A hybrid neural network electromyographic system: incorporating the WISARD net

C.S. Pattichis[1], C.N. Schizas[1], A. Sergiou[2], F. Schnorrenberg[1]

[1]Dept. of Computer Science, University of Cyprus, Kallipoleos 75, P.O. Box 537, Nicosia, Cyprus
[2]The Cyprus Institute of Neurology and Genetics, P.O. Box 3462, Nicosia, Cyprus

Abstract

Clinical electromyography (EMG) provides useful information for the diagnosis of neuromuscular disorders. The utility of artificial neural networks trained with the backpropagation, the Kohonen's self-organizing feature maps algorithm, and the genetics based machine learning (GBML) in classifying EMG data has recently been demonstrated. A hybrid diagnostic system was also introduced that combines the above neural network and GBML models. In this paper the WISARD net is applied on the same set of EMG data. The WISARD (Wilkie, Stonham, Aleksander Recognition Device) is an implementation in hardware or software of an n-tuple sampling technique. Results suggest that although the diagnostic performance of the WISARD models is of the order of 80%, that being comparable to the above mentioned three systems, training time has been significantly reduced. In addition, the hardware or software implementation of the WISARD net is simpler than the other three systems.

1. Introduction

Electromyography (EMG) is the study of the electrical activity of muscle and is very important in the diagnosis of patients suffering with neuromuscular disorders. Advances in computer technology and digital signal processing over the last two decades made the development of an automated EMG diagnostic system feasible. Different approaches have been followed to address this problem, including knowledge engineering [1], causal probabilistic networks [2], artificial neural networks (ANN) [3-5], and genetics based machine learning (GBML) [6], [7]. A hybrid EMG diagnostic system was also built [6], [7] incorporating selected models trained with the backpropagation algorithm [8], the self-organizing feature maps algorithm [9], and the GBML classifier system [10]. The motivation for developing the hybrid system is to 'mimic' the examination procedure where more than one physician can independently provide their diagnosis, given the same information. The aim of this paper is to examine the performance of the WISARD net [11], [12], and compare its behaviour with the neural network models trained with back propagation, and Kohonen's self organizing feature maps and GBML paradigms.

The WISARD (Wilkie, Stonham, Aleksander Recognition Device) is an implementation in hardware or software of the n-tuple sampling technique first described in [11]. What prompted the consideration of the WISARD net as a possible solution to the EMG problem is: i) the comparatively short training time required (WISARD involves 'one-shot' training as opposed to the perceptron progressive training that is a time consuming process), ii) the simplicity of the logical structure of the net allowing fast implementation and tailoring to the particular requirements of the problem, and iii) the data reduction inherently introduced by WISARD since it's mode of input involves the systematic reduction of input data accuracy through quantization.

2. EMG Method and Material

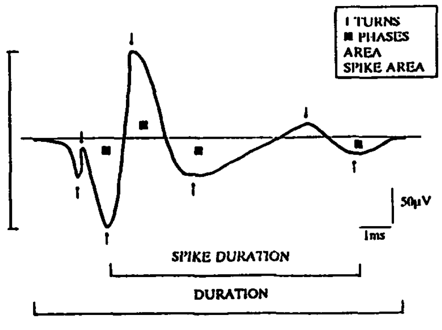

Fig.1 MUAP parameters.

EMG data was recorded from the biceps brachii muscle at slight voluntary contraction for 5 seconds using a needle electrode. Motor unit action potentials (MUAPs) were identified and selected from the EMG recording based on predetermined criteria [4], with the following MUAP features measured automatically (see Fig. 1): i) Duration (Dur), beginning and ending of the MUAP were identified by sliding a measuring window of 3 ms in length and 10 μV in width; ii) Spike duration (SpDur), measured from the first to the last positive peak; iii) Amplitude (Amp), maximum peak to peak measure of the MUAP; iv) Area sum of the rectified MUAP integrated over the duration; v) Spike area (SpArea), sum of the rectified MUAP integrated over the spike duration; vi) Phases (Ph), number of baseline crossings that exceed 25 μV, plus one; vii) Turns (T), number of positive and negative peaks separated from the preceding and following peak by 25 μV. Twenty MUAP sets were recorded from the biceps muscle of each subject. An 14 element feature vector for each subject was formed by calculating the mean (**mn**) and the standard deviation (**sd**) of the above seven features for the 20 MUAP sets.

A total of 680 MUAPs were recorded and analysed from 12 normal (NOR) subjects, 11 patients suffering with motor neuron disease (MND), and 11 patients suffering with various forms of myopathy (MYO). Mean duration of NOR subjects varies from 8 to 12 ms, mean amplitude varies from 0.280 to 0.520 mV and mean number of phases varies from 2 to 4. Myopathy patients usually have MUAPs with short duration, low amplitude, and small number of phases, whereas MND patients have MUAPs with long duration, high amplitude, and large number of phases.

