NEURAL NETWORKS FOR
ANALYSING SPORTS
TECHNIQUES

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Summary

The coordination of many components of the movement system involved with most sports actions makes technique analysis a difficult endeavour. Usually discrete biomechanical variables are created in order to simplify the process. However, with converging acceptance among many researchers that coordination emerges by means of a self-organising interaction with all of the relevant constraints, the importance of an analysis tool for making these complex interactions discoverable becomes apparent. Artificial neural networks are able, through an iterative training process, to learn complex patterns, which make them attractive for analysing sports techniques. This chapter introduces self-organising maps (SOMs), a specific type of artificial neural network (ANN), as a potential tool for technique analysts, mainly because of the ability to provide a simple visualisation of the SOM output which represents the original complex movement pattern. A simple example to demonstrate SOMs is provided, followed by an overview of several techniques for visualising the output layer. Finally, a review of recent literature using SOMs for technique analysis is presented. Our outlook on the use of SOMs in technique analysis involves practitioners using them to focus on the coordination pattern itself, rather than narrowing the scope of the analysis to a few predefined key events in the action or in fact simply by judging the performance outcome.

Introduction

Technique analysis is concerned with understanding both the most effective way movements are made as well as their effect on performance (Lees, 2002). By understanding these concepts, a performance analyst should be able to advise the athlete so that the technique used reduces risk of injury, improves performance or both. The main components of technique analysis, according to Lees (2002), are the identification of faults in performance and the remediation or intervention to alleviate the performance symptoms associated with such faults. These components will be referred to throughout this chapter.
The process of diagnosing faults is certainly not unanimously agreed upon. In qualitative analysis, the performance analyst often visually inspects the movement and decides on components of the movements which have negative effects on performance. These are the components which should be modified in accordance with biomechanical principles (Knudson and Morrison, 2002). The faults the analyst chooses, however, subjectively depend on past experiences and the knowledge of the analyst. Furthermore, it has been suggested that visual observation, on which analysts may rely, is particularly vulnerable to being over-influenced by the motion of distal segments, thus threatening the validity of the analysis. The reason the motion of distal segments weigh so heavily in visual analysis is probably because these segments move through a greater range of motion than proximal segments and they usually achieve high velocities at the moment of release or contact, depending on the action (Hodges et al., 2007; Lamb et al., 2010).

Quantitative techniques are not without their limitations and have often been misused by performance analysts to convey to the coach very specific information (such as a joint angular velocity) at a specific instant in the movement (such as the top of the backswing in golf). The information relayed to the athlete is far too specific for the athlete to make use of, and information from a discrete instance in the movement has little use in explaining the movement as a whole. The transition from beginning to end of any phase of the movement should be at least as important to the analyst as any arbitrarily chosen event during the movement. A more appropriate approach has been to view the movement as a ‘movement pattern’, which is more conducive to qualitative analyses.

Research on the organisation and control of coordinated movement has led to the discovery of several key characteristics of human movement (we refer the reader to Kelso, 1995, and Davids et al., 2006). Particularly relevant to performance analysis of sports techniques is the inherent, functional role of variability and the self-organising emergence of ordered behaviour. These insights come from dynamical systems theory and the mathematics of complex systems and are rooted in the view that coordinated movement collectively represents the unordered behaviour of the sub-components of the movement system. These theoretical insights have typically been off limits to performance analysts because of the limited practical applications put forth by researchers. However, relatively recently, many qualitative methods for performance analysis of sports techniques have become available, which have made the insights into coordination available to performance analysts. For example, the time-series coupling of moving segments is central to modern systems perspectives on human movement. These couplings can be observed, for example, with the use of angle–angle diagrams, phase plane portraits (Bartlett, 2007), continuous relative phase (Hamill et al., 2000) and cross-correlation functions (e.g. Bartlett and Bussey, 2012). Unfortunately, in studying joint coordination, these techniques are limited to the coordination of only two joint angles for angle–angle diagrams, two joint angles and their angular velocities for phase planes and continuous relative phase, and two joint angles or two joint angular velocities for cross-correlation functions.

Artificial neural networks (ANNs) represent an attractive method for analysing human movement because of their non-linear characteristics. As a beneficial side effect, ANNs thrive on data and, considering the large data sets representing biomechanical variables performance analysts are faced with analysing, ANNs seem particularly useful. This chapter will introduce ANNs and outline their application in performance analysis of sports techniques.

