Flexible Neural Trees for Online Hand Gesture Recognition using Surface Electromyography

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***Abstract*—Normal hand gesture recognition methods using surface Electromyography (sEMG) signals require designers to use digital signal processing hardware or ensemble methods as tools to solve real time hand gesture classification. Some methods could also result in complicated computational models, complex circuit connection and lower online recognition rate. It is therefore imperative to have good methods to explore a more suitable online design choice, which can avoid the problems mentioned above. An online hand gesture recognition model by using Flexible Neural Trees (FNT) and based on sEMG signals is proposed in this paper. The sEMG is a non-invasive, easy to record signal of superficial muscles from the skin surface, which has been applied in many fields of treatment and rehabilitation. The FNT model is generated and evolved based on the pre-defined simple instruction sets, which can solve highly structure dependent problem of the Artificial Neural Network (ANN). FNT method avoids complicated computation and inconvenience of circuit connection and also has an higher online recognition rate. Testing has been conducted using several continuous experiments conducted with five participants. The results indicate that the model is able to classify six different hand gestures up to 97.46% accuracy in real time.**

***Index Terms*—surface Electromyography (sEMG), Flexible Neural Trees (FNT), online pattern recognition, Artificial Neural Network (ANN)**

I. INTRODUCTION

A sign language is a language, which uses visually transmitted sign patterns (manual communication, body language and lip patterns) to convey meaning—simultaneously combining hand shapes, orientation and movement of the hands, arms or body, and facial expressions to fluidly express a speaker's thoughts. Recently, the sign language as an important interact method of body languages is paid attention by many scientists of all over the world. From the recognition signals, the recognition methods of the sign language are mainly divided into hand gesture signals, visual hand gesture images and surface Electromyography (sEMG) signals. In 2008, Ganesh N. Naik, Dinesh K. Kumar and Sridhar P. Arjunan of RMIT University proposed Multi run Independent Component Analysis (ICA) and sEMG based signal processing system for recognizing hand gestures. This method improved the offline hand gesture recognizing rate to 99% [2]. However, the separated signals of Blind Source Separation (BSS) based on ICA are disorder and not available for online hand gesture recognition. In 2007, Mahdi Khezri and Mehran Jahed proposed to use an intelligent approach based on adaptive neuro-fuzzy inference system (ANFIS) integrated with a real-time learning scheme to identify palm and wrist flexion and extension with 96.7% average accuracy[5]. This algorithm is not applied to finger flexion in recent reports nevertheless. It is of great importance to have good methods to explore a more suitable online choice, which can avoid the problems mentioned above as more as possible [1].

An online hand gesture recognition model by using flexible neural trees (FNT) based on sEMG signals is proposed in this paper. With a view of non-intramuscular and easy to record electrical activity of superficial muscles from the skin surface, the sEMG is adopted in the model. In consideration of avoiding complicated computation, solving inconvenience of circuit connection, providing flexible time-series forecasting and having higher online recognition rate, the FNT model is generated initially as a flexible multi-layer feed-forward neural network and evolved using an evolutionary procedure. Testing has been conducted using several continuous experiments conducted with five participants. The results indicate that the model is able to recognize six different hand gestures up to 97.46% accuracy in real time.

II. THEORY

A. *Feature Selection of sEMG*

A time domain feature is described in this section. Root Mean Square (RMS) can be done in real-time and

Manuscript received February 20, 2011; accepted May 4, 2011.
Funding for this work was provided by the grants of Study Abroad of Shanxi Scholarship Council of China [No. 20101069] and Youth Foundation of Taiyuan University of Science and Technology of China [No. 20103004].
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doi:10.4304/jcp.7.5.1099-1103

electronically and it is simple for implementation. The features are normally used for onset detection, muscle contraction and muscle activity detection.

RMS is modeled as amplitude modulated Gaussian random process whose RMS is related to the constant force and non-fatiguing contraction. It relates to standard deviation, which can be expressed as in

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

where N denotes the length of the signal and x_n represents the sEMG signal in a segment.

