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Review article

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ARTIFICIAL INTELLIGENCE IN SPORTS BIOMECHANICS: NEW DAWN OR FALSE HOPE?

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ABSTRACT
This article reviews developments in the use of Artificial Intelligence (AI) in sports biomechanics over the last decade. It outlines possible uses of Expert Systems as diagnostic tools for evaluating faults in sports movements ('techniques') and presents some example knowledge rules for such an expert system. It then compares the analysis of sports techniques, in which Expert Systems have found little place to date, with gait analysis, in which they are routinely used. Consideration is then given to the use of Artificial Neural Networks (ANNs) in sports biomechanics, focusing on Kohonen self-organizing maps, which have been the most widely used in technique analysis, and multi-layer networks, which have been far more widely used in biomechanics in general. Examples of the use of ANNs in sports biomechanics are presented for javelin and discus throwing, shot putting and football kicking. I also present an example of the use of Evolutionary Computation in movement optimization in the soccer throw in, which predicted an optimal technique close to that in the coaching literature. After briefly overviewing the use of AI in both sports science and biomechanics in general, the article concludes with some speculations about future uses of AI in sports biomechanics.

KEY WORDS: Artificial intelligence, artificial neural networks, evolutionary computation, expert systems, Kohonen self-organizing maps, sports biomechanics.

INTRODUCTION

Where we were in 1995

Lapham and Bartlett (1995) published a review of the use of Artificial Intelligence (AI) in sports biomechanics. In this, we reported no evidence of the use of AI in sports biomechanics, although Expert Systems and Artificial Neural Networks (ANNs) were being used in gait analysis. We did, however, predict a bright future for the use, in particular, of Expert Systems in sports biomechanics. So what has happened in the decade since?

EXPERT SYSTEMS

Expert Systems are, effectively, a database combined with a knowledge base, 'reasoning' and a user interface. The knowledge base contains specific knowledge, or facts, for the 'domain'. The knowledge rules can also include logic operations, managed by probability theory, as in this example from a hypothetical Expert System for the analysis of fast bowling in cricket: IF 'shoulder-axis counter-rotation' is high; THEN 'technique' is mixed ($p = 0.8$).