**Artificial neural networks**

Artificial neural networks are adaptive, non-linear systems that are loosely modelled on the human brain. They have been applied for two main purposes in sport science: prediction and classification.
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Networks used for prediction typically involve a feed-forward design, in which a set of input variables is used to predict an output variable. These types of networks, although fairly commonly used in sport science, have relatively little to contribute specifically to analysing sports techniques. Feed-forward networks have been used to model training and predict performance (Edelmann-Nusser et al., 2002), and have also been used to model biomechanical data and predict the outcome of movement patterns (Yan and Li, 2000). The usefulness, however, is limited to identifying the contribution of the input variables to the variability in the outcome. Feed-forward networks cannot tell the performance analyst about the structure of the movement pattern. For this reason, supervised networks will not be discussed further in this chapter, but remain relevant for other disciplines within sport science.

For classification, ANNs learn to identify features in input patterns. This means that, without the user defining the outcome, certain patterns may be discovered. In performance analysis, certain movement patterns hidden within the kinematic and kinetic data may be discovered. This technique has been particularly useful because it can be used in qualitative analyses and is robust to the biases associated with visual observation.

Self-organising networks

Kohonen’s self-organising map (SOM; Kohonen, 2001) is a specific type of ANN useful for visualising and clustering data, and is by far the most common type of ANN used in technique analysis. The real strength of SOMs lies in their ability to compress redundant, high-dimensional information into a simple, low-dimensional mapping, while retaining the original topological relationships within the data. The actions studied using SOMs include javelin (Bauer and Schöllhorn, 1997) and discus throwing (Schöllhorn and Bauer, 1998), basketball shooting (Lamb et al., 2010; Memmert and Perl, 2009), golf shots (Lamb et al., 2011a), soccer kicking (Lees and Barton, 2005), as well as gait (Barton et al., 2006, 2007; Lamb et al., 2011b).

The Kohonen algorithm

The output of a SOM is commonly visualised as a layer of grid nodes, each with an associated weight vector connected to a layer of input nodes (see Figure 18.1). The dimensionality of the weight vectors is the same as the dimensionality of the input data set. For example, an input may represent a single time frame for any number of kinematic variables representing a movement. The dimensionality of the input vectors (and weight vectors) is equal to the number of kinematic variables used for training. The number of nodes is typically fewer than the number of inputs, thereby reducing the data and forcing them into clusters of similar data.

![Figure 18.1 Model of the SOM input and output layers](image-url)
A brief description of the SOM algorithm is provided below (for a more detailed description, see Negnevitsky, 2002):

**Initialisation.** Map dimensions, training parameters and initial values for the weight vectors are chosen (often based on the principal components of the input data set).

**Find best-matching node.** For each input vector, the node whose weight vector has the shortest Euclidean distance to the respective input is identified and declared the ‘best-matching node’ (this is called a competitive learning strategy). The Euclidean distance between the input vector \( x = (ξ_1, …, ξ_p) \) and weight vector \( y = (η_1, …, η_p) \) is shown by

\[
d_{E}(x, y) = \sqrt{(ξ_1 - η_1)^2 + (ξ_2 - η_2)^2 + \ldots + (ξ_p - η_p)^2},
\]

where \( p \) is the number of variables.

**Adjust weight vectors.** The weight vectors are adjusted during an iterative training process to model the input distribution. The weight vector of the best-matching node is adjusted the most, while nodes close to the best-matching node (see output layer in Figure 18.1) are adjusted less, as their proximity decreases. The neighbourhood relation determines the magnitude of these adjustments and is the feature which preserves the topology of the input data set and, therefore, allows the nodes to ‘self-organise’.

**Example**

Before going further, a brief example will be made to clarify how SOMs retain a link between the input data set and the output. Feed-forward networks, on the other hand, usually adjust training parameters based on the training data, which earns them the moniker ‘black box’. In this example, we use the coordination of three sine waves with the possibility of each wave being \( y = \sin x \), which we will call A, or \( y = -\sin x \), which we will call B. This gives eight \( (2^3) \) possible coordination patterns: AAA, AAB, ABA, ABB, BBA, BBA, BAB and BAA. The coordination of these waves is considered three-dimensional, as there are three variables. Although a seemingly abstract example, AA and BB represent in-phase coordination, while AB and BA represent anti-phase coordination, which are important coordination phases in technique analysis.

The data were represented as an \([800 \times 3]\) matrix and were used to train a SOM. Notice that there are 800 inputs, each consisting of three dimensions. The original time series for AAA and AAB are shown in Figure 18.2a and c. Default parameters from the ‘somtoolbox’ for MATLAB® were used for the example (Vesanto et al., 2000).

