A Neural Network Based Technique for Muscle Coordination and Vertical Jump Height Prediction

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Abstract

The purpose of this study was to investigate the training of Artificial Neural Networks (ANNs) to predict muscle coordination and vertical jump height. The paper presents the structure and training techniques of ANNs that give the best prediction of muscle coordination and jump height. In training the ANNs different electromyography (EMG) characteristics were investigated for optimal ANN muscle coordination and jump height prediction. The technique has been implemented in C++ on the SP2 supercomputer. The preliminary results are very promising, some of which are presented in this paper.

Keywords: Neural Networks, Electromyography, Medical Applications, Muscle Coordination, Vertical Jump

1. Introduction

The use of biomechanical analysis techniques and ANNs in the constructive analysis of biomechanics is relatively new due to recent advances in technology [11, 24]. The combination of human evaluation and ANN fields has been applied to many medical applications but the use of ANNs in biomechanical analysis techniques is only in its infancy.

The acquisition of a sporting skill takes many hours of training [12]. The athlete not only uses his or her success as a guide to improvement but the coach's feedback as a guide to improvement. The coach often is unable to identify the areas in which the athlete did not perform correctly. The use of biomechanical analysis and ANNs to give the coach and athlete biofeedback of the success of muscle coordination may improve sporting performance.

The central nervous system is the major contributor to the ability of an individual to have muscular coordination or control [6]. The nervous system has stored information of the mechanical characteristics of the muscle [6]. If this is not the case the nervous system may have some type of feedback to the mechanical

characteristic of the muscle activation. In most cases individual talent begins with the ability of an individual to perform a task from a given set of initial conditions [6].

Muscular coordination can have two distinct patterns. The first being a temporal sequence in which the coordination is a task and is ideal to repeat on each occasion. An example of this task would be the vertical jump whereby the task is completed identically every time. The second technique of muscular coordination is when variations of the basic temporal sequence are applied due to certain conditions. An example of this technique is cycling on a flat or horizontal plane compared to a hill or vertical climb [6].

Although there may be variations of either technique the overall conclusion is that an ideal sequence of muscular coordination will allow the individual to perform a task to maximal performance [6]. The ability to analyse the muscular coordination of the individual may allow the coach or athlete to get biofeedback which in turn will aid the individuals nervous system in the control of the muscle action [6]. A number of techniques can be used to analyse muscular coordination. One such method is the direct measurement of muscular activation through electromyography [6].

As a whole, the area of EMG analysis examines three main aspects of both clinical and kinesiological fields. The ability of the muscle to switch on/off at a particular time, the amplitude of the contraction and the fatigue of the muscle under contraction. In the analysis of muscle coordination on/off timing and extent of muscle contraction become the significant independent variables for performance [6, 10].

The amplitude and pattern of muscle activity is critical in all areas of muscle movements, but it is of foremost importance in complex musculoskeletal movements. Research has shown that it is possible using ANN analysis to distinguish between subjects with chronic back pain and control subjects with a success rate in the order of 75% [15]. It was also discovered that ANNs could distinguish two patterns of muscular activation to perform the same task [13].

Abel, Zacharia, Forster & Farrow (1995) examined the use of different ANN types and training methods in electromyography diagnosis of muscular disorders. Four different training methods were investigated using different ANN models. It was found that a feedforward, backward connective two layer ANN with a modified back propagation algorithm for training yielded the same if not higher performance in diagnosis.

This paper investigates three key areas for the development of a real-time biomechanical biofeedback system. The first area of investigation is the EMG data processing and characteristics that best suit the training of ANNs for prediction. The second area of interest is the best ANN topology. Finally, which ANN topology would best predict muscle coordination for biofeedback to the coach or athlete.

The remainder of this paper is organised as follows: In Section 2, we describe the proposed technique. Some experimental results are shown in Section 3. A discussion of the results is presented in Section 4. Finally, Section 5 concludes the paper.

2. Proposed Technique

2.1 Input Data

2.1.1 Testing Equipment

The tests were conducted using a combination of three separate systems (Figure 1). The first system was the EMG telemetry system which obtained EMG signals and communicated these signals to computer number one. The second system consisted of a kistler force plate and amplifiers connected to a peak motion analysis system using computer two. The final system needed the development of a Lab View data acquisition program. The software program used a National Instruments data acquisition card to sample the EMG signal and synchronise this with the peak motion analysis system. The software program sampled the EMG signal at 1000Hz. The EMG signal was acquired after a trigger was set when a force of 0 N and 260 N was applied to the force plate. A pre-trigger sample of 400 was recorded with a post-trigger of 600 samples.