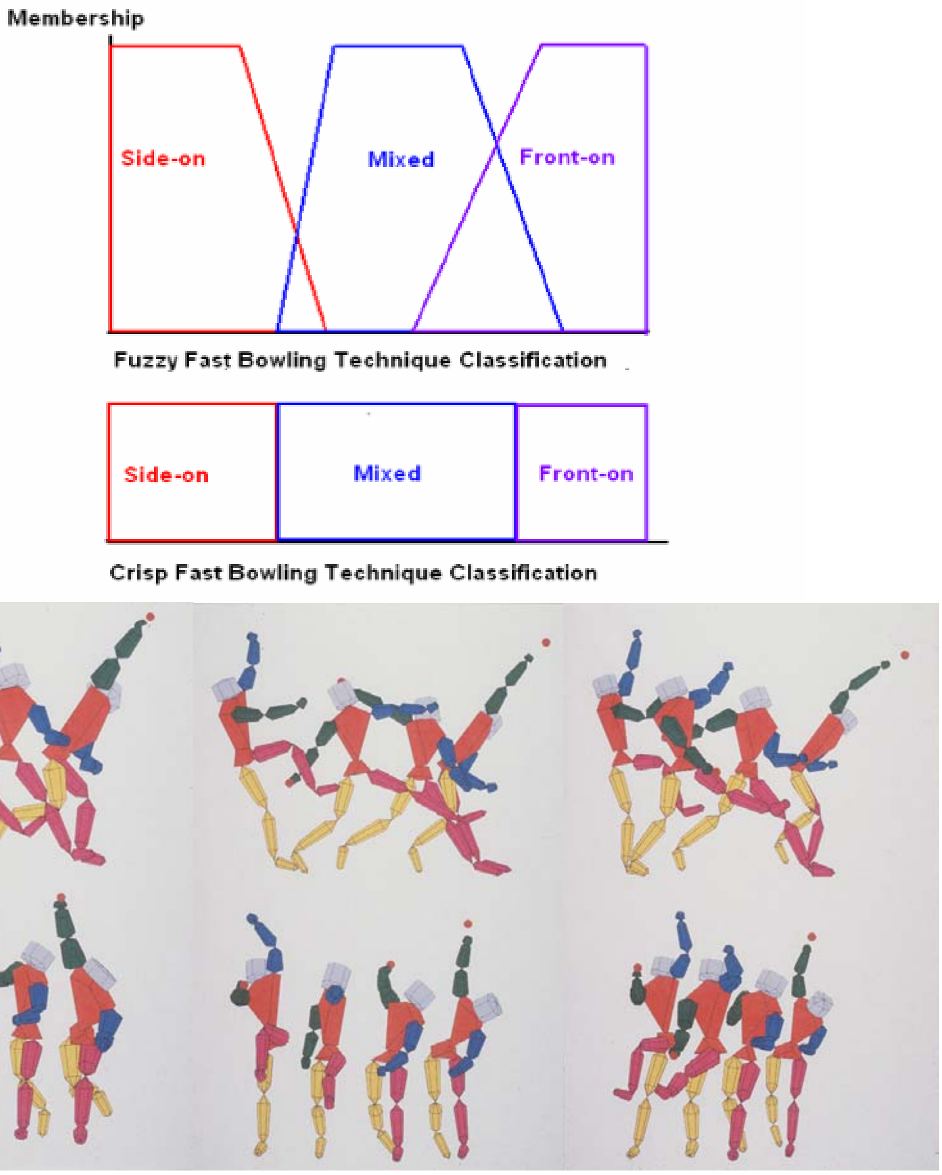

Figure 1. Classification of cricket fast bowling techniques.

This example was chosen to illustrate that much information is vague – 'high' in the above example has varied from 10 to 20 to 30 to 40º in the scientific literature on fast bowling (see, for example, Bartlett, 2003), showing that much information is ‘fuzzy’. The difference between ‘crisp’ and ‘fuzzy’ knowledge is shown in Figure 1 for fast bowling. Note that in the fuzzy representation, side-on and mixed techniques overlap as do mixed and front-on. These fuzzy overlaps are supported by the division of the mixed technique into side-on-mixed and front-on-mixed.

So, as Expert Systems are good diagnostic tools and system ‘shells’ are readily available, it is surprising that they are rare in sports science. The closest thing to Expert Systems in sports biomechanics at present is found within qualitative video analysis packages, such as SiliconCOACH’s ‘wizards’. Although not, strictly speaking, Expert Systems, these wizards do provide a formula engine that could be used by wizard developers to arrive at decisions by taking into account one or more responses to other data entered into the wizard; whether this provision is used is up to the wizard developer. This reality conflicts with the positive view of the utility of Expert Systems by Lapham and Bartlett (1995).

The use of Expert Systems in gait analysis (e.g. Bekey et al., 1992) suggests an extension to the analysis of sports techniques; both are branches of biomechanics. In gait analysis, however, there is a strong developmental motivation – patient health – which helps to attract funding. Clinicians are expensive, making investment in complex software development worthwhile financially. Gait analysis is a confined expert domain - gait and its variants with many experts. It is laboratory-based, so automatic