A visualisation, called a U-matrix, of the output is shown in Figure 18.2b, d and e. The U-matrix shows not only the geometrical configuration of the nodes on the output map (grid space) but also the similarity between the weight vectors of the nodes (weight space). Dark areas on the U-matrix represent similar information (short Euclidean distance between neighbouring nodes), while lighter-coloured areas represent dissimilar information (large Euclidean distance between neighbouring nodes). To enhance the visualisation, the Euclidean distance between neighbouring nodes is shown on the \( z \)-axis. This makes the U-matrix a visualisation of both grid space and weight space – an important distinction that will be clear later.

The trained network can be simulated with a subset of the input so as to learn about the organisation of the output. This is done by identifying, for any input, its best-matching node in the output. To visualise the change in coordination within the input, the corresponding consecutive best-matching nodes on the output can be connected with a trajectory. Accordingly, the U-matrices in Figure 18.2 should be read as follows: the start of the pattern \( t_1 \), in which the values of the three variables are \([0 \ 0 \ 0]\), is best represented by nodes in the middle of the U-matrix. As the pattern progresses to the respective maximum and minimum of each wave...
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For example, input AAB has values \([1 \ 1 \ -1]\), the trajectory on the U-matrix moves to the appropriate valley at the edges of the map (shown by dark areas and representing low values on the z-axis) and returns to the centre of the U-matrix at \(t_{100}\) when the values are, once again, \([0 \ 0 \ 0]\). Each of the eight valleys represents the eight different combinations of maxima and

\[
\begin{array}{ccc}
\text{Number of samples (\%)} \\
0 & 50 & 100 \\
\hline
f(x) & 1 & -1 \\
\end{array}
\]

\[
\begin{array}{ccc}
\text{Variable 1} \\
\text{Variable 2} \\
\text{Variable 3} \\
\end{array}
\]

\(|x|, y|, z|

Figure 18.2 Two example input patterns (AAA and AAB) are shown in a) and c). Their respective best-matching node trajectories shown on U-matrices are shown in b) and d). All eight best-matching node trajectories are shown on the U-matrix in e). Each trajectory is labelled with the corresponding input.
minima in the input data set of our example. The contours of the U-matrix reveal the gradual change in coordination of the three variables with time.

This simple example may seem trivial but one can surely imagine that, as the dimensionality of the data set grows and the subtlety of the coordination increases, the task of visualising the coordination becomes far from trivial. The next section reviews some of the studies of sports techniques which have used SOMs.

**SOMs in technique analysis**

In a study by Bauer and Schöllhorn (1997), the kinematics of a decathlete and a specialist javelin thrower were shown on an $11 \times 11$ grid visualisation. The kinematic data were represented by 34 variables and 53 throws, each consisting of 51 normalised time samples. This gives a training set of $[2703 \ 34]$. The visualisation was used to compare the throws to one reference throw by the specialist (see Figure 18.3a). The Euclidean distances from the reference throw were calculated and used as input into a cluster analysis. The cluster analysis revealed that the specialist thrower was most similar to the reference throw, which was not surprising since the reference throw was performed by the specialist (see Figure 18.3b). More interestingly, however, was the variability between and within sessions by the decathlete.

The SOM trajectories were much more similar within sessions than between sessions, suggesting high day-to-day variability compared to within-day variability, even for elite throwers. This finding was strong evidence that coaches and athletes should not strive for an invariant optimal throwing technique; rather they should find ways to increase the functionality of movement variability (Müller and Sternad, 2004). The Bauer and Schöllhorn study was important because it used SOMs, a new technique in biomechanics, to deny the existence of an optimal movement pattern – something which many biomechanists at the time were trying to define.

One point of criticism on the visualisation of the output map in Figure 18.3a is that it does not accurately reflect the similarity in weight vectors of the nodes. The visualisation, which only shows the geometric orientation of the nodes in the output, gives the impression that the similarity between the weight vectors associated with each node is evenly distributed. In fairness, the authors did not draw much attention to the visualisation, rather to the clustering of similar trials.