2.1.2 Testing Protocol

The assessment of the best paradigms and training algorithms requires the need to process 60 squat vertical jumps of a subject. A male subject between the ages of 20-30 performed a warming up of a number of squat vertical jumps. The subject was instructed to keep their arms akimbo and to perform 10 maximum squat jumps to obtain maximum voluntary contraction (MVC) data value for normalisation of each muscle measured.

The EMG data collection and processing required the analysis of 8 major muscle groups of the lower limb of a leg shown in Figure 2 below.

Figure 1: Testing Equipment

Figure 2: Eight Major Muscles of the Lower Limb

2.1.3. Data Processing

The 1000 EMG data points acquired represent 1 ms with the software program removing any offset or drift that may occur [15, 16, 18]. The EMG data will be rectified and passed through a butterworth low pass digital filter with a cutoff frequency of 5 Hz [16]. The filtered EMG data was then normalised between the range of zero to one with MVC representing a value of one [18, 23].

The maximum amplitude of each muscle contraction will be extracted and placed into two separate data files. The time of muscle activation was calculated when each muscle reaches 20% of MVC. In the first situation the trigger impulse force of 260 N was 0.4 of a second into the jump. It was then said that event time 0 seconds occurred 0.4 seconds prior to the impulse force. In the second situation the data collected was re-synchronised so that 0 N was 0.1 of a second into the

jump. It was then calculated that event time 0 seconds occurred 0.1 seconds prior to the impulse force. Each time value was appended to the separate data files that contained the maximum amplitude of each muscle. The data processing and EMG parameter extraction is shown in Figure 3.

Figure 3: The Software Program Structure.

2.1.4 Desired Output

The reaction forces of the vertical jump were calculated using software from a peak motion analysis system. The data was exported to a text file to be used by another program. A Lab View program was developed to calculate the impulse of each jump allowing for calculation of vertical jump height in meters.

2.2 Artificial Neural Network

The biological brain is a multitude of biological neurons, similarly an ANN as shown in Figure 4 is a combination of numerous artificial neurons, each having a small amount of local memory. The artificial neurons are connected by unidirectional communication channel "connections", which carry numeric data as opposed to symbolic data. The units operate only on their local data and on the inputs they receive via the connections [17].

All ANNs in this study were 3 layered and completely connected. It can be said that an ANN has three distinct components. The input layer that receives the stimuli from the external environment. The output layer which interfaces the ANN back to the external environment and as shown in Figure 4 the hidden layer that can consist of a multitude of layers [25]. The hidden layer can be considered the computation area of the ANN [17]. The amount of hidden layers that consist in the ANN is measured without the inclusion of the input layer. This is due to the fact the input layer plays no significant role in the computation and acts only as an interface between the environment and the ANN.

Figure4: The ANN Structure.

The timing and amplitude of the EMG signal of each muscle was fed into the input layer, which had 7, 8, 14 and 16 nodes. The input nodes were dependent on which muscles and whether timing or amplitude or both were applied. The middle, "hidden layer" consisted of 1, 2, 4, 7, 8, 14 or 16 nodes and the output layer consisted of 1 node. The ANN topology can be represented as 16:4:1, indicating 16 input layer nodes, 4 hidden layer nodes and 1 output layer nodes. All network topologies were trained using the backpropagation algorithm.

The training process consisted of set parameters of learning-rate 0.4, momentum 0.5, rms-error cutoff 0.0005 and iterations of 200,000. The number of training and testing pairs varied between 50-10, 40-20, 45-10 and 35-20. After each test the rms-error in training was recorded and if an error cutoff was reached iterations were recorded. Also test result accuracy was calculated and the total accuracy on each test group recorded. If each test was above 90% accurate it was recorded as a positive classification. A set of parameters of less than 0.3 metre, greater than 0.35 metre was set to examine good and bad jump classification. If the jump was between these parameters then to distinguish a correct classification the jump prediction must lie within 0.02 metre.