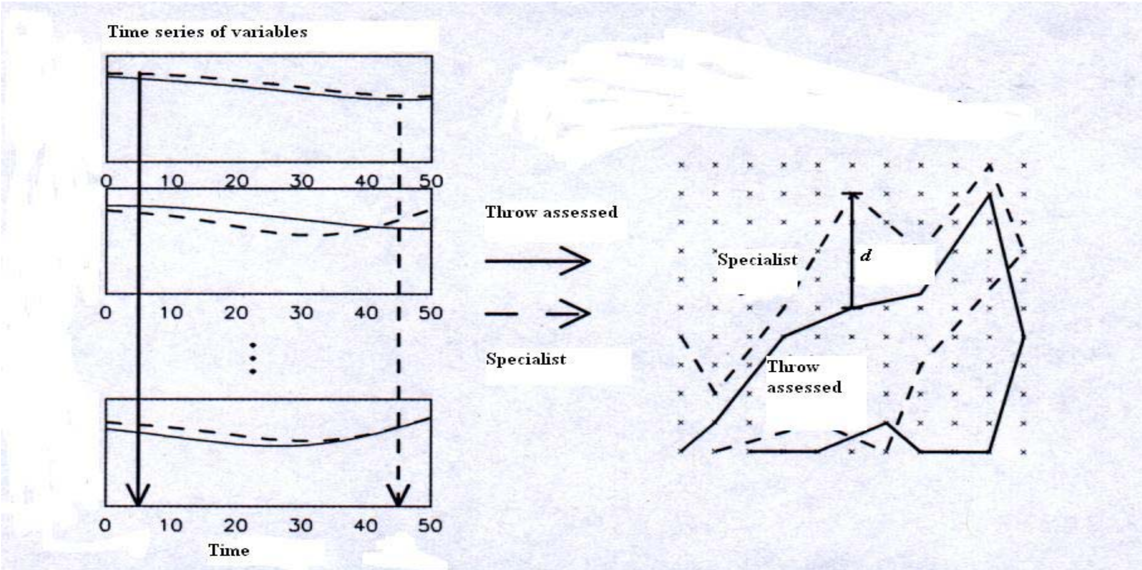

Figure 2. Use of Kohonen self-organizing maps in discus technique analysis (adapted from Bauer and Schöllhorn, 1997).

marker tracking systems are commonplace and data are abundant. Analysis of sports techniques is more complex than gait analysis and there is a weak developmental motivation: research into sport performance is not well funded. Coaches and sport scientists are not expensive; technique analysis is often field-based, preventing the automatic tracking of markers; and it is a broad expert domain, involving many sports. There is little data for technique analysis Expert Systems and there are fewer experts than for gait analysis.

ARTIFICIAL NEURAL NETWORKS

Artificial Neural Networks (ANNs) allow computers to learn from experience and by analogy. They are computer programs that try to create a mathematical model of neurons in the brain. An ANN is an interconnection of simple adaptable processing elements or nodes. They are non-linear programs that represent non-linear systems, such as the human movement system, and, from a notational analysis perspective, games. Artificial Neural Networks have nodes, which are simplified models of brain neurons, inputs, outputs and weights. The network stores experiential knowledge as a pattern of connected nodes and synaptic weights between them. Multi-layer ANNs have several 'hidden' layers and normally learn using the 'back-propagation learning law'.

Kohonen self-organizing maps have one hidden layer and using 'competitive learning' – only one neuron is selected for weight adjustment each iteration, based on the minimum 'distance' between the sums of its inputs and its weight. These networks require lots of 'training' data and, once trained, can only be used for testing, not further learning.

ARTIFICIAL NEURAL NETWORKS IN SPORTS BIOMECHANICS

Given their usefulness for classification, clustering and prediction, and that they are easily available, how widespread is the use of ANN in sports biomechanics? Well, unlike Expert Systems, they have been used, as well as in notational analysis and elsewhere in sport and exercise science (see, for example, Perl, 2001, 2005). Perl (2005) and Perl and Weber (2004) highlighted the importance of pattern recognition using ANNs; the patterns can be tactical ones from a game, performance patterns in training, or – the focus of the rest of this paper – movement patterns of sports performers. In this last application, the ANN is normally used to transform a high-dimensional vector space of biomechanical time series into a low-dimensional output map.

Kohonen self-organizing maps were used to analyze discus throws by Bauer and Schöllhorn (1997). They used 53 throws (45 of a decathlete, 8 of a specialist) recorded using semi-automated marker tracking over a one-year training period. Each throw had 34 kinematic time series, for 51 normalised times; these complex, multi-dimensional time series were mapped on to a simple 11x11 neuron output space (Figure 2). Each sequence was then expressed as the mean deviation (*d* in Figure 2) of the output map – the continuous line - from that of one of the throws by the specialist thrower, shown by the dashed line.

The deviations for the eight specialist throws are shown on the right of Figure 3, the decathlete's

