THE USE OF KOHONEN FEATURE MAPS IN THE KINEMATIC ANALYSIS OF ROWING PERFORMANCE

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This study used the self organising map (SOM) as a processing step in reducing the complexity of human movement dynamics obtained from execution of a rowing stroke. The SOM is an artificial neural network (ANN), adapted in an unsupervised manner using a self organising learning process. Three-dimensional joint angles, produced by the rowers, were projected onto a 2 dimensional topological neural map, thereby identifying rowing movement patterns. Unsupervised clustering allowed the time series rowing strokes to be positioned on the map in relation to each other and this enabled movement patterns to be compared. The larger kinematic variation of the novice rowers was observed. The weight vector associated with each SOM cluster illustrated underlying task related changes in the rowing stroke patterns between elite and novice.

KEY WORDS: self organising map, rowing, kinematic

INTRODUCTION:

The motor skill of rowing may be considered to be cyclical in nature, and was chosen for this study due to the abundance of repeated multi dimensional data produced over a standard performance (2000m). The optimisation of the rowing stroke is something that athletes, coaches and sport scientists strive for. However, current researchers in the field of rowing stroke optimisation tend to seek accurate differences rather than absolute results (Atkinson, 2002); this may be due to the complexity of modelling the rowing stroke. Currently, there is insufficient evidence to support the claim that the use of movement pattern analysis improves rowing performance. The large quantity of information contained in a kinematic analysis can lead to an inconsistent interpretation. Qualitatively, an experienced rowing coach forms a hypothesis early on and knows exactly which pieces of information are necessary for analysis. This can speed up decision making, but at the same time carries the risk of over interpreting some possibly irrelevant details and neglecting some possibly relevant components. There is a clear need for a method which enables large quantities of data to be analysed and interpreted objectively. If events are not analysed in their particular process, connections, and contexts, important aspects of the actions (e.g. time-dependent, logical, and structural relations) remain unrecognized and understanding the movement correctly remains unfulfilled. It is a biomechanical research goal to have methods which allow one to objectively analyze (non-repetitive) movement patterns. The dynamics, range and velocity of the entire movement have to be taken into account appropriately, preventing simple decomposition into single limb position and joint angle patterns.

Artificial neural networks (ANNs), under the term "Artificial Intelligence" have been found to be the most prevalent non-traditional methods used for gait data analysis in recent years (Chau, 2001). Previous research carried out at the University of Limerick has assessed the use of supervised ANNs in the assessment of rowing. Another form of ANN is the self-organising map (SOM) (Kohonen, 2001) which employs unsupervised learning; the most prominent type of which is that of Kohonen Feature Map (KFM). The characteristic property of a SOM is that they are self-organizing; training runs without any controlling activities. SOMs project data points from the input space to a position in a low-dimensional output space. A SOM is given in terms of weight vectors, which map a data point to a neuron located in the map output space. Similar patterns are assigned to neighbouring neurons in a way that clusters of neighbouring neurons represent assemblies of similar patterns in an objective process. Having been trained, the recognized objects are associated with the neurons of the network. The trained network can be used to recognize or identify new objects, which have not been learned yet. These will be associated by the network with its respectively best fitting neurons. The best fitting neuron itself is member of a cluster, which in turn classifies a type of similar objects. In the context of kinematic data analysis, the SOM can be regarded as a software tool that reduces the amount of data with minimal loss of information content. Classes of input values are mapped to clusters of neurons. After the learning phase, input values can be classified as belonging to specific clusters, and in general hidden structures of the input data set can be detected. While the use of SOMs in gait analysis has been prevalent, their use in the analysis of sporting performance has not been so extensive. Examples from gait classification have used kinetic as well as kinematic data. Koehle and Merkl (1996) classified patients into groups automatically with a SOM using the vertical component of the ground reaction force under both feet with results agreeing with the clinical classification of the patients. SOMs have been used with as little as three joint angles as in the case of Lakany (2001) who used SOMs successfully to group patients into clusters based on sagittal plane angles of the hip, knee and ankle joints. In a study by Barton *et al.* (2000) joint range of motion angles were projected onto a SOM; with SOM results matching the classification by gait experts. The work of Barton (1999), Koehle and Merkl (1996) and Lakany (2001) have demonstrated that SOMs can visualise gait data and the rules underlying visualisation can be linked to gait patterns. Following a review of the literature on the classification of movement, the aim of this study was to develop and explore a method that facilitates identification of rowing movement patterns by visualising complex data in a simplified format, using SOMs, focusing on the kinematic data of the rowers.