3. The WISARD net

The WISARD net is composed of the following logical components (Fig. 2):

• ***Retina:*** This constitutes the input to the WISARD model. It is an n-dimensional array onto which input data are mapped.

• **Interconnection network:** This is a random connection mapping from the retina to the random access memories (RAMs). The mapping is 1-1 between the retina and the discriminator of each class. The set of connections made to each discriminator are further subdivided into tuples. Each tuple is used to address a distinct RAM location within a given discriminator. The number of connections per tuple determines the corresponding RAM capacity.

• ***Memory:*** This represents the WISARD model's storage space. In the implementation proposed by Aleksander and Stoneman [12] it takes the form of a set of RAMs which are content adressable. The memory is connected to the retina via the interconnection network. The size of the retina and the configuration of the interconnection network determine the number and size of the RAMs. The interconnection network organizes the memory into a set of subcomponents referred to as discriminators. Each discriminator stores the input data patterns of one class.

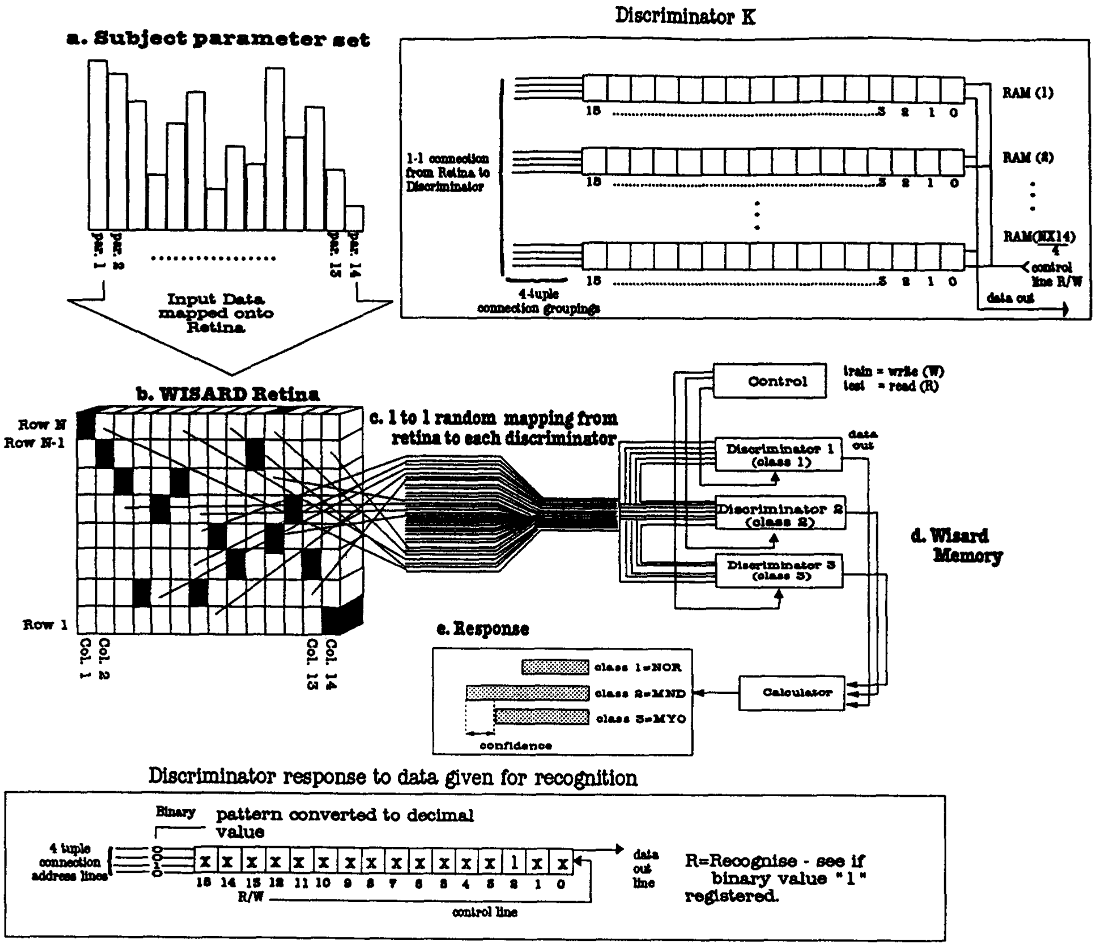

Fig. 2 WISARD net logical structure.

•**A training/recognition scheme:** i) *Training:* Each discriminator is trained on a set of patterns belonging to a given class i.e. discriminator. Patterns belonging to the class are successively mapped onto the retina. The data values are propagated from the retina to each of the RAMs of the discriminator corresponding to the class to be learned. The data values feeding into each of the RAMs through the interconnection network are used to index the RAM arrays. The indexed location is assigned the binary value '1' indicating that the given RAM has stored the specific part of the pattern (tuple) presented to it. ii) *Recognition:* The data pattern to be recognised is mapped onto the retina. A similar process as described in 'training' takes place. However, if the RAM location indexed by the tuple has been assigned the binary value '1' during the training phase then the RAM 'recognises' this part of the input pattern as one on which it has been trained. The responses of all the RAMs in the given discriminator are aggregated and compared to responses obtained by the other discriminators on the same data input. The discriminator with the highest response wins.