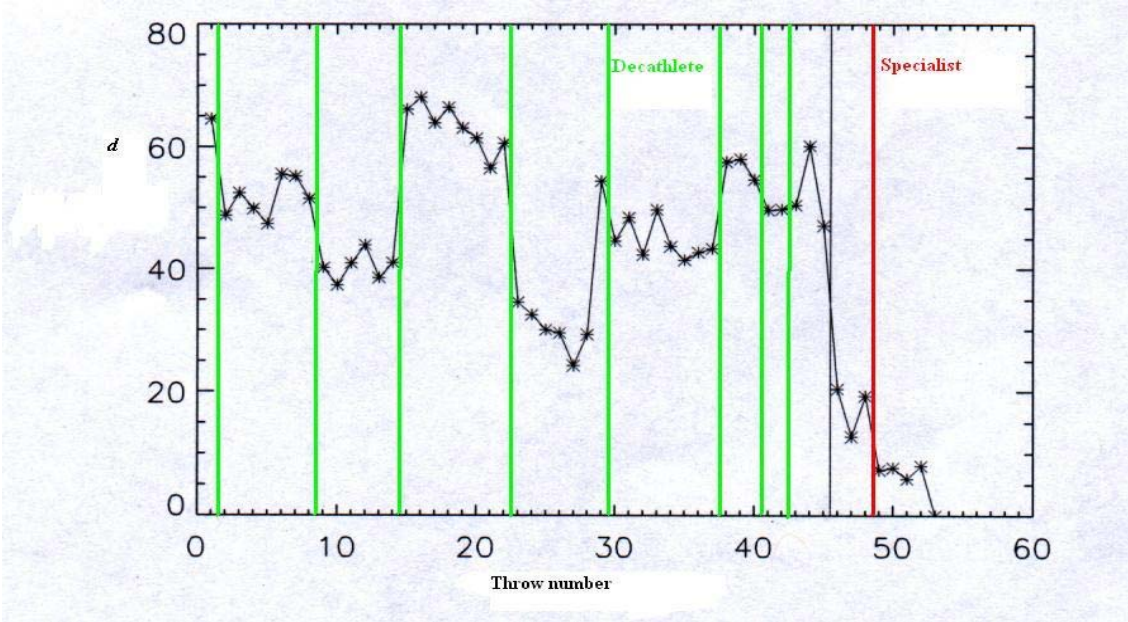

Figure 3. Grouping of throws within sessions, between vertical lines (adapted from Bauer and Schöllhorn, 1997).

45 throws on the left. The 'distances' are less for the specialist thrower as the comparator was one of his throws. Note the clustering of groups of throws, between the vertical lines, within training or competition sessions. There was more variability between than within sessions; for five groups of five trials, the authors computed inter- and intra-cluster variances, giving an inter-to-intra variance ratio of 3.3±0.6. This shows that even elite throwers cannot reproduce invariant movement patterns between sessions. The supposed existence of such invariant patterns – which arises from the motor programs of cognitive motor control - has often been used, explicitly or implicitly, to justify the use of a 'representative trial' in sports biomechanics.

Bauer and Schöllhorn (1997) claimed that the map output reveals information about the whole movement that is not discernable from the detailed kinematics. It is, undoubtedly, simpler and different. What we have here is, in effect, the detection and recognition of a pattern that is obscured by the enormous fine detail of the multiple time series.

Schöllhorn and Bauer (1998) reported a similar approach to analyse 49 javelin throws from eight elite males, nine elite females and ten heptathletes. This time, manual digitising of estimated joint centre locations was used. Clustering was found for the male throwers – as a group - and for the two females for whom multiple trials were recorded. Variations in the cluster for international male athletes were held to contradict any existence of an 'optimal movement pattern'. This view was supported by an analysis at the 1995 World Athletics championships with a focus on arm contributions to release speed. The large shoulder angular velocity for the silver medalist suggested reliance on shoulder extension and horizontal flexion to accelerate the javelin, suiting his linear throwing technique. In contrast, the gold medalist used medial rotation of the shoulder to accelerate the javelin; this movement, plus an elbow extension angular velocity at least 18% faster than for any other finalist, was the reason he was able to achieve the greatest release speed. However, some scepticism about the results of both these studies is warranted in the light of recent research by Bartlett et al. (2006). We found, in a two-dimensional laboratory study of treadmill running, that it is impossible to distinguish movement variability between trials from variability within and between operators who manually digitized joint centres without the use of markers. This would be far worse for a field-based three-dimensional study.

Lees et al. (2003) reported the results of a study that used Kohonen maps to analyse instep kicks by two soccer players for distance or accuracy. Joint angles were obtained from the three-dimensional coordinates of automatically-tracked markers. These were then mapped on to a 12x8 output matrix and showed differences between tasks and players; these output patterns were repeatable for the same task for one player. The authors claimed that the output map 'nodes' were related to characteristics of the movement technique, although what these characteristics are remains to be determined. Lees and Barton (2005) used a similar approach for several kicks by six soccer players, three right- and three left-footed. In this study, 14 joint angles were obtained from the three-dimensional coordinates of automatically-tracked markers for 80 equispaced time instants from take-off for the last stride to the end of the follow through of the kick. The output maps distinguished well between the right- and left-footed groups, which the authors stated was a non-trivial problem using just the joint kinematics. Again, intra-player differences were small.

