Estimation of Forearm Motion by Electromyogram using Complex-valued Neural Network

Haslinibinti Abdullah[1] and Takehiko Ogawa[2]

***Abstract*—Recently, the myoelectric potential generated by the movement of human muscle used as interface for controlling a robot arm and prosthetic device has been studied. The changes of myoelectric potential by muscle motion gave the impact of the robot arm control. It is proposed that electromyography (EMG) patterns can be analyzed and clarified by Neural Network (NN) for the motion determination. Thus, this paper proposes a pattern estimation method of forearm motion by Complex-Valued Neural Network (CVNN).The forearm motion was recorded by Surface Electromyography (SEMG) method as the analysis data from the area of the back and front of the arm intermediate part. We focused on how to estimate between the four movements in this study using Complex-Valued Neural Network (CVNN). The results show how the methodology we adopted allows us to obtain good accuracy in estimating the forearm motion.**

***Keywords*— myoelectric potential, surface electromyography, neural network, complex-valued neural network**

1. Introduction

Since every motion of a human operator is realized by muscular contraction controlled by the central nervous system (CNS), EMG signal accompanied by muscular contraction involve information on muscle contributing to the motion. If the information on the human operator's intended motion can be extracted from the EMG signals, it can be used as a new interface tool for a communication tool for a handicapped person. For example, in the case of a physically handicapped person who has his/her upper limb amputated by an accident, if the CNS and a part of the muscles which have actuated the original limb still remained after amputation, it can be expected that natural feeling of prosthetic control similar to that of the original limb is realized using the EMG signals.

Until now, many investigations and research of EMG pattern recognition and classification were carried out for varied purposes. There were several review reports regarding the recognitions and determination techniques of EMG signal for arm motion and diagnostic purposes[1, 2]. The time-series recorded EMG signal from the upper arm to classify the pattern motion using neural networks [2]. A separate study suggested that when reaching, distal arm kinematics can be predicted by using shoulder orientation as the input to a neural network [3].

A few papers presenting results in a similar task are available. Some have applied fuzzy rules to analyze EMG signals as [1, 2]. Other developed neural networks, as [3]. Our work partially originates from Tamaru, et. al. [1], who obtained the classifier able to recognize 6 motions by neural networks without any of Fast Fourier Transform (FFT). About positioning the electrodes, we decided to set them as used in [1].

Recently, the complex-valued neural networks has been studied in the field of the computational intelligence [7]. Complex-valued neural networks are effective in the processing of high-dimensional signals [8]. However, in our approach, we proposed the estimation of 4 motions by using complex-valued neural network with some following proposed method that will be mentioned in another section of this paper.

This paper will be organized as follows.The EMG signal recording method and some motion determination problems are described in section 2. While, in section 3, explained the complex-valued neural network. The experiments of pattern estimation, the structure of the proposed network and result of the proposed method are conducted in Section 4. The final section, Section 5, a brief concluding discussion of this paper is given.

2. Electromyography

2.1 *Surface Electromyography*

Electromyography (EMG) is a study of muscles function through analysis of electrical activity produced from muscles. This electrical activity which is displayed in the form of signal is the result of neuromuscular activation associated with muscle contraction. The origin of EMG is closely related to the work of the nervous system. Electrochemical transmission between nerves starting from the brain produces action potential which propagates through nerve fibers. Action potential moves along the nerve fiber and it will finally stimulate the skeletal muscle. This stimulation creates muscle contraction which is resulting in the movement of human limbs. Action potential acts on

[1]Haslinibinti Abdullah is from the Electronics and Information Science Course, Graduate School of Engineering, Takushoku University, 815-1 Tatemachi, Hachioji, Tokyo, 193-0985 Japan.

[2]Takehiko Ogawa is from the Department of Electronics and Computer Systems, Faculty of Engineering, Takushoku University, 815-1 Tatemachi, Hachioji, Tokyo, 193-0985 Japan.

single nerve and there is a vast number of skeletal muscle fibers.

Thus, the electrical potential of muscle recorded for EMG is actually a superposition of action potentials acting on skeletal fiber muscles [4]. Representation of electrical potential in the form of time varying signal is what we called as EMG signal. By studying the EMG, one is actually looking into the characteristics of body movement due to muscle contraction activity. The obtaining EMG signal from human includes several processes involving recording, data acquisition, signal conditioning and processing. Recording of EMG signal is done by means of electrodes. Three types of electrodes that commonly used is wire, needle and surface electrode where the latter being the most widely used since it is non-invasive[5]. In this paper, we use the Surface Electromyography (SEMG) in its methodology.

