A NEURAL NETWORK APPROACH IN PERFORMING NON-INVASIVE ANALYSIS OF MUSCLE IMPULSES FOR HAND GESTURE RECOGNITION

Akinrotimi, Akinyemi Omololu; Mabayoje, Modinat Abolore

Department of Computer Science, Faculty of Communication and Information Sciences, University of Ilorin, PMB 1515, Ilorin, Kwara State, Nigeria

Corresponding Author: Akinrotimi A. O., akinrotimiakinyemi@ieee.org

ABSTRACT: Surface Electromyography (sEMG) signals have been found to be useful in developing methods of recognizing hand gestures using digital signal processing devices or ensemble approaches. In building hand gesture recognition models, it is essential to avoid or reduce computational complications which may result in complex circuit connections while implementing the model. As such, simple but efficient approaches in achieving the desired results are required. A explicable model for hand gesture recognition, using Flexible Neural Trees (FNTs) and sEMG signals is presented in this paper. sEMG is an approach of detecting and documenting the electrical impulses of the muscles, from the surface of the skin. The feed forward Neural Network approach is first used in generating the FNT model before improving it, using predefined simple instruction sets. The FNT model helped to avoid complex computations while building the model and provided a high recognition rate. The experimental outcomes obtained from the developed model shows that the model is capable of classifying six different hand gestures at an accuracy of 98.56%.

KEYWORDS: Artificial Neural Networks (ANN), Flexible Neural Trees (FNTs); Probabilistic Incremental Program Evolution (PIPE); Pattern Recognition Surface Electromyography (sEMG).

1. INTRODUCTION

Recognition of hand gestures has found its usefulness in situations where communication is virtually impossible or not allowed. It is useful for the speaker, in communicating his ideas, thoughts and intentions. It is also ideal in communicating with the hearing impaired. Hand gestures are rendered using sign languages, which make use of sign patterns to pass across information. Computer recognition of gestures of the hand could provide better Human-Computer Interaction (HCI). For instance the performance of computer games can be improved if the computer recognition of the hand gestures is enhanced. Improved hand gesture recognition can also help in the design of more efficient automatic and remote house hold appliances. Generally, gestures are spatio-temporal patterns, and they are often grouped into two categories, namely: static and dynamic. Specific and various flexion of the hand to assume different forms, is known as posture, while series of postures which are linked by movements of the hand within a short period of time are called gestures. Methods of recognizing sign languages which are usually made of hand gestures or combining the movement of the hands, arms, body or facial expressions mainly include: hand gesture signals, hand gesture images and sEMG signals.

In this paper, the FNT approach is employed in building a hand recognition model, hinged on sEMG signal analysis, with a view of recording the electrical impulses received from the muscles of the hand, directly from the surface of the skin while avoiding complicated calculations or electrical circuitry, and achieving a high recognition rate. The testing of the model was carried out on five individuals and the results reveal that the developed model is capable of recognizing six different hand gestures with an accuracy of 98.56%.

