Application of Quaternion Neural Network to EMG-Based Estimation of Forearm Motion

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Abstract – This paper presents the Application of Quaternion Neural Network (QNN) to Electromyography (EMG) based Estimation of Forearm Motion. Motion of human body can be modeled as a set of rotations in three-dimensional space by various joints. The aim of this research is to show the efficiency of QNN in estimation from EMG. We are trying to learn, estimate and simulate combined motion using QNN as well as comparing the estimation efficiency with the feedforward neural network (FNN). We are measuring EMG signal of target muscles while performing basic forearm motion. The efficiency of the estimation then determines by simulation with combine motion of forearm. It is expected in better performance of estimation in QNN compare to FNN.

Keywords: Quaternion Neural Network, Surface Electromyography, Forearm Motion

1 Introduction

In previous year, research on neural networks extended to the application of quaternion has been conducted, and various models such as multilayer neural network and interconnecting neural network system have been proposed \cite{1,2}. Quaternions are useful especially for expressing data in three-dimensional space, and are often used for three-dimensional computer graphics and robot control. There are several remarkable practical applications such as in image compression \cite{2}, and in image processing called color night vision \cite{3}. However, the application of Quaternion Neural Network (QNN) in bio signal estimation such as in Electromyogram (EMG) signal is almost none. Motion of human body can be modeled as a set of rotations in three-dimensional space by various joints. For instance, human forearm motion can be modeled mainly by posture in three-dimensional space centered on elbow joint. Thus, in our previous paper, we are proposing the application of QNN to EMG based estimation of basic forearm motion \cite{4}. We estimated three forearm motions; flexion, pronation and external rotation using data that is not used as learning data. The result of the research is quite impressive; it has been shown that it is possible to estimate forearm motion with significantly small estimation error. Nevertheless, we think there is a need to research on higher level of estimation problem to show the efficiency of QNN, since feedforward neural network (FNN) can also perform well in basic estimation problem of forearm motion.

Consequently, in this research, we are trying to learn and estimate combined motion using QNN as well as comparing the estimation efficiency with the feedforward neural network. We are measuring EMG signal of target muscles while performing basic forearm motion. After EMG signal acquisition, the features are extracted using time domain analysis and tested using ANOVA \cite{5} to determine feature’s validity before being employ to the network as learning data. The efficiency of the estimation then determines by simulation. Through estimation and classification of EMG signal in three-dimensional space, it is possible to generate control commands for prosthesis and robot control.

2 Neural Network Application

2.1 Quaternion Neural Network

In mathematics, the quaternions are a number system that extends the complex numbers. It is one of higher dimensional numbers, and it consists of one real part and three imaginary parts. Given the imaginary units as \(i, j, k\), a quaternion can be written as \(x = x_0 + ix_1 + jx_2 + kx_3\). Here, \(x_0, x_1, x_2, x_3\) are real numbers representing each component of the quaternion. The imaginary units satisfies \(i^2 = j^2 = k^2 = ijk = -1\), \(ij = -ji = k, jk = -kj = i, ki = -ik = j\). Quaternion have the characteristic of satisfying the associative law with the respect to the multiplication but not satisfying commutative law.

The advantage of using quaternions is that it is easy to express the coordinate system in three-dimensional space, particularly in expressing arbitrary rotation. In the multilayer model, we can learn the relation between input and output expanded to quaternion number using quaternion weight and quaternion neuron. In this research, we consider a neuron that uses a sigmoid function independently for each part of a quaternion input. For input \(s = s_0 + is_1 + js_2 + ks_3\),

\[g(s) = f(s_0) + is_1 + jf(s_2) + kf(s_3),\]
\[f(u) = \frac{1 - e^{-u}}{1 + e^{-u}}\]  \hspace{1cm} (1)

This is three-layer network. In learning process, weight updating is performed by using quaternion learning input/output data based on error back propagation method extended to quaternion number. The error function is the square error of quaternion output.
\[
E = \frac{1}{2} \sum_r (d_r - y_r)^2
\]  