B. *Flexible Neural Trees*

Artificial neural networks (ANNs) have been successfully applied to a number of scientific and engineering fields in recent years, i.e., function approximation, system identification and control, image processing, time series prediction. However, a neural network's performance is highly dependent on its structure. Depending on the problem, it may be appropriate to have more than one hidden layer, feed-forward or feedback connections, or in some cases, direct connections between input and output layer [2].

The flexible neural tree (FNT) is a fuzzy model which is proposed initially for solving highly structure dependent problem of the artificial neural network (ANN). The model is computed as an irregular flexible multi-layer feed-forward neural network. Based on the pre-defined instruction/operator sets, a flexible neural tree can be created and evolved. In this approach, over-layer connections, different activation functions for different nodes and input variables selection are allowed. The hierarchical structure could be evolved by using tree-structure based evolutionary algorithms with specific instructions. The interaction allowed between the various nodes of the network is no longer specified using the structure only.

The function instruction operators F and instruction terminals T used for evolving a FNT model are described as in

$$S = F \cup T = \{+_2, +_3, \cdots, +_{\mathrm{N}}\} \cup \{x_1, x_2, \cdots, x_n\} \tag{2}$$

Where $+_i \; (i = 2,3,\cdots,N)$ denote instructions of non-leaf nodes which taking i arguments and $x_1, x_2, \cdots, x_n$ represent instructions of leaf nodes which taking no other arguments.

It is shown clearly that the output of a non-leaf node $+_n$, which is also called a flexible neuron operator, is calculated as a flexible neuron model with n arguments in Fig. 1.

In the construction process of FNT, when a non-leaf instruction $+_i \; (i = 2,3,\cdots,N)$ is selected, i real values are evolved automatically and used for demonstrating the connection strength between the node $+_i$ and its' children. The output of a flexible neuron $+_n$ can be calculated as in

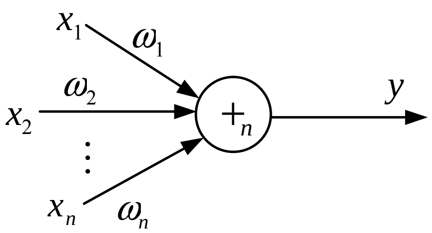

Figure. 1 A flexible neuron operator

$$net_n = \sum_{j=1}^{n} \omega_j * x_j \tag{3}$$

Where $x_j \; (j = 1,2,\cdots,n)$ are the inputs to node $+_n$. Gaussian function, Unipolar sigmoid function, Bipolar sigmoid function, Non-local radial coordinates, Thin-plate s-spline function and General multiquadratics all can be adopted as flexible activation function[3]. In flexible activation function $f(a_i, b_i, x)$, two adjustable parameters a_i and b_i are randomly created for using as flexible activation function parameters.

When flexible activation function is determined, the output of the node $+_n$ is then calculated by

$$out_n = f(a_n, b_n, net_n) \tag{4}$$

A typical flexible neuron operator and a neural tree model are illustrated in Fig. 2. The overall output of flexible neural tree can be computed recursively from left to right by depth-first method.

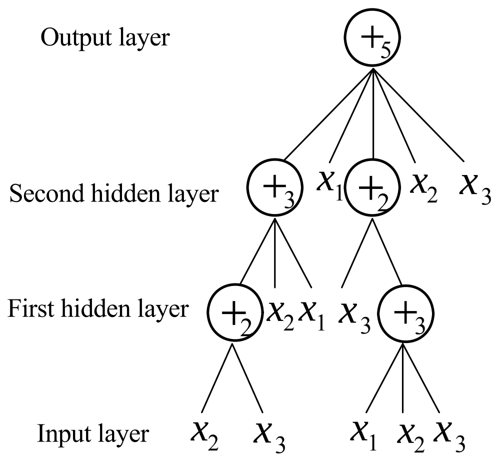

Figure 2.
A typical representation of neural tree with function instruction operators F ={+2,+3,+4,+5} and instruction terminals T = {x1, x2, x3}.