2. LITERATURE REVIEW

Studies have revealed that 35 % of human communication is verbal while 65 % of it consists of non-verbal gesture based communication [Hal73]. In Watson and O'Neil, 1995 [WN95] gestures are represented by a sequence of critical points (local minima and maxima) of the motion of the hand and wrist. The approach was found to be more efficient in matching a gesture both spatially and temporally and thus reducing the computational requirement. Liang and Ouhyoung, 1996 [LO96] proposed a sign language recognition system. They used the Hidden Markov Model (HMM) and integrated statistical approach, which is often used in computational linguistics. This system was designed to recognize large sets of vocabularies in a sign language by recognizing constructive postures and context information. Pavlovic et al., 1997 [PSH97] carried out a review of over the outcome of about a hundred related to visual interpretation of hand gestures in context to HCI. The results obtained from the developed method, was utilized in analyzing, modeling, and recognizing gestures. They were also analyzed and as part of the outcome of the review, the researchers suggested the integration of hand gestures with gaze, speech and other naturally related modes of communication in multimodal interfaces, for raising the limitations discovered toward gestural human computer interaction. Wu and Huang [WH99] carried out a survey on vision based gesture recognition approaches. The researchers examined various techniques of recognizing different gestures. These techniques comprised of recognition of gestures which were determined by simulating the varying aspects, the syntax and the background of the Human Markov Model. The study focused on intricate gestures for which techniques in machine learning, computer vision and some aspects of linguistics are necessary to interpret. The researcher s indicated those techniques which involved examining the posture of a static hand often aim at obtaining fixed rotational outcomes and an object recognition that is independent of a particular view, which needs to be, investigated more, in detail. Noury et al. [N+03] developed a system for helping user to study specific gestures. The researchers also presented a technique of detecting motion, using variations of artificial magnetic fields measured, obtained from magnetic primed devices. Bourke et al., 2007 [BBL07] proposed a recognition system to detect gestures that are frequently used in day-to-day human activities using an accelerometer. Mahdi and Mehran, 2007 [MM07] proposed a method which employs the use of Adaptive Neuro-Fuzzy Inference System (ANFIS), together with a concurrent learning pattern, in order to detect palm and wrist flexion and extension. The experiment achieved an accuracy of 96.7%. Ganesh et al, 2008 [GD09] proposed an offline hand gesture recognition system, using a sEMG based signal processing system and Multi-run Independent Component Analysis (MICA), for identifying hand gestures. Schlomer et al., 2008 [S+08] proposed gesture recognition system, using wireless controller and a Human Markov Model which is not dependent on the target system. Stergiopoulou and Papamarkos, 2009 [SP09] used Self-Growing and Self-Organized Neural Gas (SGONG) neural algorithm to capture the shape of the hand, three features were obtained; Palm region, Palm center, and Hand slope. Chaudhary et al., 2011 [C+11] carried out a detailed study of various gesture recognition methods, involving hand and facial movements. The researchers suggested that there is a need for building different recognition algorithms considering the amount of data and the number of gestures to be processed. Nam's system [NW96] tried to recognize hand movement patterns. The system was successfully able to recognize ten different kinds of hand movement primes. The system was able to detect hand gestures with an accuracy of 99%. Hassan, 2012 [HM12] applied multivariate Gaussian distribution to recognize hand gestures, using non-geometric features. The input hand image is segmented using skin color based segmentation by applying HSV color model and clustering based thresholding techniques.

2.1 Surface Electromyography and the Root Mean Square

Surface Electromyography **(**sEMG) is a variable within the Root Mean Square (RMS) function and it is capable of being computed in real-time. As such, is easy to implement. The attributes of the Root Mean Square are often used for detecting the contraction of the muscles and all activities relating to the muscles. The Root Mean Square is often modeled as an amplitude Modulated Gaussian random process. In this context, the RMS is interrelated with standard deviation and it can be expressed as follows:

$$RMS = \sqrt{\frac{1}{N}\sum_{n=1}^{N} x_n^2}$$

where, N is the signal length and x_n is the sEMG signal in a segment.

2.2 Flexible Neural Tree

The past few years has witnessed the dense application of Artificial Neural Networks (ANN) to various areas in the field of science: such as, system identification and control function approximation, time series prediction and damage processing. On the whole, the efficiency of Artificial Neural Networks has been found to be directly linked to the kind of structure they possess [WN95]. In Artificial Neural Networks, there are often problems that are highly dependent on structure. Flexible Neural Trees (FNTs) are fuzzy models which are capable of solving structure dependent problems. These models are often computed as an asymmetrical a feed forward artificial neural network, consisting of many layers. FNTs are often developed and do evolve, based on certain pre-defined instruction sets.

3. METHODOLOGY

The tree-structural based encoding method used is PIPE (Probabilistic Incremental Program Evolution).