Finally a third type of ANN was implemented to give the coach and athlete biofeedback to the performance of the vertical jump. The structure of the ANN was a combination of three ANNs as shown in figure 5. The two input ANNs one each for timing and amplitude were trained using the same set of parameters as above. The amount of hidden units was restricted to one. The predicted vertical height of the jump was also read from the timing and amplitude ANNs. If the timing or amplitude ANNs were able to classify the vertical jump height then we could suggest through biofeedback to

the coach or athlete that the timing and amplitude characteristics of that vertical jump were correct for the intensity of the jump.

Figure 5: ANN for Biofeedback

3. Experimental Results

The proposed approach has been implemented in C/C++ on the SP2 Supercomputer. Once the data is preprocessed it is placed in a training matrix and transferred to the SP2 Supercomputer at Griffith University in Brisbane. The SP2 Supercomputer is an IBM based machine that consists of eight RS/6000 390 machines and 14 RS/6000 590 machines connected with high speed switches. The SP2 operating system is UNIX with programming implementation languages of C and C++.

3.1 Training Pairs and Testing Variation

Two different sets of training pairs were trained using five different ANN topologies to examine the effect of network conformation on rate and likelihood of convergence. The first set of test training data consisted of 8 muscles with amplitude and timing inputs. Each test was synchronised to 260N of impulse force on the force plate. In the first tests no corrupt tests were removed.

Table 1: Training 50 pairs / Testing 10 pairs synchronised to 260 N of force.

Inputs	Hidden Units	RMS Error	Accuracy	>90%	Class
16	1	0.0385	79.4 %	5/10	6/10
16	2	0.0164	82.7 %	5/10	5/10
16	4	0.0057	81.9 %	4/10	4/10
16	8	0.0062	82.7 %	5/10	6/10
16	16	0.0006	75.0 %	4/10	7/10

The second test comprised the adjustment of the training pairs to 40 and the testing set to 20. All other parameters remained the same as the previous test.

The third test comprised the adjustment of the training pairs to 45 and the testing set to 10. In this test the tibialis anterior muscle amplitude and timing values and five corrupt tests were removed. The synchronisation of vertical jumps was then set to zero force production on the force plate.

Table 2: Training 40 pairs / Testing 20 pairs synchronised to 260 N of force.

Inputs	Hidden Units	RMS Error	Accuracy	>90%	Class
16	1	0.0357	87.7 %	12/20	11/20
16	2	0.0179	79.6 %	11/20	12/20
16	4	0.0032	82.7 %	8/20	12/20
16	8	0.0006	88.6 %	12/20	13/20
16	16	0.0011	87.0 %	8/20	17/20

Table 3: Training 50 pairs / Testing 10 pairs synchronised to 0 N of force.

Inputs	Hidden Units	RMS Error	Accuracy	>90%	Class
14	1	0.0264	92.6 %	6/10	7/10
14	2	0.0188	77.2 %	1/10	5/10
14	4	0.0090	86.5 %	4/10	7/10
14	7	0.0023	84.9 %	5/10	8/10
14	14	0.0011	78.7 %	4/10	6/10

The forth test comprised the adjustment of the training pairs to 35 and the testing set to 20. All other parameters remained the same as the previous test.

Table 4: Training 40 pairs / Testing 20 pairs synchronised to 0 N of force.

Inputs	Hidden Units	RMS Error	Accuracy	>90%	Class
14	1	0.0249	88.8 %	13/20	15/20
14	2	0.0179	85.0 %	10/20	14/20
14	4	0.0032	87.5 %	8/20	13/20
14	7	0.0006	89.5 %	12/20	15/20
14	14	0.0011	79.8 %	8/20	11/20

3.2 Timing and Amplitude Topology

Two different sets of training pairs, amplitude were trained using five different ANN topologies to examine the effect of network conformation on rate and likelihood of convergence. The first set of training data consisted of 8 muscles with amplitude inputs. Each test was synchronised to 260N of positive force on the force plate. In the first tests no corrupt tests were removed.

Table 5: Amplitude ANN synchronised to 260N of force.

Inputs	Hidden Units	RMS Error	Accuracy	>90%	Class
16	1	0.0521	89.2 %	5/10	8/10
16	2	0.0380	81.7 %	3/10	6/10
16	4	0.0241	58.8 %	0/10	5/10
16	8	0.0088	77.8 %	1/10	4/10
16	16	0.0037	77.3 %	2/10	4/10

The second test comprised a set of training data consisting of 8 muscles with 7 timing inputs. All other parameters remained the same as the previous test.

Table 6: Timing ANN synchronised to 260 N of force.