The FNT model can be created and evolved using the existing or modified tree-structure-based approaches which include Genetic Programming (GP), Probabilistic Incremental Program Evolution (PIPE) and Ant

Programming (AP). Normally, the fitness function used for the PIPE and SA can be given by mean square error (MSE) or root mean square error (RMSE).

III. METHODOLOGY

The structure of the sEMG model is depicted in Fig.3, which is composed of sEMG data record part, feature selection part and FNT classification part. sEMG record circuit and sEMG record interface are components of the sEMG data record part. Feature selection part takes the responsibilities for selecting and computing features of sEMG signals. In FNT classification part, the FNT is adopted to train a fuzzy classification model according to the selected sEMG features and the initialization construction. The trained classification model is applied in online test of FNT classification part.

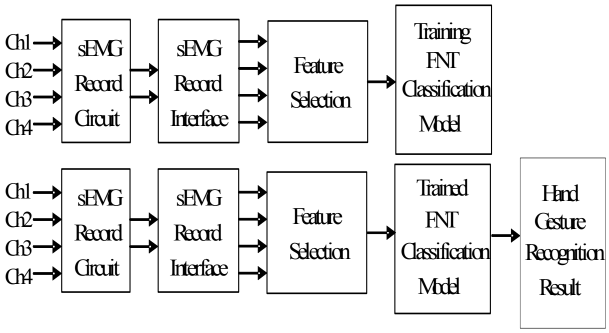

Figure 3. The structure of online hand gesture recognition model

Five volunteers participated in the experiments. Each participant has tested one kind of flexion for 6 times. Electrodes were placed on the forearm muscles of Brachioradialis, Flexor Carpi Radialis (FCR), Extensor digitorum superficialis (EDS) and Flexor Digitorum Superficialis (FDS). sEMG signals record when the participant maintain specific finger flexions of middle finger flexion, all fingers flexion and so on. The flexions have been performed without any resistance. These flexions are chosen as they are very convenient to and easily reproducible by the participant. The order of the flexions is arbitrary and each flexion is maintained for about 10 secs to record sEMG and the duration of each run of the experiment is about 60 secs.

When hand gestures change alternately, sEMG signals change accordingly. However, transitional signals between two hand gestures are easy to reduce the hand gestures classification rate. In this work, we used a time domain window of 500 (ms) for collecting sEMG signal. For above reason, overlapped length of sEMG signals used 200 (ms) segmented signal (see Fig.4). The rms is applied in each window of the experiments as sEMG feature. The overlapped method solves part effect of transitional signals.

The online hand gesture recognition model is approximated by using the neural tree model with the pre-defined instruction sets. The instructions of root node, hidden nodes and input nodes are selected from three instruction sets.

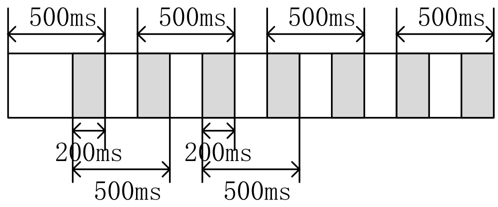

Figure 4. Segment theory of collection window

We have used two instructions in the experiments. The instruction sets are as follows (see Fig.5):

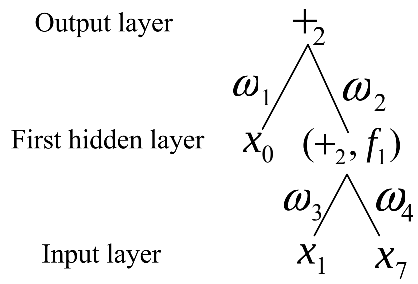

Figure 5. A flexible neural tree with function instruction sets

$$I=\{+_2, x_0, x_1, x_2, x_3, x_4, x_5, x_6, x_7\} \quad (5)$$

For developing the FNT classifier, the following flexible activation function is used:

$$f(a_i, b_i, x) = e^{-((x-a_i)/b_i)^2} \quad (6)$$

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

$$out_n = f(a_n, b_n, net_n) = e^{-((net_n - a_n)/b_n)^2} \quad (7)$$

The PIPE is selected as a tree-structural based encoding method with specific instruction set for fine tuning the parameters encoded in the structure.