PIPE attempts to improve the structure, beginning with the initial set structures. As soon as the structure is improved, its parameters are adjusted or fine tunned. The process (loop) then re-occurs to produce a better structure. This also involves the fine tuning of the attributes of the rules pertaining to the structure. The FNT is arranged to scalar and fitness values (that mirror the performance of the FNT according to certain tasks given to it) using a fitness function. The fitness function is represented as the Mean Square Error (MSE) in the experiment. The process or loop is terminated after an acceptable result has been obtained or a specific time limit is reached.

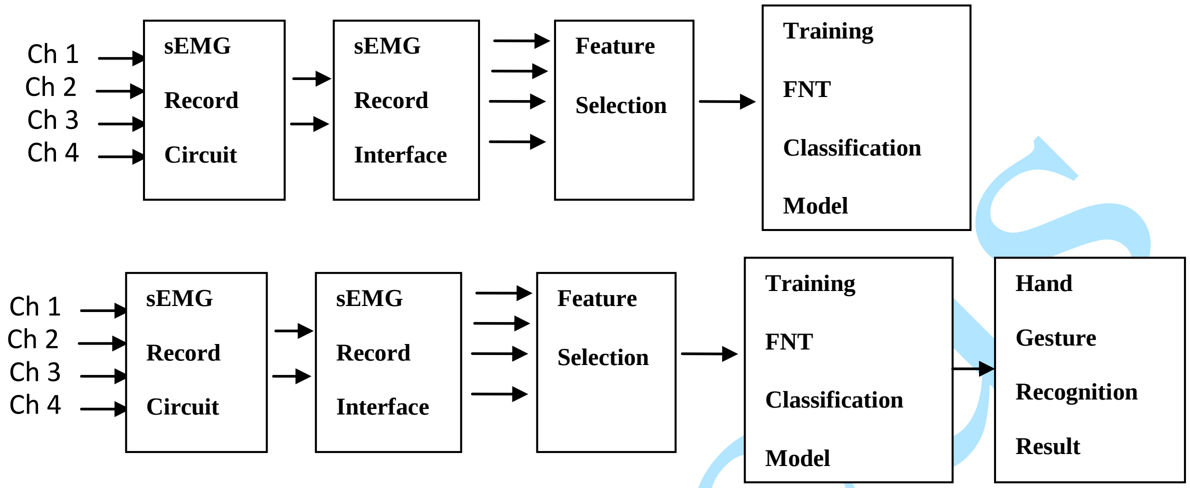

Figure 1: Structure of the gesture recognition model

In the experiment, participants were examined on a single flexion of the hand, six times. Each of the times, electrodes were attached to the muscles of the fore arm. (Brachioradialis), the Flexor Digitorum Superficialis (FDS), the Flexor Carpi Radials (FCR) and the Extensor Digitorum Superficialis (EDS). The flexions were carried out without any known opposition, with the sEMG signals being recorded as the participants performed certain finger flexions such as: Flexion of middle finger, the index finger, the ring finger, all the fingers and the wrist. These named flexions are specifically selected, as they are found to be capable of being done almost effortlessly and can be assumed by the participants as many times as necessary and as quickly as possible. The order in which flexions can be made is not taken into account, however each flexion is meant to last for about 10 seconds during which the sEMG is recorded. The period of running each of the experiments is 60 secs.

sEMG signals change as hand gestures are changed. In collecting the sEMG we used a time domain window of 500ms. As such, sEMG signals which had overlapped spans, used 200ms (figure 4), thereby helping to improve the hand gestures classification rate, by reducing the effect of transitional signals between two hand gestures.

$$S = F \cup T = \{+_2, +_3, \dots, +_N\} \cup \{x_1, x_3, \dots, x_n\} \quad (2)$$

Where F = function instruction operators, T= instruction terminals, $+_i$ (i=2, 3, ,…, N) denote instructions of non-leaf nodes, taking i arguments and $x_1, x_2, \dots x_n$.