4. Results and Discussion

Training of the WISARD models was carried out using eight subjects from each group (8 NOR, 8 MND, and 8 MYO). The diagnostic performance of the trained models was investigated using the remaining subjects (4 NOR, 3 MND, and 3 MYO). A subject is represented by the 14 element feature vector that is mapped on to the WISARD retina, with the column dimension of the retina being always 14 (Fig. 2.a and 2.b). Each MUAP parameter was scaled to a 0 to 100 range with the number of retina rows being equal to the number of scale subdivisions (quantization levels).

For each parameter value the row in which range the value was contained was assigned the binary value '1' while the rest of the rows of the particular column were set to the binary value '0'. Training of the net was carried out as analysed in the previous section. Table 1 summarises the WISARD net performance for retina dimensions (rows x columns) 8x14, 16x14, 32x14, and 64x14. As it is shown in Table 1 the best diagnostic performance on the evaluation set (EV) was 90%, when the retina dimensions were 16x14. By increasing the retina dimensions further, performance decreased to 60%.

Table 1 WISARD EMG diagnostic models.

	Retina Size Rows x Columns	**Evaluation Set (EV)** Diagnostic Yield	**Training time (Tr)** Seconds
1	8x14	80%	0.49
2	16x14	90%	0.60
3	32x14	60%	0.77
4	64x14	60%	1.30

The diagnostic performance of the WISARD models is comparable to the backpropagation neural network, and the Kohonen's self-organizing feature maps and GBML models for classifying the same EMG data set that was used in this study. All four paradigms of learning achieved similar diagnostic performance of the order of 80% for the evaluation set. However, computational effort during training was considerably reduced for the WISARD system as compared with the other three systems. Training time for the WISARD net varied from 0.49 to 1.30 seconds, as shown in Table 1. Several backpropagation models with different architectures, gain and momentum factors were investigated [4], [5]:

i) [1]14-10-15-3/λ=0.1/μ=0.1/Epochs=1033/Tr=207 seconds/EV=80%,
ii) 14-40-10-3/λ=0.1/μ=0.1/Epochs=392/Tr=216 seconds/EV=90%, and
iii) 14-100-20-3/λ=0.5/μ=0.5/Epochs=67/Tr=135 seconds/EV=90%.

Models with small architectures, required more epochs during training, thus were more demanding in computational power. However, for models with bigger architectures the number of epochs and training time were also reduced. For neural network models trained with the Kohonen's self-organizing feature maps algorithm, training time was smaller compared to the backpropagation [4], [5]:

[1]No. of inputs - no. of nodes in first hidden layer - no. of nodes in second hidden layer - no. of output classes/gain or learning rate/momentum

i) [2]8x8/0.09/Epochs=1550/Tr=341 seconds/EV=80%,
ii) 10x10/0.9/Epochs=630/Tr=101 seconds/EV=80%, and
iii) 12x12/0.9/Epochs=630/Tr=63 seconds/EV=80%.

Computational time for GBML models was better than the above two systems, but worst than the WISARD models [6], [7]:

i) [3]size=49/cl=200/ltax=0.002/T_{GA}=50/pc=1.0/pm=0.001/Epochs=100/Tr=33 seconds/EV=80%,
ii) size=74/cl=300/ltax=0/T_{GA}=500/pc=1.0/pm=0/Epochs=100/Tr=40 seconds/EV=80%, and,
iii) size=74/cl=500/ltax=0.002/T_{GA}=100/pc=0.5/pm=0.02/Epochs=100/Tr=72 seconds/EV=80%.

A hybrid EMG diagnostic system was built incorporating the selected models trained with the backpropagation algorithm, the self-organizing feature maps algorithm, and the GBML methodology [6], [7]. The output of the hybrid system is expressed as a string, indicating the number of models that classified a certain subject under investigation as NOR, and/or MND, and/or MYO. The advantage of such a system is that idiosyncrasies of any one system may be compensated for by the group. Given the promising results of this study, WISARD models 1 and 2 of Table 1 can also be added to the hybrid system.

5. Concluding Remarks

The application of the WISARD net to the EMG classification problem has rendered promising results. The correct classification score of 90% obtained is near optimum for the given evaluation set. Furthermore, training time is small compared to models trained with the GBML methodology as well as with neural network models trained with backpropagation, and Kohonen self organizing feature maps algorithms. Moreover, the WISARD net is also very simple to implement both in software and in hardware. Thus, the WISARD model presents itself as an adequate solution to the EMG classification problem.

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[2]Grid size/initial gain
[3]Classifier size/no. of classifiers/lifetax/period of introducing the genetic algorithm/probability of crossover/probability of mutation

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