Starting with initial set structures and corresponding parameters, it first tries to improve the structure and then as soon as an improved structure is found. The parameters of the structure are fine tuned. It then goes back to improving the structure again and finds a better structure. The rules' parameters are fine tuned again.

A fitness function arranges FNT to scalar and real-valued fitness values that reflect the FNT performances according to a given task. In experiments, the fitness function used for the PIPE is given by mean square error (MSE).

$$Fit(i) = \frac{\sum_{j=1}^{P} (y_1^j - y_2^j)^2}{P} \quad (8)$$

When a satisfactory solution is found or a time limit is reached, loop stops.

The evolved neural tree model is obtained at generation 20 with function instruction sets $\mathrm{I} = \{+_2, x_0, x_1, x_2, x_3, x_4, x_5, x_6, x_7\}$.

IV. EXPERIMENTAL RESULTS

Experiments have been conducted to test the proposed online hand gesture recognition model. Five volunteers participated in the experiments. Each participant has tested one kind of flexion for 6 times (see Fig.6).

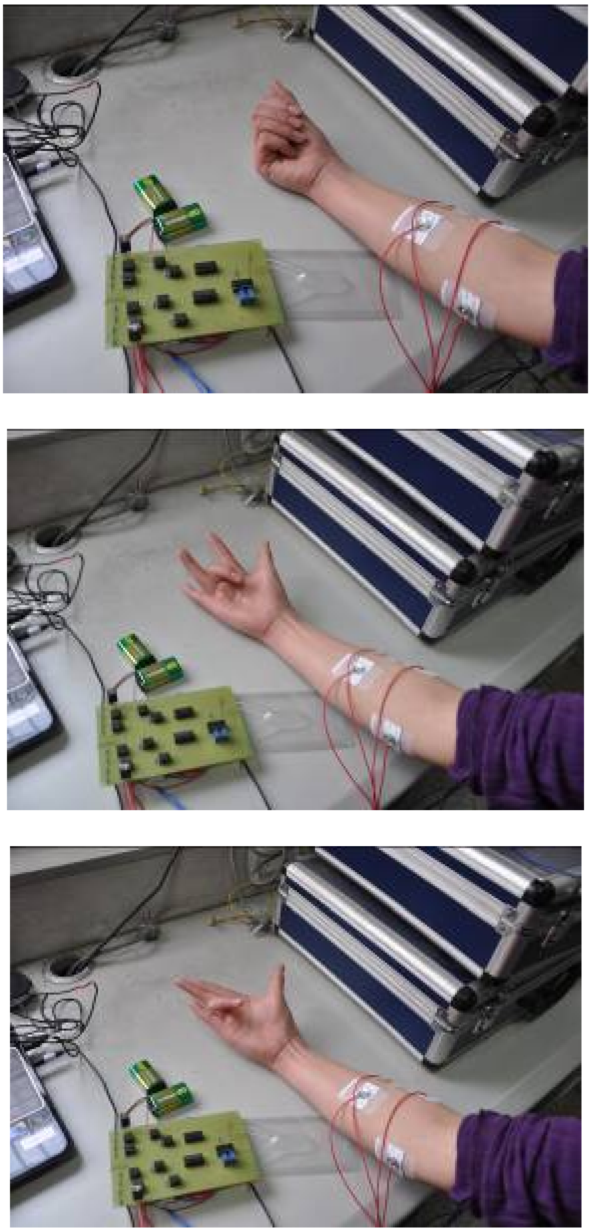

Figure 6. Examples of hand gestures (Middle finger flexion, Wrist Flexion, Ring finger flexion)

Fig.7 shows the main window of recognition system. Four channels of surface EMG signals are used in the experiment. The selected feature is RMS. FNT is applied as classifier in the experiment.