The node output $+_n$ is calculated by:

$$out_m = f(a_n, b_n, net_n) \quad (3)$$

In building an FNT, when a leaf node instruction is selected, *i* real values are evolved automatically and used for demonstrating the connection strength between the node $+_i$ and its children.

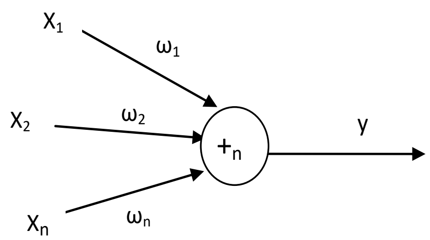

Figure 2: A flexible neutron operator

The output of the flexible neuron $+_n$ can be calculated as in:

$$net_n = \sum_{j=1}^{n} \omega_j \times x_j \quad (4)$$

Where net_n = output of the flexible neuron, $x_i(j)$ =1, 2, …, n) are the inputs to node $+_n$. In flexible activation function f (a_1, b_1, x), a_i and b_i are flexible activation function parameters.

Two instructions sets are used in this experiment. The instruction sets are as follows (Fig. 5).

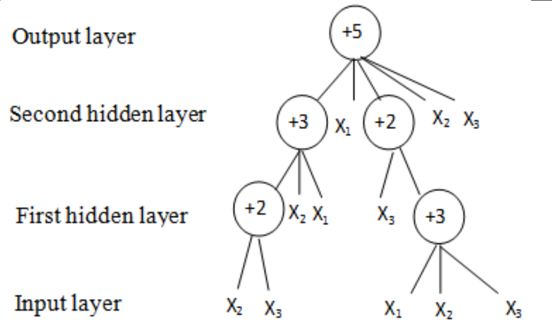

Figure 3: A typical representation of neural tree with function instruction operators F = {$+_2$, $+_3$, $+_4$, $+_5$} and instruction terminals T ={x_1, x_2, x_3}

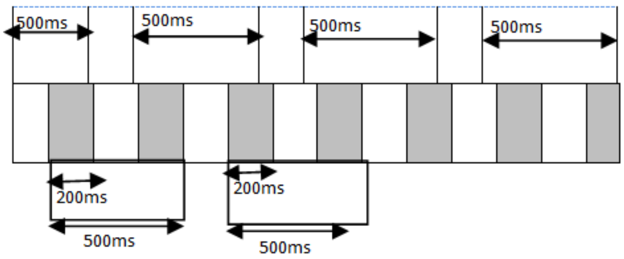

Figure 4: Segment theory of collection window

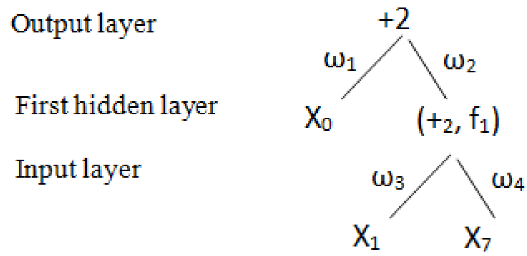

Figure 5: A flexible neural tree with function instruction sets

$$I = (+_2, +_0, +_1, +_2, +_3, +_4, +_5, +_6, +_7) \tag{5}$$

Also,

$$F(a,b,c) = e^{-(\frac{x-a}{b_i})^2} \tag{6}$$

The output of the node $+_n$ is then calculated by a_i

$$Out_n = F(a_n, b_n, net_n) = e^{-(\frac{net-a}{b_i})^2} \tag{7}$$

Equation 7 gives the output of the node $+_n$

$$fit(i) = \frac{\sum_{j=1}^{p}(y_i^j - y_2^1)^2}{P} \tag{8}$$

Equation 8 represents the fitness function. The loop terminates at a when a suitable solution is reached and the following instruction set is used in obtaining the neural tree: set 1 = { $+_2$, x_0, x_1, x_2, x_3, x_4, x_5, x_6, x_7}.

