Practical Surface EMG Pattern Classification by Using a Selective Desensitization Neural Network

Hiroshi Kawata[1], Fumihide Tanaka[1], Atsuo Suemitsu[2], and Masahiko Morita[1]

[1] Graduate School of Systems and Information Engineering, University of Tsukuba
1-1-1 Tennodai, Tsukuba, Ibaraki, Japan
[2] School of Information Science, Japan Advanced Institute of Science and Technology
1-1 Asahidai, Nomi, Ishikawa, Japan
kawata@bcl.esys.tsukuba.ac.jp, fumihide@iit.tsukuba.ac.jp,
sue@jaist.ac.jp, mor@bcl.esys.tsukuba.ac.jp

Abstract. Real-time pattern classification of electromyogram (EMG) signals is significant and useful for developing prosthetic limbs. However, the existing approaches are not practical enough because of several limitations in their usage, such as the large amount of data required to train the classifier. Here, we introduce a method employing a selective desensitization neural network (SDNN) to solve this problem. The proposed approach can train the EMG classifier to perform various hand movements by using a few data samples, which provides a highly practical method for real-time EMG pattern classification.

Keywords: EMG Pattern Classification, Selective Desensitization Neural Network, Prosthetic Limb, Hand Movement Classification.

1 Introduction

Hands play an important role in our lives. The classification of hand movements by using surface electromyogram (EMG) signals is an important research issue in the development of prosthetic limbs. Although there is an extensive history of research in this field, the real-time robust implementation of this methodology is still practically very difficult [1,2]. First, because each hand movement is associated with multiple muscles, the surface EMG signal obtained from a sensor is the superposition of all the signals obtained from the related muscle activity; hence, complicating the correspondence relationship between movements and signals. Second, surface EMG signals are not reproducible, because there is a large difference between individuals, and even within a person the signals tend to fluctuate on every trial. As a result, in order for the existing approaches to work, the following conditions have been assumed:

- Collect sufficient data samples from the subject.
- Choose the number of sensors carefully in order to avoid redundancy, which often causes harmful effects while learning the data.

K.W. Wong et al. (Eds.): ICONIP 2010, Part II, LNCS 6444, pp. 42–49, 2010.

– Choose the positions of the sensors carefully.
– The subject needs to be trained in advance, so that he/she can deliver stable EMG signals.
– Preprocess the obtained signals carefully, so that the data-learning algorithm can produce a satisfactory EMG classifier.
– Extract suitable features from the data samples (for the same reason as above).

All these requirements made the real-time EMG pattern classification practically difficult to implement.

On the other hand, a selective desensitization neural network (SDNN) [3] performs significantly better in approximating a wide range of functions by using few training data samples. Therefore, in this paper, we will exploit the SDNN for the classification of the surface EMG pattern. In particular, we will apply this method to the problem of hand-movement classification, wherein real-time performance is crucial, particularly for prosthetic limbs.

2 Research Background

2.1 Electromyogram

Muscle contraction is triggered by the excitement of muscle fibers, which is invoked by a signal from the alpha motor neurons in the spinal cord. The electrical potential difference measured through the muscle contraction is called a myogenic potential, and its time-series signal is called an EMG. Since an EMG occurs 30–100 ms before the muscle contraction, it is considered theoretically possible to estimate the occurrence of the corresponding bodily movement from the EMG signals before the actual movement (muscle contraction) occurs.

For measuring the EMG signals, two types of electrodes can be used: needle electrodes and surface electrodes. The needle electrodes target specific muscle fibers and measure EMG signals with precision. However, they are accompanied with a physical pain to the subject, because the needle has to be inserted into the subject's skin. On the other hand, in the case of surface electrodes, there is little pain, as there is no needle insertion involved to measure the EMG signals. Instead, the electrical potential measured by the surface electrodes is a summation of the local electrical potentials, which makes the exact estimation of the corresponding bodily movement more difficult than that in the case of using needle electrodes.

In this study, we will use surface electrodes, considering the advantage and to try overcoming the disadvantage described above by introducing the SDNN.

2.2 Selective Desensitization Neural Network

The SDNN [3] is known to have overcome the several limitations of the multilayer perceptron, and to ably approximate a wide range of functions by using few training data samples. Here, we will be illustrating an example of approximating a function $y = f(x)$ by employing the SDNN, given a continuous-valued input vector $\boldsymbol{x} = (x_1, \ldots, x_m)$, where $m \geq 2$.