2.2 *Motion Determination Problem*

In the developing prosthetic devices, researchers had made use of various types of input to the device for mean control. Due to the fact that prosthetic devices are often used to replace the missing part of human body, bioelectrical signal apparently fit in well into the system. A study on the use of EMG for prosthetic device had initiated back from 1960s [6]. Initial work on the development of EMG controlled prosthetic device would involve analysis of signal for discrimination, classification or feature extraction.

Since the problem of EMG controlled prosthetic device are such as discrimination, classification or feature extraction, thus, in this study, we proposed the method to estimate the pattern of 4 different types of forearm motion. The EMG signals of those motions are captured and recorded by Surface EMG method. Those signals are processed and analyzed by going through the proposed system below.

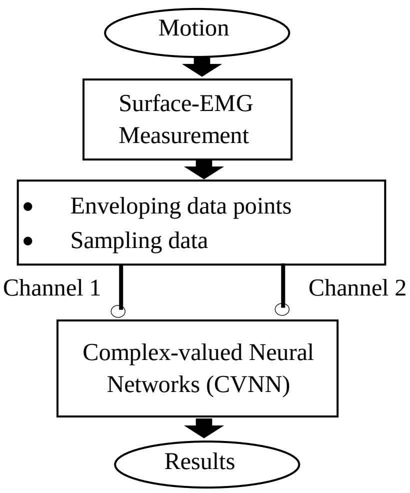


Figure.1 The proposed system

3. Complex-Valued Neural Network

The Complex-Valued Neural Network (CVNN) is an extension of Real-Valued Neural Network (RVNN) whose input and output signals and parameters such as weights and thresholds are all complex numbers (the activation function is inevitably a complex-valued function).

Neural networks are fitted to the data by learning algorithms during the training process. The CVNN training process is the same as the training process for Complex Multi-layered Neural Network. The input error function is defined as $E = E_R + iE_I$, where real and imaginary parts of error function are defined like squared error,

$$E_R = \frac{1}{2}\Sigma_r(y'_{rR} - y_{rR})^2,$$
$$E_I = \frac{1}{2}\Sigma_r(y'_{rI} - y_{rI})^2, \qquad (1)$$

as follows respectively. Here, $y'_r = y'_{rR} + iy'_{rI}$ and $y_r = y_{rR} + iy_{rI}$ denote *r-th* of teacher-output and output, respectively. The complex-weights between intermediate layer and output error layer, $w_{rk} = w_{rkR} + iw_{rkI}$ against gradient can be calculated as the mentioned equation below.

$$\delta_{rR} = (y'_{rR} - y_{rR}) \cdot (1 - y_{rR}) \cdot y_{rR},$$
$$\delta_{rI} = (y'_{rI} - y_{rI}) \cdot (1 - y_{rI}) \cdot y_{rI}, \qquad (2)$$

Then,

$$\frac{\delta E_R}{\delta w_{rkR}} = \delta_{rR} \cdot v_{kR}, \quad \frac{\delta E_I}{\delta w_{rkR}} = \delta_{rI} \cdot v_{kI},$$
$$\frac{\delta E_R}{\delta w_{rkI}} = -\delta_{rR} \cdot v_{kI}, \quad \frac{\delta E_I}{\delta w_{rkI}} = \delta_{rI} \cdot v_{kR}, \qquad (3)$$

Here, $v_k = v_{kR} + iv_{kI}$ shows the input from *k-th* of intermediate layer element to output layer element. Thus, it is defined as,

$$w_{rkR}^{new} = w_{rkR}^{old} - \varepsilon_t(\delta_{rR} \cdot v_{kR} + \delta_{rI} \cdot v_{kI}),$$
$$w_{rkI}^{new} = w_{rkI}^{old} - \varepsilon_t(\delta_{rI} \cdot v_{kR} - \delta_{rR} \cdot v_{kI}), \qquad (4)$$

where it is to correct the complex-weights between the intermediate and output layer. While, ε_t denotes the training coefficient. Besides that, the complex-weights between the input layer of output error and intermediate layer, $w_{km} = w_{kmR} + iw_{kmI}$ against gradient are defined as,

$$\delta_{kR} = (1 - v_{kR}) \cdot v_{kR} \cdot \Sigma_r(\delta_{rR} \cdot w_{rkR} + \delta_{rI} \cdot w_{rkI}),$$

$$\delta_{kI} = (1 - v_{kI}) \cdot v_{kI} \cdot \Sigma_r(\delta_{rI} \cdot w_{rkI} + \delta_{rR} \cdot w_{rkI}), \qquad (5)$$