METHOD:

Data Collection: Five rowers (four novices, one experienced; age 26±4.6 yrs; height 173±5 cm; weight 74±4.3 kg) participated in the study. Ethical approval for this study was obtained from the University Research Ethics Committee. The participants performed a 2000m row on a RowPerfect ergometer (RowPerfect, CARE RowPerfect, The Netherlands). This distance was completed in 326±78 strokes. The participants' kinematic data were captured at 200Hz (Motion Analysis Inc, USA). Reflective body markers were placed on seven bony landmarks. From these joint markers five joint angles for the entire movement were identified. Fundamentally, from a biomechanical perspective, the joint kinematics of five major joints in the body can be used to define the performance of the rowing stroke. A programme written in LabVIEW (V8.0, National Instruments Corporation, USA) was used to divide the data up into individual strokes. It took in the entire data set from the motion analysis system, and using the coordinates of the handle and the flywheel, identified the beginning of each stroke (i.e. frontstops position). The software used these points in time to divide up the data set into individual strokes, from frontstops to backstops, and up to frontstops position again. Three dimensional joint angles (altogether 5 continuous joint angle variables) were presented to SOMs. Subsets of these files were processed and the generated results enabled an alternative analysis of the 3D kinematics of the rower.

Normalisation considerations: First, it was considered to normalise variables on the abscissa. This would involve normalising the joint angle time series data set variables to the entire rowing cycle (from frontstops position of one stroke to the frontstops position of the next stroke). However, to normalise the data based upon this would be to nullify the importance of velocity in the rowing stroke. The exact same movement pattern, completed in a shorter time would result in a superior power output. Second, it was considered to normalise variables on the ordinate axis; using the range of each variable to determine the normalisation ranges of each curve. When applied to the current rowing data, the generic method of normalisation suggested by Kohonen (2001) (variance of each variable is 1) would result in the unwanted effect of cancelling out curve offsets carrying analytic information. Also, different datasets would be normalised in different ways that would invalidate comparison between datasets. The temporal nature of the data was maintained by grouping three time slices of data at $t_{(i)}$, $t_{(i+5\%)}$ and $t_{(i+10\%)}$ of the movement cycle. Dynamical embedding (See Broomhead & King, 1986) was used to determine the optimal representation of rowing dynamics. A program written in MATLAB (V6.5 – The Mathworks Inc, USA) performed the above tasks. MATLAB reads data files generated by the LabVIEW software and plots any subject's kinematics on conventional line charts. The program also displays SOM visualisation. Following this the selected files were processed and produced values normalised both to the rowing stroke and to the ranges used. Any one row of data contained values recorded at $t_{(i)}$, $t_{(i+5\%)}$ and $t_{(i+10\%)}$ of the rowing stroke thereby representing the temporal nature of the data. The data was then imported to the MATLAB SOM software (SOM Toolbox 2.0 Vesanto *et al*. 2000).

SOM Training: A program was written in MATLAB which carries out the SOM training sequence by reading the data file, defining a SOM, training a SOM and generating the co-ordinates of the best matching units. The program searches for and finds the functions of SOM Toolbox 2.0. The size of the SOM (the number of nodes and proportions of the hexagonal matrix of nodes), the initial weights connecting the nodes, and the criterion for termination of training were determined automatically as a function of the rowing kinematic data presented to the SOM. A set of SOM nodes (an ordered sequence of joint angle co-ordinates) formed a trajectory which represents one rowing stroke. The complexity of 5 joint angle curves is converted into a single trajectory of nodes on the trained SOM. Following training the internal weight vectors of the SOM were stored in a codebook. These vectors are small sections of the movement cycle ($t_{(i)}$, $t_{(i+5\%)}$ and $t_{(i+10\%)}$, as mentioned earlier) that developed as a result of the SOM's adaptive training process. The concept of neighbourhood preservation was examined. This will not be elaborated on in this paper, but future work is examining the effect of altering this neighbourhood.