Here, \(d_r\) and \(y_r\) represent the output and network output given to the \(r\)th element, respectively. The correction amount \(\Delta w_{qr}\) of the hidden-output weight and the correction amount \(\Delta w_{pq}\) of the input-hidden are, respectively,

\[
\Delta w_{qr} = ((d_r - y_r) \cdot (1 - y_r) \cdot (1 + y_r)) \cdot \overline{v_q}
\]

\[
\Delta w_{pq} = ((1 - v_q) \cdot (1 + v_q) \cdot \sum_r \delta_r \cdot \overline{w_{qr}}) \cdot \overline{x_p}
\]

However,

\[
d_r = (d_r - y_r) \cdot (1 - y_r) \cdot (1 + y_r)
\]

Here, the multiplication of each quaternion element by the symbol “\(*\)”. \(v_q\) and \(x_p\) represent outputs from the \(q\)th hidden and \(p\)th input respectively. “\(I\)” is a quaternion whose elements are 1. These weight correction amount are updated based on the equation of,

\[
w_{\text{new}} = w_{\text{old}} - \varepsilon \Delta w
\]

\(\varepsilon\) is learning coefficient. By repeating this procedure, we can learn mapping relation between quaternion inputs and output.

### 2.2 Feedforward Neural Network

As a comparison to QNN, we are using Feedforward Neural Network (FNN) to estimate the complex forearm motion. Using back propagation, the same input signal that feed to the QNN are propagated forward through the network. The training process is iteratively adjusted to minimize error and increase performance of network. The input values are generalized between from -1 to 1. In the hidden layers, the weights and biases are updated along the learning process. The network performance will be evaluated using Mean Square Error (MSE). The lower the MSE will indicate the best network performance will be evaluated using Mean Square Error to compare the efficiency of both.

### 3 EMG Feature Extraction

In order to collect EMG signal for this research, 5 male volunteers without any physical disorder are chosen as the subject. We are taking the surface EMG signal of target muscle which is biceps brachialis, pronator teres and infraspinatus of each motion; flexion, extension, pronation, supination, external rotation and internal rotation of forearm and as for revision, surface EMG signal of intermediate position also be taken. For this experiment, we are taking 5 different data for every motion. For acquisition of EMG signal, we are using disposable electrode, which are attached to the skin layer above the biceps brachialis muscle, pronator teres muscle, and infraspinatus muscle, by bipolar induction. The surface EMG signal collected from the electrode is amplified and filtered by biological amplifier, and taken into the PC via the signal processing device to the analysis system. The surface EMG signal is measured by repeating each forearm motion describe before for multiple times.

In order to obtain satisfaction, input data for the experiments, the obtained surface EMG is subjected to full-wave rectification to convert the entire input waveform to positive polarity. As the time domain features are the most popularly used among researcher, we decide to extract Mean Absolute Value (MAV) and Variance (VAR) from the recorded EMG signal, MAV will be use as input to the network while VAR are used to conduct ANOVA test [5], to ensure validation of the feature.

### 4 Simulation

Using the data obtained by the above extraction, a simulation of motion estimation using a QNN and FNN will be conduct. For QNN, 3 input and 1 output QNN is to be used. For FNN, 3 input and 1 output network is to be used. The input for the networks is MAV from the three channel surface EMG corresponding to each motion. The output is forearm motion. The 5 different data taken for every motion of each targets earlier are divided into learning data and test data in the ratio of 60:40. Learning and estimation will be conduct 5 times by exchanging data used for learning and testing. Both network then will be test use combine motion of test data, and the performance of network will be evaluate again using MSE to compare the efficiency of both.

### 5 Conclusion

We are proposing the application of QNN to EMG based estimation of forearm motion. We will train the network with simple motion before simulate it using combine motion of forearm, and compare the efficiency with FNN. It is expected in better performance of estimation in QNN compare to FNN.

### 6 References