Inputs	Hidden Units	RMS Error	Accuracy	>90%	Class
16	1	0.0458	89.9 %	6/10	6/10
16	2	0.0430	89.9 %	6/10	6/10
16	4	0.0355	86.7 %	4/10	6/10
16	8	0.0317	86.6 %	5/10	6/10
16	16	0.0324	86.9 %	5/10	6/10

The third test comprised the adjustment of the training pairs to 45 and the testing set to 10. In this test the tibialis anterior muscle amplitude values and five corrupt tests were removed. The synchronisation of vertical jumps was then set to zero force production on the force plate.

Table 7: Amplitude ANN synchronised to 0 N of force.

Inputs	Hidden Units	RMS Error	Accuracy	>90%	Class
14	1	0.0471	88.8 %	6/10	7/10
14	2	0.0355	91.6 %	4/10	4/10
14	4	0.0292	85.0 %	4/10	4/10
14	7	0.0102	79.9 %	4/10	6/10
14	14	0.0060	72.1 %	2/10	5/10

The forth test comprised the adjustment of the training pairs to 45 and the testing set to 10. In this test the tibialis anterior muscle timing values and five corrupt tests were removed. The synchronisation of vertical jumps was then set to zero force production on the force plate.

Table 8: Timing ANN synchronised to 0 N of force.

Inputs	Hidden Unit	RMS Error	Accuracy	> 90%	Class
14	1	0.0360	89.0 %	5/10	6/10
14	2	0.0325	89.3 %	6/10	5/10
14	4	0.0214	87.0 %	5/10	4/10
14	7	0.0213	87.1 %	4/10	4/10
14	14	0.0216	87.4 %	4/10	4/10

3.3 Combination Topology

The timing and amplitude ANNs were trained with 35 training pairs and an extra 10 pairs added to these for testing. The outputs of the test set were then used to train the third ANN for classification of good or bad jumps. The ANNs were then tested using a final test set of data of 10 test pairs.

Table 9: Final ANN trained for classification.

ANNs	Hidden Unit	RMS Error	Accuracy	> 90	Class
Final ANN	1	0.0361	90.8 %	5/10	8/10

4. Discussion

It has been shown that ANNs can be trained to predict the vertical jump height reasonably well. It was found that the combination of timing and amplitude vertical jump characteristics provided the best result of 92.6% with one hidden unit. The results also reflected which EMG characteristics provided the best results. These EMG characteristics are as follows: 7 muscles not including the tibialis anterior muscle, a low pass filter of 5 Hz, a synchronisation or trigger of 0 N and removal of any corrupt test recordings in training of the ANN.

The final testing provided an insight into the ability of ANNs to give biofeedback to the coach or athlete. It was possible to train two ANNs, one for timing and the other for amplitude to predict vertical jump height. The final ANN was then trained successfully to classify the vertical jump. In this structure it was possible to feed off the outputs from both the timing and amplitude ANN. This made it possible to compare the actual vertical jump height with the predicted values. If the vertical jump height was classified by the timing ANN then it was considered that the vertical jump muscle timing patterns were characteristic of that jump height. This procedure also applies to the amplitude ANN. One limitation of the proposed technique is that the vertical jump height must be known to compare the predicted values of the timing and amplitude ANNs.

5. Conclusion

In conclusion it was possible to train an ANN to predict vertical jump height using certain EMG characteristics. It was also possible to implement a combination of ANNs to give biofeedback to the coach or athlete of muscle timing and amplitude. The influence of biofeedback to the coach and athlete is one area for further investigation. Also the training of the ANN for multiple individuals and how the ANN predicts the vertical jump height of an individual that it has not been trained with is another area for future research.

References

- [1] Abel, E. W., Zacharia, P. C., Forster, A. & Farrow, T. L. (1996) Neural network analysis of the EMG interference pattern, Medical Engineering & Physics, Vol. 18, No. 1, pp. 12-17.
- [2] Anderson, J. A. & Rosenfeld, E. (1990) Neurocomputing: Foundations of Research, MIT Press, Cambridge, MA.
- [3] Basmajian, J. V. & De Luca, C. J. (1985) Muscles Alive: Their Functions Revealed by Electromyography, Butterworths, Baltimore, MD.