Adopting a different approach from that of the previous studies, Yan and Wu (2000) used a multi-layer ANN with one hidden layer to analyse the shot putts of 155 throws by 31 national-standard Chinese females. The network was 'trained' using values of 20 global and 33 local technique parameters from manually-digitized coordinates, to predict release angle and speed from 134 throws of all throwers; it was then tested with data from 21 throws of 11 throwers. The errors between the network outputs and the measured release parameters were then compared to those obtained using regression analysis. The ANN errors were typically 25-35% less than those from regression analysis, e.g. 0.20 compared to 0.31 $m \cdot s^{-1}$ for release speed and 0.91 compared to 1.26º for release angle. Whether such an improvement merits the use of a more complicated approach is a matter of judgment, although it is worth noting that regression models cannot learn. What might need emphasizing is that the errors from both methods are smaller than the uncertainties in release parameter values that occur using manual digitizing, as in this study, for which errors in release angle of ±1.5º and in release speed of ±0.5 $m \cdot s^{-1}$ are common. This network was then used by Yan and Li (2000) to analyse the shot putting techniques. The authors claimed that this showed weaknesses of technique compared with those of the elite putters, although this was not well substantiated by the paper, possibly because the Chinese authors were writing in English.

Artificial Neural Networks have been more widely used than Expert Systems in sports biomechanics. In technique analysis, Kohonen self-organising maps have been claimed to reveal the 'forest' rather than the 'trees'. Simplification is undoubtedly an important feature of ANN, although the ways in which we can best use the outputs of these mappings remains to be determined. If the mapping rules within these opaque and very non-linear networks never become transparent, as some ANN experts predict, then explicit mappings between specific features of the kinematic time series and the output maps may never emerge. Even under these circumstances, however, this novel approach to the analysis of sports movements might still prove to be a powerful tool in the analysis of human movement in sport, such as by possibly providing a non-linear measure of movement variability. Artificial Neural Networks represent an important link to non-linear dynamical systems theory; for example, Kelso (1995) reported the use of ANNs in studies of perception and noted that the networks model hysteresis, stimulus bias, and adaptation effects, all key tenets of non-linear dynamical systems theory.

EVOLUTIONARY COMPUTATION

Evolutionary Computation includes genetic algorithms, genetic programs and evolutionary strategies, and uses artificial – numerical – 'chromosomes' to simulate evolution. Bächle (2003) used an evolutionary strategy to optimize the joint torques at hip, shoulder and elbow to maximize distance thrown in a soccer throw in. This study predicted an optimal throwing technique close to that described in the coaching literature, with the initially passive torque of the hip accelerating the trunk forwards while the negative elbow torque kept the forearm back. Then, 30 ms before release, the trunk was decelerated by a negative hip torque, while a positive elbow torque accelerated the forearm forwards. Seifriz and Mester (2002) used genetic algorithms to calculate the optimum trajectory of a skier, but this was only published as an abstract.

CONCLUSION

A rosy future for AI in sports biomechanics? Automatic marker-tracking systems allow more, and more accurate, human movement data to be collected. This could lead to the use of fuzzy Expert Systems for diagnosis of faults in sports techniques, a substantial development of the rudimentary Expert Systems currently embedded in some video analysis packages. Kohonen mapping will become commonplace in sports biomechanics, particularly if the technique elements captured by the mapping can be identified. Dynamically controlled networks will become more widely used in studying learning of movement patterns. Multi-layer ANNs will have an important role in technique analysis, a view supported by their use elsewhere in biomechanics, including the closely related domain of gait analysis. Other AI applications – particularly Evolutionary Computation and hybrid systems - will feature in future developments in the optimization of sports techniques and skill learning. Finally, the links with dynamical systems theory will become even more apparent, leading, for example, to an enhanced understanding of movement coordination and the role of movement variability. But Lapham and Bartlett were equally optimistic in 1995 and, so far, their expectations have not been fully realised.

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KEY POINTS

- Expert Systems remain almost unused in sports biomechanics, unlike in the similar discipline of gait analysis.
- Artificial Neural Networks, particularly Kohonen Maps, have been used, although their full value remains unclear.
- Other AI applications, including Evolutionary Computation, have received little attention.

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