NEURAL NETWORKS IN COMPUTER AIDED CLINICAL ELECTROMYOGRAPHY

C.N. Schizas^{1,2}, C.S. Pattichis², R.R. Livesay¹, L.T. Middleton²

¹ University of Indianapolis, 1400 East Hanna Avenue, Indianapolis, Indiana 46227, U.S.A.

² The Cyprus Institute of Neurology and Genetics, P.O. Box 3462, Nicosia, Cyprus

ABSTRACT

In concentric needle electromyography quantitative measurements are applied on the motor unit action potentials, which are recorded from the biceps muscle of normal subjects and patients suffering with neuromuscular disorders. In this study an "unsupervised" learning neural network is employed for the classification of neuromuscular disorders. The results suggest that unsupervised learning has certain advantages in cases where the classes of the training data are unknown in number, or are not easily separated. The issue of separability has always been an important aspect of clinical science, illustrated in the present study as an "unsupervised" neural network problem.

INTRODUCTION

Motor unit action potentials (MUAPs) are recorded during an electromyography (EMG) study. In quantitative EMG [1] the features of MUAPs are recorded and studied in an effort to draw conclusions regarding the nature of neuromuscular disorders involved. An automatic pattern recognition algorithm based on the MUAP features is applied for identifying the MUAPs that are recorded from the same motor unit. In an earlier study [2] an automatic technique was proposed for a complete MUAP analysis and diagnosis through the following steps:

The identification & selection and numerical pattern recognition steps lead to the derivation of the following six features that are measured from each MUAP, as illustrated in fig.1: i) duration (MUAP beginning and ending are identified by sliding a measuring window of length 3ms and width $\pm 15\mu V$); ii) amplitude (maximum peak to peak distance of the MUAP); iii) area (sum of the rectified MUAP integrated over the duration); iv) spike duration (measured from the first to the last positive peak); v) spike area (sum of the rectified MUAP integrated over the spike duration); vi) phases (number of baseline crossings that exceed $25\mu V$, plus one).

Artificial neural networks (ANN) were used by our team in previous studies for classifying both concentric needle and macro needle EMG signals [2,3]. The supervised learning back propagation ANN algorithm was employed for training several different models. These models were tested with unknown data and produced a diagnostic yield between 60-80%.

METHOD

In this study the Kohonen's self-organizing feature maps [4] is used for training in an unsupervised fashion different neural network models. These models resemble a two-dimensional array of neuron-like logic units that are weight connected to an input pathway where the feature values of the MUAPs are applied. For each subject under study, a total of twenty MUAPs were collected from the muscle biceps at slight voluntary contraction during a five-second epoch over which EMG was acquired using the Cadwell Excel electromyograph.

The twenty MUAPs collected from each subject were processed and the six features were derived from each MUAP. Further processing on the resulted data produced the average value and the standard deviation for each feature. The resulted vector of length twelve (which represented one subject), was the input vector applied for exciting the neural network.

RESULTS

Thirty seven normals and patients were subjected to concentric needle EMG, and 740 MUAPs in total were recorded. Twelve of these subjects were normal, fourteen were suffering from motor neuron disease (MND), and eleven were myopathic (MYO). The patients were classified according to clinical and pathological criteria.

An arbitrary selection from the above subjects formed the training set of 24 (8 normal, 8 MND, 8 MYO), and the remaining 13 (4 normal, 6 MND, 3 MYO) formed the evaluation set. The training set was used for training different models, which were tested later by applying the data of the evaluation set. Eight of the developed models are shown in Table 1. These models were derived by varying the size of the output grid of the net, the gain factor, and the number of training epochs. A similar procedure for developing models was followed in our earlier study [5] where Macro EMG data was analyzed. In that study more details are given about the methodology and the algorithm used.

DISCUSSION

The results of the present study suggest higher diagnostic yield through unsupervised learning, when compared to the results of an earlier study [2] where supervised learning was adopted. The significant finding, however, is not the higher diagnostic yield but the flexibility offered by the unsupervised learning ANN for producing subcategories of the various diseases that cannot be seen otherwise by simply studying the MUAPs.