Then,

$$\frac{\delta E_R}{\delta w_{kmR}} = \delta_{kR} \cdot x_{mR}, \quad \frac{\delta E_I}{\delta w_{kmR}} = \delta_{rI} \cdot x_{mI},$$
$$\frac{\delta E_R}{\delta w_{kmI}} = -\delta_{kR} \cdot x_{mI}, \quad \frac{\delta E_I}{\delta w_{kmI}} = \delta_{kI} \cdot x_{mR}, \qquad (6)$$

can be calculated as mentioned above. Here, $x_m = x_{mR} + ix_{mI}$ denote the input from *m-th* element of input layer to element of the hidden layer. Thus, the following equation

$$w_{kmR}^{new} = w_{kmR}^{old} - \varepsilon_t(\delta_{kR} \cdot x_{mR} + \delta_{kI} \cdot x_{mI}),$$
$$w_{kmI}^{new} = w_{kmI}^{old} - \varepsilon_t(\delta_{kI} \cdot x_{mR} - \delta_{kR} \cdot x_{mI}), \qquad (7)$$

Is to correct the complex-weights between input layer and the hidn layer. While, ε_t denotes the training coefficient. The input-output relations from correction of each complex-weight are trained according to those equations that mentioned above.

4. Experiments

A 25-years old unimpaired male volunteered for the reaching experiment and designated the experiment into four parts of forearm motion. The subject was seated on the chair and starting with the forearm motions from open, grasps, extension and flexion as shown in Figure.2 below.

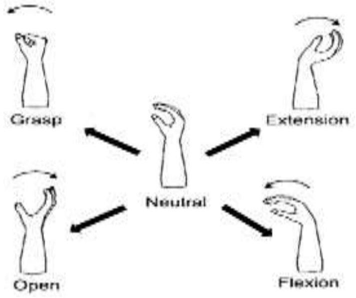


Figure.2 Image figure of forearm motion

The Surface EMG technique was used to objectively monitor the myo-electric signal during performance of the given motion tasks. Following appropriate skin preparation with pairs of disposal surface electrodes were attached to the skin overlying the area of back (Channel 1) and front (Channel 2) intermediate arm. (Figure.3)

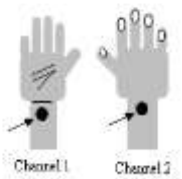


Figure.3 Position of surface electrode

4.1 Network Structure

The Surface EMG was recorded 10 times in each of pattern motion and extracted the feature data for every motion. The five data are used as training data and test data. The structure of proposed network consists of a pre-processing part, a complex-valued neural network (CVNN) and an estimation and discrimination part. First, the EMG signals is pre-processed and converted into EMG envelope using the method of *findpeaks function* which is detecting a signal point as a relative maximum value by comparing the values of interest. Then, the signal data are sampled at five points in the 0.1 sec intervals from starting point. The signals of channel 1 and channel 2 are handled as the real and imaginary parts of inputs, respectively. Thus, the sampling data are applied into CVNN. Finally, the result of CVNN process is used to estimate and determine a motion that corresponds to the most-likely motion intended by a subject.

The CVNN with three-layer; an input layer, a hidden layer, and an output layer, is used for the simulation. The input units correspond to the sampling data of five points of muscle potential. The output units correspond to the code that is assigned to each motion, which are shown in table 1. The objective of the output code is to perform a quantitative evaluation of the motion in the future, though only the determination of the motion in this stage. The number of the hidden neurons was determined to be eight by the results of trial and error. The learning was carried out in the criteria of output error of 0.001 or the number of maximum epochs of 10,000. It was confirmed the learning convergence at 900 epochs.

Table 1 Output code that is assigned to motions.

Motions	Codes	
	Neuron 1	Neuron 2
Extension	0.0+1.0i	0.0+0.0i
Flexion	1.0+0.0i	0.0+0.0i
Grasp	0.0+0.0i	1.0+0.0i
Open	0.0+0.0i	0.0+1.0i

Table 2 Network parameters.

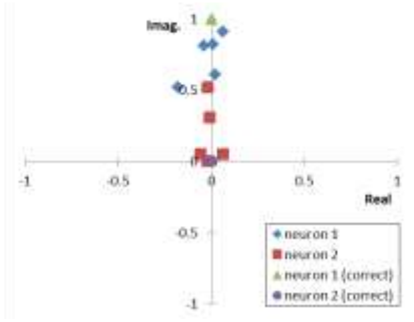
Parameters	Values
Number of input neurons	5
Number of hidden neurons	8
Number of output neurons	2
Training gain	0.01
Mean squared error to attain	0.001
Maximum training epochs	10000

4.2 Results

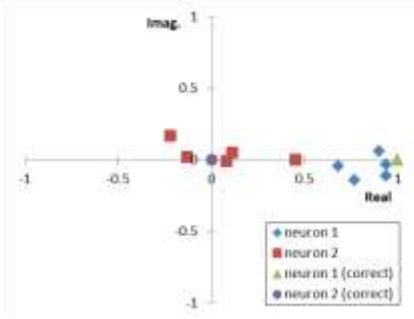
The experiment results of each motion are shown in figures as follows. Those results show a plot in complex-plane of two neurons complex output when inputting the muscle potential sampling data corresponding to each motions. According to the results, it can be seen that in each case of motions, the output point distributed near around the correct output codes. Then, distance between estimated output of each motions and the correct output (error) are shown in Table 3. According to it, the average error is about 0.2, but it can be seen that there are variations depending on the data.