![Figure 18.3](a) The grid space visualisation, and b) the throw clustering, adapted from Bauer and Schöllhorn (1997)
Lees and Barton (2005) used SOMs to classify soccer kicking techniques among right- and left-footed players. Six soccer players performed several trials of kicking a soccer ball into an open goalmouth. Three different maps were created: one map trained with all trials, one map trained with just right-footed kicking trials and one map created with just left-footed kicking trials. Like Bauer and Schöllhorn (1997), the best-matching node trajectory on a grid space visualisation was used for a qualitative analysis of the movement patterns. The authors stated that the map trajectories separated left- and right-footed kicking trials, which was deemed a non-trivial problem using just angular joint kinematics. The map trained with all trials definitely showed a qualitative difference between trajectories of right- and left-footed kicking trials. On the maps trained with either right- or left-legged kicking trials, there were qualitative differences between performers, showing evidence of inter-individual differences in soccer kicking. This is thought to add to the validity of the SOM as a tool to assess movement patterning and supports the argument that neither optimal nor invariant movement patterns exist in sport techniques.

Recently, Lamb et al. (2010) looked at the performance of basketball shots by four professional basketball players. The shots performed were: free throw, three-point shot and the hook shot. The authors hypothesised that the free throw shot would be more similar to the three-point shot than either would be to the hook shot. Ten trials of each shot were performed by each player and ten kinematic joint angles were used to train one SOM. The sequence of best-matching node trajectories was used for analysis with two additions: instead of grid space, the trajectories were superimposed on a U-matrix and a hit histogram was used to show any long ‘jumps’ between best-matching nodes (Figure 18.4).

![Figure 18.4](https://example.com/figure18_4.png)

Figure 18.4 U-matrix and hit histogram visualisations for two players in Lamb et al. (2010). The left figure for each shot type shows the best-matching node trajectory in white on the U-matrix; to the right of the U-matrices are the hit histograms, which show the ‘jumps’ between best-matching nodes. The size of the white areas on the hit histograms represents the frequency of hits for each node – as frequency increases, size increases. The labelled U-matrix on the right identifies the phases of the movement: A – Preparation, B – Extension, C – Release and D – unique coordination. Adapted from Lamb et al. (2010)
The study showed that, for two of the players, the free-throw shot and three-point shot were more similar to each other than was either to the hook shot. However, for the other two players, the three-point shot and the hook shot were more similar to each other than was either to the free throw. This was an unexpected finding, which the authors speculated could be because of the jumping kinematics involved in the hook shot for the latter two players. The three-point is usually performed as a jump shot so that the point of ball release is high, making it difficult for opponents to block. The hook shot is also a shot played in a way so that the ball release is protected from the defender. The subtle differences in the kinematics of the proximal and inferior joints (ankle, knee, hip joint angles) separated the techniques of two of the players from the other two. These differences were not discernible from visual observation of the movement. This study provided more evidence that qualitative techniques such as SOMs could expose new characteristics in data sets representing movement patterns.

Lamb et al. (2011a) performed a study looking at the coordination involved with performing the golf chip shot to various target distances (4 m, 8 m, 12 m, 16 m, 20 m, 24 m). Six kinematic joint angles (hip, torso, spine, right and left shoulder, and club shaft) and their angular velocities were used, as well as the $x$, $y$, $z$ linear displacement and velocity of the head as input. Because of the relationship between inter- and intra-individual variability, four SOMs were trained on the data for each respective player. Had a single SOM been trained on data for all players, the authors argued that the variability between trials would have been masked by the variability between players. The trajectories of the best-matching nodes were shown on U-matrices to visualise changes in coordination (see Figure 18.5a).

Even though the ranges of joint angles were normalised, the authors found changes in coordination for all players at different target distances. To emphasise, the changes in coordination were not attributable to scaling the range of motion as target distance increased or decreased. The stability of coordination at the target distances tested was also assessed using a second SOM.

![Figure 18.5](image)

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trained on the trajectories of the first SOMs (see Figure 18.5b). Several other studies have used a second SOM and will be discussed next.

Second SOM analyses

All the studies mentioned above used the best-matching node trajectory to visualise the change in coordination of input variables throughout the movement. Data in similar regions on the map, therefore, represent similar coordinative states during the movement – usually known as phases of the movement (Bartlett, 2007; Lees, 2002). Various methods have been used to classify the movement patterns as a whole.

Lamb et al. (2010) used a second SOM to show the relationship between the different basketball shots performed by each of the four players. The authors referred to the original SOM as the phase SOM (Figure 18.4) and the second as the trial SOM (see Figure 18.6). The output of the trial SOM was visualised on a grid for which, because of its smaller size, the distances between all nodes could be calculated fairly accurately and plotted. On that output, the assignment of each shot to a best-matching node was shown, giving a simpler representation of the similarity between the player’s shots. The type of shot was identified with text and the frequency of each type of shot represented by a single node was shown with varying text size.

