BRIDGING THE GAP BETWEEN BIOMECHANICS AND ARTIFICIAL INTELLIGENCE

Boris Bačić

School of Computer and Information Sciences, Faculty of Design & Creative Technologies, Auckland University of Technology, Auckland, New Zealand

In contrast to widely researched areas of convergence such as between Artificial Intelligence (AI) and medicine there is minimal evidence of AI in biomechanics for sports. The main focus of this paper is the development of AI coaching systems with a high degree of autonomy that can discover new knowledge from data. This paper relates to areas of AI, biomechanical data, and qualitative analysis of human movement. It first provides an overall rationale for possible AI implementations then reports machine learning related findings from AI golf coaching software and a tennis coaching prototype. A point of view, presented as a scope, is that the future role of AI in sport coaching is about automation, knowledge discovery and enhanced human-like interaction.

KEY WORDS: automated coaching.

INTRODUCTION: Contemporary sports professionals and coaches use their expertise and a variety of software systems for video indexing and analysis (Knudson and Morrison 2002). The overall aim is to facilitate visual feedback to the trainee or learner to improve techniques and to eliminate errors. In general existing systems have several limitations (Bacic and Kasabov 2002); they:

- Must be operated exclusively by sport professional experts,
- Lack adaptability (i.e. there is no *adaptive learning*),
- Lack automated explanations and reasoning that include "cause and effect" descriptions.

FIRST GENERATION AUTOMATED COACHING

To illustrate recent state of practice (in automated coaching) this section will present two examples from golf while the next section will propose a novel approach using a tennis case study.

1) LeadbetterInteractive (2005). To facilitate learning, multimedia rich content is used to convey information to enable the user to watch instructional video clips and record his/her own video (including experiment settings and video transfer to a computers' instructions). The drill-based coaching software follows the coaching paradigm of cyclic nature (i.e. preparation-observation-evaluation/diagnosis-intervention) introduced as a four-task integrated model of qualitative analysis (Knudson and Morrison 2002). From the perspective of Machine Learning (ML) the LeadbetterInteractive system employs a static set of rules implemented as a *decision tree*. Perceived individual faults can be identified by the user when comparing his/her video with video demonstrations containing superimposed animated key features. The role of the *decision tree* is to interrogate by a set of closed questions (i.e. yes/no) the user's perceived (i.e. identified) faults and generate intervention by automatically proposing only a relevant set of drills as video clips for improving swing technique.

2) SmartSwing (2005). SmartSwing uses a microelectronic device embedded in the shaft of a golf club. The device is able to record up to 100 swings at 1000 samples per second. Biomechanical 3D time series data are uploaded from the golf club via wireless link to a computer. Individualisation in software is achieved by keeping each player's biometric data along with the player's handicap - resulting in four expertise levels of swing evaluations.
Biomechanical data collection in this case imposes a minimal degree of obtrusiveness during play (i.e. only a club "feel" is limited to physical attributes of an "intelligent" club). Data acquisition requires minimal experimental set-up (i.e. recharging the batteries and deleting

old data) with no postproduction labour (e.g. manually marking events and reconstructing a stick model). Swing data of a player's body are not collected but estimated later by software analysis. The theoretical basis of correlation between the player's body and point of impact (or throw) has been reported as findings on a hypothesis that accurate 3D information of a trajectory of hitting surface around the point of impact can indicate related swing technique (Bacic 2003). With suppressed body movement data the prototype was able to *classify* strokes i.e. to categorise tennis swing technique from previously unseen data of a hitting surface around the point of impact. While the prototype did not use *coaching rules* to evaluate body action during the tennis swing, a prototype was able to provide simple Gestalt-type feedback by distinguishing swings into three *output classes* (i.e. good, bad and very bad).

THE NEXT GENERATION OF AUTOMATED COACHING – THE AI PERSPECTIVE:

The sub-disciplines of AI, most likely to be involved in next-generation coaching software, are: ML, Emerging Intelligence, Evolving Connectionist Systems (ECOS) (Kasabov 2002), and Data-mining (Witten and Frank 2005).

Requirements: In choosing an adequate connectionist system for an automated tennis coaching prototype, two approaches from kinesiology have most inspired the prototype implementation:

1. Systematic Observational Strategy (SOS) i.e. "moving from general to specific technique points, and rating the importance of the critical features" (Knudson & Morrison, 2002, p. 162).
2. Temporal and Spatial Model (Gangstead and Beveridge 1984).

Decisions from the Machine Learning and Software Engineering perspective are:

1. SOS must be implemented in an *evolving* manner, supporting *adaptive learning*.
2. SOS must be configurable in both directions i.e. from general to specific and vice versa.
3. Rating of the critical features must be both configurable by the expert or auto configured by the prototype referring to personalised database holding information about each individual's progress.
4. The prototype must be able to learn *rules* from data. *Rules* describing relations and critical features must be extracted and presented in an understandable manner.
5. Both data and *rules* (stored as *knowledge*) can be used to *train* the system to operate with new, previously unseen data.
6. Other desirable parameters: *Real-time* and *inexpensive* computation *robustness*, high *classification accuracy*, ability to *learn* from an initially *small data set*, modular construction allowing enabling/disabling individual modules or adding new evaluation modules to the system, automation (e.g. extracting events in temporal analysis).