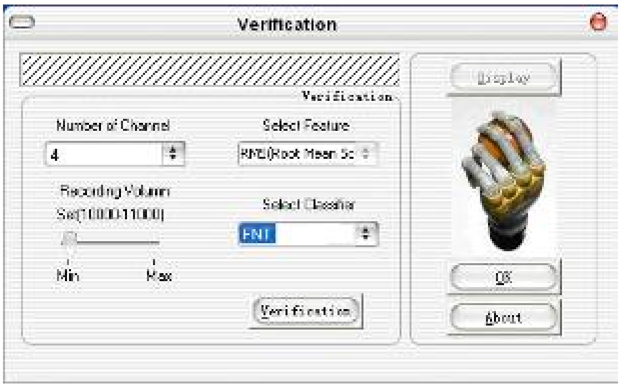

Figure 7. Recognition system main window

FNT selects proper input variables or time-lags automatically. In addition, the parameters used for experiment is listed in Table I.

TABLE I
PARAMETERS USED IN PIPE ALGORITHM FOR ARCHITECTURE OPTIMIZATION OF THE NEURAL TREE

Population size PS	100
Elitist learning probability P_{el}	0.01
Learning rate l_r	0.01
Fitness constant	0.000001
Overall mutation probability P_M	0.4
Mutation rate m_r	0.4
Prune threshold T_p	0.999
Maximum random search steps	2000
Initial connection weights	rand[-1, 1]
Initial parameters a_p and b_p	rand[0,1]

For the experiment, 10 inputs variables are used for constructing a FNT model. The instruction set is $I = \{+_2, x_0, x_1, x_2, x_3, x_4, x_5, x_6, x_7\}$ (see Fig. 5).

Fig.8 shows it obviously that real outputs are close to model outputs. RMSE mean value is 0.000444 for training data and 0.000595 for testing data, respectively.

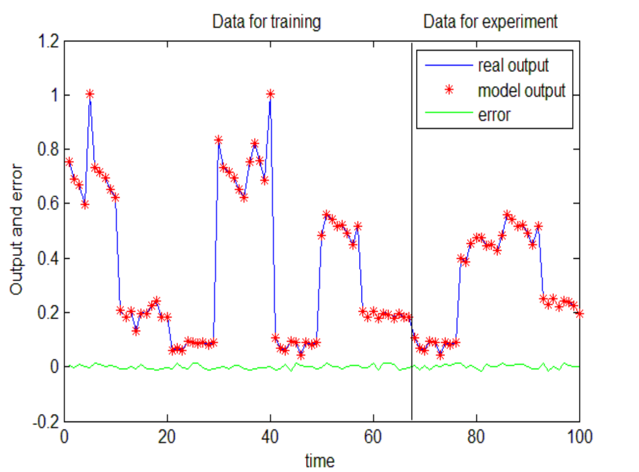

Figure 8. Output and RMSE error

The six special hand gestures of the experiment are shown in Table II. From the results, the model is able to classify six different hand gestures up to 97.46% accuracy in real time.

TABLE II
LIST OF CLASSIFICATION RATES WITH DIFFERENT HAND MOVEMENTS

Hand gesture	Ring finger	Index finger	Wrist	Middle finger	All fingers	Relax
Mean recognition rate	93.72%	92.43%	92.16%	97.28%	97.46%	97.31%

V. CONCLUSION

A real time hand gesture recognition model by using flexible neural trees (FNT) based on sEMG signals is proposed in this paper. With a view of non-intramuscular and easy to record electrical activity of superficial muscles from the skin surface, the sEMG is adopted in the model. In consideration of avoiding complicated computation, solving inconvenience of circuit connection, providing flexible time-series forecasting and having higher online recognition rate, the FNT model is generated initially as a flexible multi-layer feed-forward neural network and evolved using an evolutionary procedure. Testing has been conducted using several continuous experiments conducted with five participants. The results indicate that the model is able to recognize six different hand gestures up to 97.46% accuracy in real time. The work demonstrates that the FNT model with automatically selected input variables has better accuracy (low error) and good generalization ability.

ACKNOWLEDGEMENT

This work was supported by the grants of Study Abroad of Shanxi Scholarship Council of China [No. 20101069] and Youth Foundation of Taiyuan University of Science and Technology of China [No. 20103004].

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