Returning to the golf study by Lamb et al. (2011a), the second SOM was used to classify the similarity of coordination patterns as well as their frequency (Figure 18.5). In this case, the second SOM was created differently from the basketball study. For relevance in motor control studies using the coordination dynamics framework, the original SOM trajectories were used as an order parameter, or collective variable. The second SOM showed stability of coordination at each of the chipping distances (Figure 18.5b). In this sense, stability refers to the player’s ten-

![Figure 18.6](image-url)  
Second SOM representing the similarity of different basketball shot types by each of the players in Lamb et al. (2010). FT = free throw; H = hook shot; 3p = three-point shot. For example, Player 1’s hook shot is abbreviated as 1(H). Adapted from Lamb et al. (2010)
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dency to recruit similar movement patterns for similar shot types. Non-linear phase transitions were shown for three of the players between what the authors termed ‘short distance’ and ‘long distance’ movement patterns for chipping. Certain distances displayed instability, which might be targeted in practice sessions by the performance analyst as a weakness in movement patterning. Furthermore, the theoretical framework of coordination dynamics has been typically limited to researchers studying low-dimensional rhythmic movements (Obhi, 2004); however, the SOM trajectory as a low-dimensional representation of high-dimensional coordination may represent an opportunity for those studying discrete multi-dimensional movements to benefit from the theoretical understanding of movement coordination (Davids and Glazier, 2010).

Concluding remarks

Self-organising maps allow the analyst to look at one (or many) movement pattern(s) and make comparisons to movement patterns which occur at different parameter values (e.g. target distances) or movement patterns performed by other athletes. Coordination variability is easily seen using the trajectory of consecutive best-matching nodes. Determining variables and phases in the movement in which unexpected variability occurs is essentially what fault diagnosis in technique analysis is all about. One major difference between the SOM approach and conventional techniques is that, when using conventional techniques, the performance analyst is looking for a narrow set of faults, whereas, in light of recent work using SOMs, when using SOMs the analyst may have to be willing to explore unknown aspects of the movement. Using SOMs may require a re-evaluation of what technique faults are. In the past, a segment out of place would represent a flaw in the movement and the technique would be adjusted so that the segment moved in an acceptable range. However, the ability to look at high-dimensional coordination may reveal that one segment out of place does not pose a problem for the movement because other joints compensate for it. This is an opinion that performance analysts and coaches have held for a long time but they have not had the analytical tools to observe high-dimensional coordination.

A new component that may be added to the process of technique analysis might involve finding a good way of understanding how movement patterns differ between athletes and how they relate to success. The redundancy of the movement patterns involved in performing sports techniques has puzzled performance analysts for a long time. Indeed, it is puzzling to think of how two elite athletes can perform an action so differently while both achieving success (e.g. Bauer and Schöllhorn, 1997; Lamb et al., 2010). The use of SOMs may provide a broad, objective view of the movement so that task- and individual-specific variability can be understood. When should actions look the same (e.g. impact position of professional golfers) and when can they look different (e.g. top of backswing for professional golfers)?

SOMs also provide the performance analyst with new tools for identifying strengths and weaknesses in an athlete’s technique and, therefore, a basis for remediation. If an athlete displays instability at certain parameter values (e.g. shooting distance, fatigue level, shot type), an observation that only SOMs have been able to provide so far, the athlete might have new cues for training, although not necessarily specifically aimed at changing technique. Instead, the analyst might look at ways of building up stability in those movement patterns. The role of dealing with and controlling variability may find a more prominent role in technique analysis than in the past. This may provide a better opportunity for improving performance (or reducing the risk of injury) than trying to achieve a desired movement pattern.

The next step in technique analysis might be to look at the structure of the movement in a new way and to try to force the movement pattern through different levels of stability. This
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would have implications for skill acquisition (at many developmental levels) as well as technique analysis. The path to reliable and stable technique, resilient to the pressure of competition, may be to manipulate indirectly an athlete’s movement pattern repertoire. If so, SOMs represent a qualitative technique for determining how to manipulate and measure an athlete’s coordination stability. With continued use, and advances in visualisation and processing time, we expect that SOMs will provide a valuable tool for the analyst to continue the growing trend promoted by cognitive scientists (e.g. Riley et al., 2012), motor control theorists (e.g. Latash, 2008) and biomechanists (e.g. Bartlett et al., 2007; Glazier et al., 2006) to include understandings from motor control, concepts from dynamical systems theory and the considerations of functional role of variability in practice.

References