RESULTS:

The results of SOM visualisation illustrates how the SOM arranged the joint angle data following the complete training. Each curve on the SOM represents a stroke. This is then extended to include the larger data set, including in all the strokes. Of key importance here is the variation between the movement patterns of the subjects while completing the performance. We can then compare these patterns to the variation of the normal movement patterns and normal variation seen when analysing time series, angle-angle, or relative phase plots. The dimensions of the data are different based upon the individual rower analysed as the SOM determines the dimension size based upon the input data (See Method). The larger variation in the raw data of some subjects leads to larger number of nodes in the output map. The individual SOM curves follow a path on the map which differ dramatically from each other. Of particular note is the difference between the experienced rower and the novices. The experienced rower has a much smaller map and that the data is more concentrated on particular areas. The novices (similar in their variability, but not their pattern) take up a larger area, again given by the number of nodes in the map.

DISCUSSION:

The complexity of kinematic joint angle rowing data can be reduced by projecting a large number of joint kinematic curves into a single curve on the SOM. The shape of these strokes follows the rowing patterns stored in the SOM's CV and so the single curve is tightly linked to the underlying complex patterns hidden inside the SOM. The dimensionality reduction from five joint angles to one curve of the SOM allows it to handle the subject's movement as a whole and to focus on joint angle patterns. The finer facets are also available by visualising the CV of the SOM. The trained SOM is a simplified representation of relative distances among rowing kinematic patterns residing in a multi-dimensional data space. The deviation of a rowers SOM curve from that of another subject is not assessed quantitatively in this study. However, it could give a qualitative reflection of how the two rowers attempt to biomechanically overcome the task. All of the data presented to the SOM was used to cover the available SOM surface. The flexibility of the SOM to the input data can be further utilised to focus on small details. Following training the resultant curves look different but show the ranking of subjects in more detail. The movement of the SOM curve can in the future be used as an indicator of how well the rower is progressing in a longitudinal study. The effect of instruction and different techniques and styles could be measured using the SOM projections as overall measures of how well rower performs.

This study shows that most of the SOM trajectories are closed – the joint angles at the beginning and the end of a rowing stroke are nearly identical (and in some cases are exactly identical) and so are mapped to the same location of the SOM. The gap between the first and last nodes of the SOM curve is due to only 90% of the movement pattern being presented to the SOM. The patterns that exist in the codebook only cannot be found in any of the rowing patterns presented to the SOM as they are compressed forms of all the patterns that are close to each other. Each individual SOM contains several such clusters all representing a rowing stroke. Some of the clusters represent previously unidentified complex patterns that involve 3D joint angles. These unnamed clusters are the ones that are difficult to identify unless a multivariate data processing tool can visualise them. These clusters are related to their topology on the SOM expressing all the features, which make up the rowing stroke pattern.

CONCLUSION:

In this study, the power of KFM was used to visualise complex rowing patterns in the form of single curves. The SOM operates by convergence of the movement data to stem-patterns that are arranged on a relational map in the context of the total data space presented to the SOM during training. The method enables identification of existing movement patterns and opens up the possibility of defining new possible patterns that are otherwise difficult to find in the multidimensional data space. The method gives repeatable dimensionality reduction with a resolution that can be controlled by careful selection of the input data. The multidimensional ranking of subjects is possible both cross sectional and longitudinally. The method used in this study may provide an alternative representation of movement analysis results, which can cope with the complexity of the data and can help to make decision making more repeatable and so more objective.

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