The input layer of the SDNN consists of m neuronal groups $(G^1_1, \ldots, G^1_m)$. Each group is composed of n neurons and represents an input variable x_μ, i.e., the input variable is represented in a distributed manner by the activity patterns of the neurons. Then, the middle layer of the SDNN consists of $m(m-1)$ neuronal groups $G^2_{\mu,\nu}$ $(\mu, \nu = 1, \ldots, m; \mu \neq \nu)$. The neurons in $G^2_{\mu,\nu}$ are connected with both the neurons in G^1_μ and G^1_ν $(\mu \neq \nu)$, in the input layer. This realizes a procedure called desensitization, which neutralizes the output of the neuron regardless of its input and inner potential. For example, if a neuron is configured to output either 1 or -1 with equal probabilities as its default output, it will output 0 in the case that the neuron is desensitized. Finally, the output layer of the SDNN consists of n' neurons, each of which is connected with all the neurons in the middle layer. The output of the i-th neuron in the output layer is calculated by

$$y_i = g\left(\sum_{\mu,\nu(\neq\mu)} \sum_{j=1}^{n} \omega^{\mu,\nu}_{ij} x^{\mu,\nu}_j - h_i \right), \tag{1}$$

where h_i is a threshold, $\omega^{\mu,\nu}_{ij}$ is a synaptic weight from the j-th neuron of $G^2_{\mu,\nu}$ in the middle layer, and $g(u)$ is the activation function, where $g(u) = 1$ for $u > 0$ and 0 for $u \leq 0$.

Learning of this network is performed using a target vector $\boldsymbol{p} = (p_1, \ldots, p_{n'})$. The threshold and the synaptic weights between the middle layer and the output layer are specifically updated by

$$\omega^{\mu,\nu}_{i,j} \leftarrow \omega^{\mu,\nu}_{i,j} + c(p_i - y_i)x^{\mu,\nu}_j, \tag{2}$$
$$h_i \leftarrow h_i - c(p_i - y_i), \tag{3}$$

where c is a learning coefficient.

3 Methods

3.1 Signal Measurement

Personal-EMG (Oisaka Electronic Device Ltd. [4]) equipment is used to measure the surface EMG signals. This can measure the integral of the EMG signal (IEMG) and the original EMG at the same time. In this study, the EMG and IEMG signals are sampled at 3 kHz by using a 12-bit A/D converter, and for the classification of hand movements, an IEMG signal is used, which is low-pass filtered with a cut-off frequency of 4.8 Hz.

Regarding the myoelectric sensors, we use 10 pairs of wet-electrodes, which are pasted around the subject's right arm (Fig. 1). The sensors target the following six muscles: flexor carpi radialis, flexor digitorum profundus, flexor carpi ulnaris, extensor digitorum, flexor carpi long radialis, brachioradialis, and biceps brachii [5]. However, the sensors do not need to be positioned accurately.

Fig. 1. Placement of wet electrodes

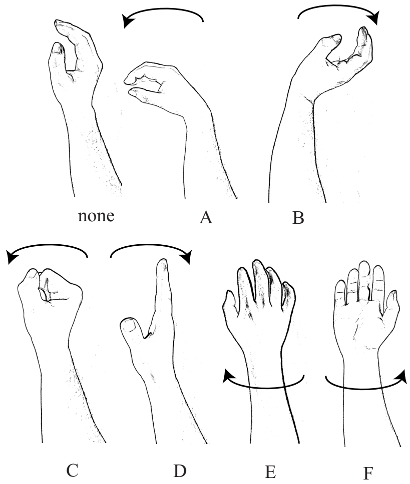

Fig. 2. Seven categories to be classified from the EMG signals [6]

3.2 Target Hand Movements

In this study, six hand movements (wrist flexion, wrist extension, grasping, opening up, wrist supination, and wrist pronation) and no-movement conditions are targeted for the classification. In the following sections, we denote the no-movement condition by "basic position (none)," wrist flexion by "movement-A," wrist extension by "movement-B," grasping by "movement-C," opening up by "movement-D," wrist supination by "movement-E," and wrist pronation by "movement-F" (Fig. 2).

3.3 Preprocessing of IEMG Signals

Preprocessing is performed to handle the IEMG signals with the SDNN (Fig. 3). First, each IEMG signal is normalized by the maximum value at each channel, and the normalized IEMG signals are then normalized again by the maximum value at each time step. Next, each IEMG channel is connected to a neuronal group in the input layer of the SDNN, and each neuronal group is composed of multiple neurons, as described in the previous section. In consequence, we code the value of the IEMG signal so that only 50% of the neurons can be in a continual excited state, and the pattern of excitement can depict the continuous change in the IEMG value consecutively (Fig. 4).