4. EXPERIMENTAL RESULTS

The experiments were conducted to test the hand gesture recognition system, using five participants and having each of the participants make six different flexions. A diagram of a participant performing a specific flexion which involves all the fingers of the hand is shown in below (Fig. 5).The parameters used in pipe algorithm for architecture optimization of the neural tree is shown in Table 1.

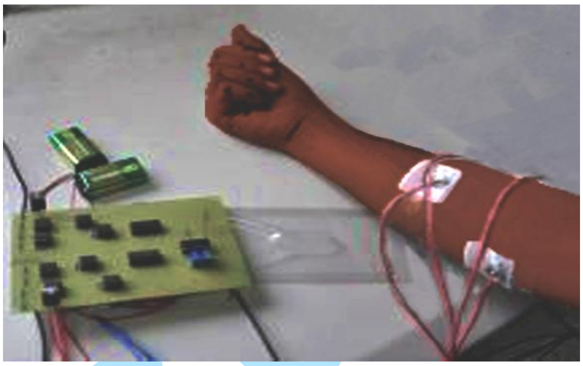

Figure 5: One of the hand gestures used in the experiment (All fingers flexion)

Table 1. Parameters Used In Pipe Algorithm for Architecture Optimization of the Neural Tree

Parameter	**Value**
Population size (PS)	200
Elitist learning probability (P_{el})	0.02
Learning rate (I_r)	0.02
Fitness constant	0.000002
Overall mutation probability (P_M)	0.5
Mutation rate (m_r)	0.5
Prune threshold (T_p)	1.0
Maximum random search steps	3000
Initial parameters (a_p and b_p)	rand[0,1]

Ten input variables were used for building the FNT model. The instruction set used is I= {$+_2$, $+_0$, $+_1$, $+_2$, $+_3$, $+_4$, $+_5$, $+_6$, $+_7$}. From Fig. 6 the RMSE mean value is seen to be 0.000534 for the training data, and 0.00625 for the testing data, respectively.

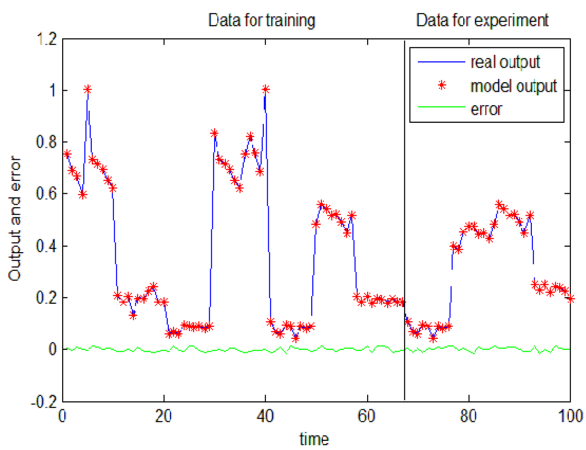

Figure 6: Output and RMSE error

Table 2. List of classification rates with different hand movements

Hand Gesture	Ring Finger %	Index Finger %	Wrist %	Middle Finger %	All Fingers %	Relax %
Mean Recogni-tion Rate	92.62	92.48	93.17	98.26	98.56	97.48

The final result of the six hand gestures is revealed in Table 2, which shows that an accuracy of 98.56% is attained in classifying the six different hand gestures.

5. CONCLUSION

In this research work, we have built a model for recognizing hand gestures using neural trees (FNTs) based on sEMG signals. The sEMG was specifically selected for use in this research work for the purpose of recording of the electrical signal activity of simulated muscles of the hand from the surface of the skin. The FNT model was evolved using an evolutionary procedure after it had been initially produced as a multi-layer feed-forward neural network. Several experiments were carried out to test the model, using five participants. The results of the experiment revealed that the model is capable of recognizing six different gestures with up to 98.56% accuracy in real time. The developed model proved that the FNT model with input variables that were automatically selected, had a lower error rate and as such, a higher accuracy.

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