple correlational analysis.

Artificial neural networks and motion analysis

Motion analysis is based on time-depending sensor data which give information about position, speed, acceleration, or angles of body segments. Assumed that a high-speed camera takes only 100 frames per second, and the sensors take 20 pieces of information per frame, a 10-second motion produces 1000 frames and 20,000 data, which is way too many for conventional analysis. Neural networks of the SOM type can help to reduce those data to its characteristic contents. For example, a motion can be reduced to a corresponding sequence of its specific phases. Moreover, in a second step of the SOM application, those phase sequences can be replaced by the corresponding sequence type, thus reducing the whole complex motion to just a characteristic type number, simplifying intra-individual stability and inter-individual similarity analyses by far.

Artificial neural networks and game analysis

Besides motion analysis, game analysis is the second and most important area in sports where artificial neural networks of type SOM can be extremely helpful. While in motion analysis correlation and coordination of body segments have to be analyzed, in games the player positions and group constellations and their tactical meaning are of interest. Again, the amount of data is the main problem: Even with just one data point taken per second, the number of player positions per soccer game adds up to $22 \times 60 \times 90 = 118{,}800$. Again, networks can help to reduce this huge amount to reasonable sizes by replacing data with types and processes by sequences of phases. Moreover, the whole tactical behavior of a team can be recognized by means of net-based type analysis.

In the case of games, also feed forward networks can be used if the combination of multiple reasons or influences to complex effects is of interest – e.g., in how far combination of particular players influences the success of the team. This aspect leads back to motions and sports in general, where normally the combination of a lot of different reasons is responsible for a successful or unsuccessful result.

Artificial neural networks and multiple correlation analysis

Normally, not just one but a lot of reasons cause the effect of an activity in sports. Some quite different examples are interaction of players in a game, sub-sequences or phases of a motion or the contribution of training parts to a complex performance profile. Statistical correlation analysis can be used to find the priorities or main influences of such indicators or components. It is often easier to conduct such a multiple correlation analysis by means of artificial neural networks – SOMs as well as FFNs: While feed forward networks find new correlations through the training with well-known examples and learned associations, self-organizing maps first learn clusters of similar behavior, which then can be semantically characterized through a calibration process.

Contributions

On the one hand, this special issue is intended to illustrate the state of the art in research on neural networks in sports. The contributions to the special issue will act as tutorial reviews which at the same time focus on the merits and possibilities of neural networks in current research. On the other hand, research papers are intended to inform the readership of HMS about recent applications in the area of neural networks. The nature of the neural network research ranges from fundamental studies of motor control and learning, including the perceptual support of movement, to more applied studies in the fields of, for example, sport and rehabilitation, with the proviso that also the latter studies have a distinct theoretical bearing.

With respect to this spectrum, the contributions can be positioned as follows: A first group is characterized by the analysis of movements. Two approaches can be distinguished: The first is the recognition and forecast of controlling parameters, a topic *Lai, Taylor, and Begg* are dealing with by means of FFNs in the field of health care. A second approach, which usually implies the use of SOMs, is that of pattern recognition and optimization: While *Barton, Hawken, Scott, and Schwartz* deal with gait analysis, the contributions of *Baca and Kornfeind* and *Schmidt* are made in the field of biathlon aiming and basketball free-throw shooting, respectively.

A second group deals with team and group tactics. Again, the FFN-approach is used if the focus is on cause and effect analysis, as is presented by *Jäger and Schöllhorn* for the example of team tactics in volleyball and by *Glöckner, Heinen, Johnson, and Raab* for the example of group tactics and decision making in handball. In contrast, pattern recognition in tactical processes is usually accomplished by means of SOMs. Grunz's contribution presents an approach to recognize complex tactical patterns in soccer while the contribution of *Pfeiffer and Hohman* compares three approaches of tactical pattern analysis and decision making.

In sum, the selected contributions not only demonstrate the variety of successful network applications in movement and process analysis but also provide a promising outlook to future work in the field.

Finally, we would like to sincerely thank the following experts who served as reviewers. The community of researchers in the area of neuronal networks is still small but with the current special issue we hope that this field will start to show exponential growth.

List of reviewers

Arnold Baca, University of Vienna (Austria)
Rezaul K. Begg, Victoria University (Australia)
Till Bockemühl, University of Bielefeld (Germany)
Robin Trulssen Bye, Ålesund University College (Norwegen)
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Edgar Erdfelder, University of Mannheim (Germany)
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Kartin Witte, University of Magdeburg (Germany)

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