3.4 Learning of the SDNN

The internal structure of the SDNN is shown in Fig. 5. In this study, the input layer of the SDNN is composed of 360 neurons: 300 neurons for 10 IEMG channels, 30 neurons for the total value of all the IEMG signals, and 30 neurons

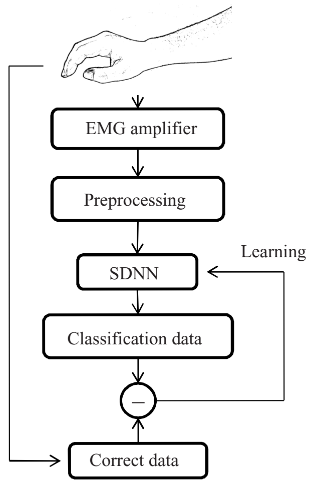

Fig. 3. Training process of the proposed system

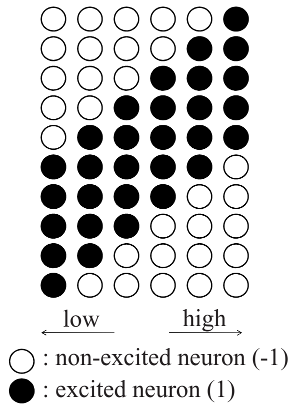

Fig. 4. Distributed coding of IEMG signals

for the difference of the total IEMG value from a step in the past. There are two middle layers composed of a total of 6600 neurons: in the first layer, half of the neurons are desensitized by the corresponding neurons in the input layer, except for the neurons representing the total value of the IEMG signals; and in the second layer, the desensitization procedure is repeated by the neurons representing the total value of the IEMG signals. The output layer is composed of six neurons, each of which corresponds to the classifier of each movement.

In the learning cycle, we train the SDNN by supplying the preprocessed input signals greater than the noise threshold and the target patterns representing the corresponding movement. The synaptic weights from the middle layer to the output layer and the thresholds in the output layer are specifically modified according to Eqs. (2) and (3). Here, the training is repeated 10 times and the learning coefficient c is set to 0.1.

3.5 Evaluation of Classification

In order to evaluate the classification ability of the proposed system after learning, we define a classification rate for each movement as follows. First, a test data sample is fed into the system and movement detection is performed in every frame. Second, if any movement has been detected more than six times, the test data sample is classified into the movement detected most frequently; otherwise, it is classified into "none". Third, we judge whether the classification is correct or not. For example, the classification is regarded as correct if the classified movement is the same as that corresponding to the test data sample. Finally, we apply this procedure to all the test data samples corresponding to the same movement, and then calculate the classification rate as a percentage of the number of correct classifications to the total number of the test data samples.

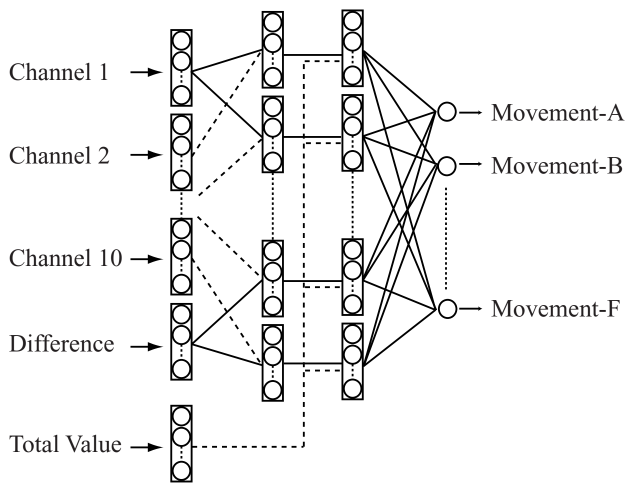

Fig. 5. Structure of SDNN

4 Experiment

To collect the IEMG data, five male subjects are asked to execute one movement for 2 s and repeat all the six movements (Fig. 2), three times in the same order in a session. The session is repeated nine times, which provides the total number of data samples.

After the measurement, a cross validation is performed to calculate the final classification rate: (1) pick up one session data (which contains three data samples for every movement) to train the SDNN whose classification rates are calculated by using the other eight session data as test data, (2) repeat it by changing the training data samples for all combinations, and (3) compute the total average as the final classification rate.

Figure 6 shows an example of the IEMG signals obtained from one subject when the subject performs the six movements. Each line corresponds to the signal from a channel, and each shaded box represents the movement that is labeled. From this figure, it can be seen that the signals are very unstable and fluctuate at every trial.

Figure 7 plots the final classification rate for each movement of each subject. The average classification rates over the six movement categories are (s1) 86.73%, (s2) 100.00%, (s3) 92.44%, (s4) 97.15%, and (s5) 100.00%. The total average classification rate over the five subjects and the six movements is 95.26%.

Figure 8 shows an example of the total value of the IEMG signals together with the outputs (classified movements) of six neurons in the output layer of the SDNN. The shaded regions represent the movements classified by the SDNN.