From the results, it shows that the proposed method we adopted give the effective in estimation and determination of forearm motions. However, from the obtained data and correct values, it shows varies widely.

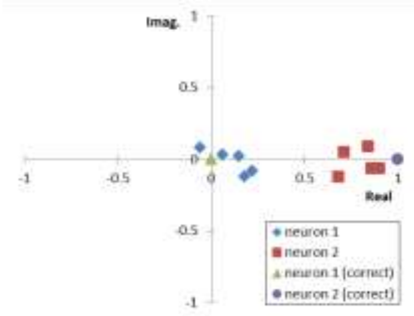
Future study into such as improvement of pre-processing, removal of unnecessary data, improvement of network structure and parameters may lead to even better estimation accuracy and quantitative evaluation motion.



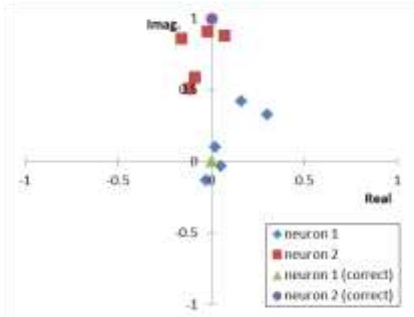
(a)



(b)



(c)



(d)

Figure.5 Output results for each motion input; (a) extension, (b) flexion, (c) grasp, and (d) open.

5. *Conclusion*

In this paper, a method of neural network in complex plane, which is called Complex-Valued Neural Network (CVNN), was proposed to estimate the forearm motions from the recorded myoelectric signal by Surface EMG (SEMG). Furthermore, the computer simulation was performed by using the obtained data in the experiment of SEMG. The obtained results show that the proposed method can make the effective estimation of forearm motion. In addition, in this paper we also discussed about the estimation accuracy from four different of forearm motion.

In future study, in order to improve the estimation accuracy, we would like to improve the pre-processing method of varying EMG signal. Estimation and discrimination performance could possibly be improved as the improvement of encoding output or a new pre-processing method.

Table 3 Distance between estimated output and correct output code in each motion.

Test sets		Error	Ave. error
Extension	1	0.129	0.239
	2	0.093	
	3	0.517	
	4	0.107	
	5	0.350	
Flexion	6	0.099	0.196
	7	0.202	
	8	0.360	
	9	0.222	
	10	0.099	
Grasp	11	0.110	0.186
	12	0.108	
	13	0.264	
	14	0.200	
	15	0.247	
Open	16	0.136	0.256
	17	0.475	
	18	0.075	
	19	0.435	
	20	0.157	
Average		0.219	

References

[1] Hiroki Tamura, Dai Okumura, Koichi Tanno, "A study of Motion Recognition without FFT from Surface-EMG", Institute of Electronics, Information and Communication Engineering Conference, 2007/9 , Vol. J90-D, No.9.

[2] Toshio Tsuji, Osamu Fukuda, Makoto Kaneko, and Koji Ito, "Pattern classification of time-series EMG signals using neural networks", Int. J. Adapt. Control Signal Process. 2000; 14:829-848.

[3] R. Kaliki, R. Davoodi, and G.loeb, "Prediction of Distal Arm Posture in 3-D Space from Shoulder Movements for Control of Upper Limb Prostheses", Proceedings of the IEEE, vol.96, no.7, pp.1217-1225, Jul, 2008.

[4] J.V Basmajian and C.J. De Luca, "Muscle Alive, Their Function Revealed by Electromyography", Baltimore: Williams &Wilkens, 1985.

[5] B. Gerdle, S. Karlsson, S. Day, and M. Djupsjöbacka, "Acquisition, Processing and Analysis of the Surface Electromyogram ", in Modern Techniques in Neuroscience, U. Windhorst and H. Johansson, Eds. Berlin : Springer Verlag, 1999, pp. 705-755.

[6] K. Englehart, B. Hudgins, P. Parker, "Multifunction control of prostheses using the myoelectric signal", in Intelligent systems and technologies in rehabilitation engineering, H.-N. Teodorescu, L. C. Jain, Eds. Florida: CRC Press Inc., 2001, pp. 153-208.

[7] A. Hirose, "Complex-valued neural networks", Springer 2006.

[8] T. Nitta (ed), "Complex-valued neural networks: Utilizing high-dimensional parameters", IGI-Global, 2009.