There are several neuromuscular disorders that have a similar clinical appearance but different underlying pathologies. The

Figure 1. The quantitative features of a MUAP illustrated

336	336	336	336	115	336	336	114	114	331
336	336	336	336	337	337	111	114	114	331
336	336	115	115	1310*	337	111	114	331	331
115	336	115	115	337	111	114	114	1110*	116
118	118	118	1112*	111	114	114	114	1111*	116
1210*	112	112	119*	332	228	2212*	228	228	331
113	332	332	225	225	226	226	226	226	223
2213*	332	225	225	225	226	226	226	226	223
2214*	224	225	225	225	226	226	226	229*	222
227	227	225	225	225	226	226	223	223	221

Figure 2. Evaluation Map for Model 1, 50% Confidence Level

336	336	336	336	115	336	336	114	114	331
336	336	336	336	337	337	111	114	114	331
336	336	115	115	1310*	337	111	114	000	331
115	336	115	115	337	111	114	114	1110*	116
118	118	118	1112*	111	114	114	114	1111*	116
1210*	112	112	119*	332	228	2212*	228	000	331
113	332	332	225	225	226	226	226	226	223
2213*	332	225	225	225	226	226	226	226	223
2214*	224	225	225	225	226	226	226	229*	222
227	227	225	225	225	226	226	223	223	221

Figure 3. Evaluation Map for Model 1, 75% Confidence Level

336	000	336	336	115	336	336	000	000	000
000	000	336	336	000	000	000	000	114	000
336	336	000	115	1310*	337	111	000	000	331
000	336	000	115	337	111	000	114	1110*	116
118	118	118	1112*	111	114	114	114	1111*	000
0210*	000	112	119*	332	000	0212*	000	000	331
113	332	332	000	000	226	226	226	226	223
2213*	332	000	225	225	226	226	226	226	223
2214*	224	000	225	225	226	226	226	229*	222
000	227	000	225	225	000	226	223	223	221

Figure 4. Evaluation Map for Model 1, 95% Confidence Level

Legend for figures 2, 3, 4

336 means class 3 (MYO) node, MYO patient number 6

2213* The MND patient number 13 was correctly diagnosed

1210* The MND patient number 10 was diagnosed as normal

1310* The MYO patient number 10 was diagnosed as normal

000 node not sensitive to any class for that confidence level

Table 1. Diagnostic Yield of the Evaluation Data

Model	Output Grid	Gain Factor	Number of Epochs	Diagnostic Yield		
				Confidence 50%	Confidence 75%	Confidence 95%
1	10x10	0.90	30	85	85	77
2	10x10	0.90	150	85	85	77
3	10x10	0.09	30	62	62	54
4	10x10	0.09	150	62	62	54
5	12x12	0.09	30	77	77	69
6	12x12	0.09	150	77	77	69
7	8x8	0.90	30	77	77	69
8	8x8	0.90	150	77	77	69

expectation is that coherent differences between pathological groups might be evident as clustered associations of findings. Pathology in practice, however, is not a discrete process, but forms a continuum from normality to disease.

Typical maps produced by the proposed method, illustrated in fig. 2, 3, and 4 (reflecting model 1 of table 1) show how subjects with similar data are grouped together. Besides the clustering these maps can be used as a diagnostic tool; data with the EMG features of the subject under study are applied to the ANN and the node where maximum response is obtained is noted; the subject is then classified into the class of that node unless the node is a "zero" node [5], in which case no conclusion is reached for that level of confidence as determined by the map.

The introduction of the confidence level [5] adds another dimension to the diagnostic capability of an ANN, by making it more reliable and realistic.

ACKNOWLEDGEMENTS

The authors would like to thank Dr. C.A. Bonsett, MD, Director of the Muscular Dystrophy Clinic - Riley Hospital, Indiana University, for reviewing this paper, and Mr. L.S. Walters, University of Indianapolis, Technical Assistant.

REFERENCES

- [1] F. Buchthal, P. Pinelli, P. Rosefalck, "Action Potential Parameters in Normal Human Muscle and Their Physiological Determination", Acta. Physiol. Scand. Vol. 32, pp. 219-229, 1954.
- [2] C.S. Pattichis, C.N. Schizas, L.T. Middleton, W.F. Fincham, "Computer Aided Clinical Electromyography", Proc. 12th Annual Int. Conf. IEEE, Engineering in Medicine and Biology Society, pp. 2229-2231, 1990.
- [3] C.N. Schizas, C.S. Pattichis, I.S. Schofield, P.R. Fawcett, L.T. Middleton, "Artificial Neural Nets in Computer-Aided Macro Motor Unit Potential Classification", IEEE, Engineering in Medicine and Biology Magazine, Vol 9, 3, pp 31 - 38, 1990.
- [4] T. Kohonen, "Self Organization and Associative Memory", Springer-Verlag, Berlin, 1984.
- [5] C.N. Schizas, C.S. Pattichis, R.R. Livesay, I.S. Schofield, K.X. Lazarou, L.T. Middleton, "Unsupervised Learning in Computer Aided Macro Electromyography", Proc. 4th IEEE Symposium on Computer-based Medical Systems, Baltimore, MD, 1991.

Dr. Christos N. Schizas, Corresponding Author
University of Indianapolis, 1400 East Hanna Avenue
Indianapolis, Indiana 46227 Tel. (317) 788-3374