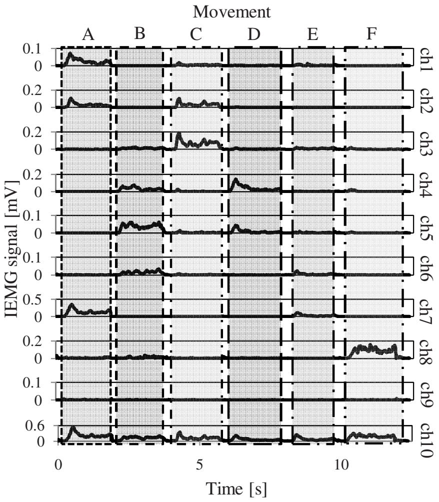

Fig. 6. Example of IEMG signals from a subject

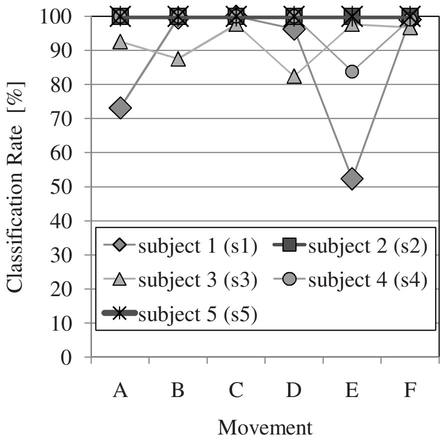

Fig. 7. Final classification rate for movements A–F for five subjects

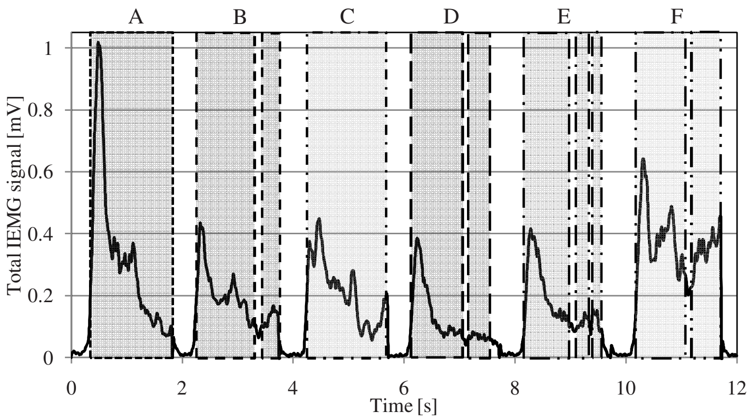

Fig. 8. Example of real-time classification of six movements

Each classification is computed together with an increase in the total IEMG value, implying that the real-time classification is achieved (see the video at [7]).

5 Conclusion

By introducing the SDNN into the pattern classifier, the real-time pattern classification of multiple hand movements was presented. The experimental results from the five human subjects showed that only three training data samples for each movement are sufficient for the proposed system to output a classification accuracy of >95% (average) for the six targeted hand movements. This approach is considered to be more practical than the existing methods for the following reasons:

– It does not require large number of training data samples to obtain a good classifier.
– It does not require the user to position sensors on optimal locations.
– It does not require complicated preprocessing of the signal data.
– It does not require the subject to be trained or to be given detailed instructions in advance.

Future work includes more detailed analyses on both the number of training data samples and sensors. Furthermore, because the SDNN exhibits high performance in approximating a wide range of functions, it is considered to be able not only to classify the categories of movements but also to estimate the speed/force of each movement.

Acknowledgments

This study was supported by a Grant-in-Aid for Scientific Research on Priority Areas (21013007) and a Grant-in-Aid for Young Scientists (B) (21700576) from the Ministry of Education, Culture, Sports, Science and Technology of Japan (MEXT), and a Grant-in-Aid for Scientific Research (B) (22300079) from the Japan Society for the Promotion of Science (JSPS).

References

1. Tsuji, T., Fukuda, O., Bu, N.: New Developments in Biological Signal Analysis (in Japanese). Journal of the Japan Society of Applied Electromagnetics 13(3), 201–207 (2005)
2. Yokoi, H., Chiba, R.: Now and Future of Cyborg Technology (in Japanese). Journal of the Society of Instrument and Control Engineers 47(4), 351–358 (2008)
3. Morita, M., Murata, K., Morokami, S., Suemitsu, A.: Information Integration Ability of Layered Neural Networks with the Selective Desensitization Method (in Japanese). The IEICE Transactions on Information and Systems J87-D-II(12), 2242–2252 (2004)
4. Oisaka Electronic Device Ltd., http://www.oisaka.co.jp/P-EMG.html
5. Fujita, T.: Guide Anthropotomy (in Japanese), pp. 88–92. Nankodo (2003)
6. Yoshikawa, M., Mikawa, M., Tanaka, K.: Real-Time Hand Motion Classification and Joint Angle Estimation Using EMG Signals (in Japanese). The IEICE Transactions on Information and Systems J92-D(1), 93–103 (2009)
7. Real-Time Classification of Multiple Hand Movements, http://volga.esys.tsukuba.ac.jp/~kawata/demovideo/demovideo.wmv