Experimental Findings: To achieve automation in temporal phasing using 3D stick figure time series data a novel algorithm was proposed (Bacic 2004). Compared to expert event extraction (i.e. by manually recording each event's index of start and end frames) the algorithm's accuracy was evaluated as start frame average error 0.789 end frame average error -0.16, which in conclusion indicates reliable automated extraction of segments of forehands and backhands (including open and closed stance). Each item from a spatial observation (Gangstead and Beveridge 1984), or critical feature and/or cue (Knudson & Morrison, 2002, p. 162), represents a new *heuristic* or a *coaching rule.* Each new module is responsible for classification of a single *coaching rule* and has been *trained* with transformed data i.e. *features* obtained from further transformation of biomechanical data as in Figure 1. In Bacic and Zhang (2004) three alternative evolving architectures have been evaluated producing on average 95% prediction on a small data set. The proposed architectures of multiple *connectionist subsystems* or single *neuro-fuzzy* system are conceptually depicted in

Figure 1. Both architectures use Neuro Fuzzy ECOS modules to learn from data and extract knowledge presented as a set of rules.

How ECOS works on a problem?

After extracting the rules, another layer of abstraction is needed (see Figure 1) to present rules to humans either as visually (image, video, and graph) or as verbally using words (e.g. “Forehand”, “Arm-body relative distance”) related to sport terminology. With too many rules resulting from *multidimensional problem space* (i.e. with many cues and critical features evaluated) it may become impossible for a person to comprehend presented knowledge.

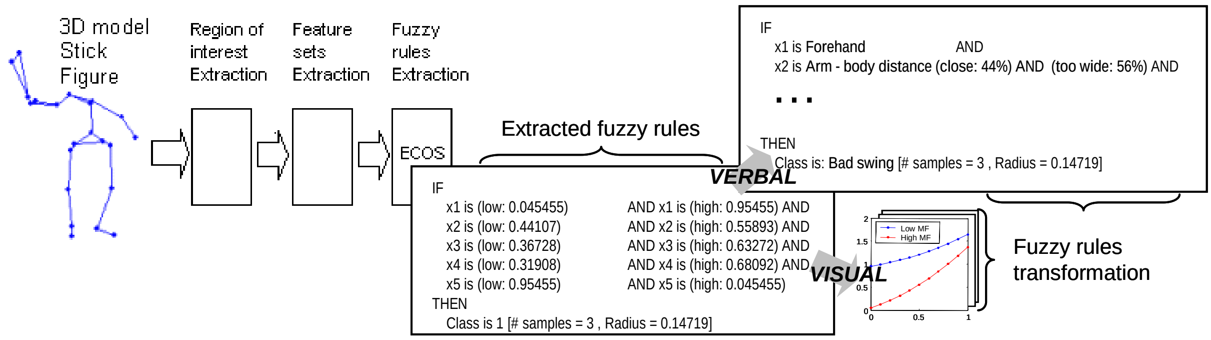

Figure 1: Extracting rules from tennis swing and their further transformation (Bacic and Zhang 2004).

Critique: The more *coaching rules* are evaluated the more data is needed for *training*. With a small initial dataset and its set of attributes:

1. It was not possible to optimise parameters or to conduct real life validation using multiple experts,
2. It was possible to extract rules related to a subsystem with known final *output class*.
3. It is not possible to claim which ECOS is better – i.e. more suitable for a particular task.

Table 1: Terminology

AI Term	Description
adaptive learning	Learning supported by ECOS. On-line learning, incremental learning and lifelong learning are also introduced in Kasabov (2002, p. 16).
classification	Associating features with existing groups.
coaching rules	Inference rules from input features to output class based on coaching experience (also called *heuristics* or “rule-of-thumb”).
decision tree	A hierarchical system that selects amongst many variants.
feature extraction	Analytical process to reduce data to most distinguishable parameters for classification made by a connectionist system
heuristics	Human common sense knowledge, difficult to program. Articulating heuristics for solving AI problems is presented in Kasabov (1996)
output classes	Result of *classification*, e.g. every input sample must belong to a group
ROI (see Figure 1)	Region of Interest – e.g. equivalent to event in temporal observation
Training	A connectionist system needs a *training phase* before autonomous operation with previously unseen data (e.g. evaluating data according to internal *knowledge* which is implemented as a *coaching rule*)

DISCUSSION: Sport professionals can use methods from machine learning on biomechanical data to “make sense” of the data by discovering rules, testing hypotheses and automating some of the time-consuming tasks. Initially, ML terminology (formatted in italic) may be confusing (given possible term overloading across domains, e.g. see Table 1) and potentially misleading. "First-time users" – researchers, should start experiments with software tools such as NeuCom (Song, Kasabov et al. 2005) and Weka (2005) – a tutorial is included in Witten and Frank (2005). Both free tools can be downloaded from:

- NeuCom www.theneucom.com
- Weka www.cs.waikato.ac.nz/ml/weka

CONCLUSION: Favourable experimental results to date encourage further cross-disciplinary research in biomechanics, sports science and AI, encompassing data acquisition techniques and the provision of personalised feedback.

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