- [4] Basmajian, J. V. (1973) Electrodes and electrode connectors, in Desmedt, J. (1973), pp. 498-501.
- [5] Basmajian, J. V., Clifford, H. C., McLeod, W. D. & Nunnally, H. N. (1975) Computers in Electromyography, Butterworths, Baltimore, MD.
- [6] Chapman, A. E. & Sanderson, D. J. (1990) Muscular Coordination in Sporting Skills, in Winter, J. M. & Woo, S. L-Y (1990), pp. 608-620.
- [7] Clarys, J. P. (1987) Application of EMG for the evaluation of performance in different sports, in Marconnet, P. & Komi, P. V. (1987), pp. 200-233.
- [8] Clarys, J. P. & Cabri, J. (1993) Electromyography and the study of sports movements: A review, *Journal of Sports Science*, Vol. 11, pp. 379-448.
- [9] Clarys, J. P., Cabri, J. & Gregor, R.J. (1988) The muscle activity paradox during circular rhythm leg movements, *Journal of Sports Science*, Vol. 6, pp. 229-237.
- [10] Enoka, R.M. (1988) *Neuromechanical Basis of Kinesiology*, Human Kinetics Books, Champaign, Illinois.
- [11] Lapham, A. C. & Bartlett, R. M. (1995) The use of artificial intelligence in the analysis of sports performance: A review of applications in human gait analysis and future directions for sports biomechanics, *Journal of Sports Science*, Vol. 13, pp. 229-237.
- [12] McLean, B & Lafortune, M. (1988) Improving pedaling technique with 'real time' biomechanical feedback, *Excel*, Vol. 5, No. 1, pp. 15-18.
- [13] Nussbaum, M. A. & Chaffin, D. B. (1997) Pattern classification reveals inter-subject group differences in lumbar muscle recruitment during static loading, *Clinical Biomechanics*, Vol. 12, No. 2, pp. 97-106.
- [14] Nussbaum, M. A., Martin, B. J. & Chaffin, D. B. (1997) A Neural Network Model for Simulation of Torso Muscle Coordination, *Journal of Biomechanics*, Vol. 30, No. 3, pp. 251-258.
- [15] Oliver, C. W. & Atsma, W. J. (1996) Artificial intelligence analysis of paraspinal power spectra, *Clinical Biomechanics*, Vol. 11, No. 7, pp. 422-424.
- [16] Oliver, C. W. (1995) Artificial intelligence in the detection of low back pain, *Journal of Orthopaedic Rheumatology*, Vol. 8, pp. 207-210.
- [17] Wasserman, P. D. (1989) *Neural Computing: Theory and Practice*, Van Nostrand Reinhold, New York, NY.
- [18] Winter, D. A. (1991) Electromyogram recording, processing, and normalization: Procedures and considerations, *Journal of Human Muscle Performance*, Vol. 1, No. 2, pp. 5-15.
- [19] Winter, D. A., Fuglevand, A. J. & Archer, S. E. (1994) Crosstalk in Surface Electromyography: Theoretical and Practical Estimates, *Journal of Electromyography and Kinesiology*, Vol. 4, No. 1, pp. 15-26.
- [20] Winter, D. A., Rau, G., Kadefors, R., Broman, H. & De Luca, C. J. (1980) Units, Terms and Standards in Reporting of EMG Research, ISEK, USA.
- [21] Winter, J. M. & Woo, S. L-Y (1990) *Multiple Muscle Systems: Biomechanics and Movement Organisation*, Springer-Verlag, New York.
- [22] Winter, D. A. and Yack, H. J. (1987) EMG profiles during normal human walking: stride-to-stride and inter-subject variability, *Electroencephalography and Clinical Neurophysiology*, Vol. 67, pp. 402-411.
- [23] Yang, J. & Winter, D. A. (1984) Electromyographic amplitude normalization methods: Improving their sensitivity as diagnostic tools in gait analysis, *Archives of Physical Medicine and Rehabilitation*, Vol. 65, pp. 517-521.
- [24] Yeadon, M. R. & Challis, J. H. (1994) The future of performance-related sports biomechanics research, *Journal of Sports Science*, Vol. 12, pp. 3-32.
- [25] Zahedi, F. (1993) *Intelligent Systems for Business, Expert Systems with Neural Networks*, Wadsworth, Boston.
- [26] Zuniga, E., Truong, X. & Simons, D. (1970) Effect of skin electrode position on averaged electromyographic potentials, *Archives of Physical Medicine*, Vol. 50, 264-272.