EMG-based Real-Time Joint Angle Extraction Method for Human Elbow: Pre-processing and Optimization Process

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Abstract—This paper proposes a real-time joint angle extraction method of human elbow by processing the biomedical signal of surface EMG (electromyogram) measured at the center point of biceps brachii. Actually, the EMG is known as non-stationary signal, but we assume that it is quasi-stationary because a physical or physiological system has limitations in the rate at which it can change its characteristics. Based on the assumption, a pre-processing method to obtain pre-angle values from raw EMG signal is firstly suggested, and then a optimization method to minimize the error between the pre-angle and real joint angle is proposed in this paper. Finally, we show the effectiveness of the suggested algorithm through experimental results.

Keywords—EMG, Signal Processing, Elbow Joint Angle

1. Introduction

There have been many researches about biomedical signal processing methodologies in [1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11]. As a matter of fact, the human body generates various bioelectrical signals such as ECG (Electrocardiogram), EEG (Electroencephalogram: popularly known as brain waves), EMG (Electromyogram), etc [1]. Among these kinds of bioelectrical signals, the EMG signal has been actively studied for the human muscle analysis, motion imitation in robotics and rehabilitation engineering [2], [3], [4], [5], [6], [10].Especially, the EMG signal has been one of the best candidates to develop the bio-mechanical system by transferring the robotics technologies to the rehabilitation ones. There are many kinds of methods for EMG signal processing, e.g., Hill-based model approach [2], learning method [3], and AR (auto-regressive) modelling method [4]. Recently, the pattern recognition of EMG signals has been used for the motion generation of prosthetic hand in [5]. Also, the ARMAX (auto-regressive-moving average with exogenous output) model has been used for the tele-operation through the EMG signal processing in [6]. The adaptive methods have been developed to cancel the noise which is present in the biomedical signals in [7], [8]. Also, though not EMG signal, the study of human motion imitation has been carried out by using a magnetic sensor plus accelerometer in [12].

In this paper, we are to suggest the elbow joint angle extraction method from the surface EMG signals attached to the biceps muscle for the real time motion tracking. Firstly, we assume that the EMG signal is quasi-stationary, in fact, most biomedical systems are dynamic and produce nonstationary signals, but a physical or physiological system has limitations in the rate at which it can change its characteristics. This limitation facilitates breaking a signal into segments of short duration, over which the statistics of interest are not varying, or may be assumed to remain the same. Then, the signal can be referred to as quasi-stationary one [1]. Algorithm to be suggested consists of two processing states: pre-processing and optimization-process. In the pre-processing, the signals are processed with taking the RMS (root-mean-squares) in a given period of moving window, filtering noises out with LPF (low pass filter) and making polynomial interpolation about given a few data. And then, the pre-angle values are obtained kinematically for elbow joint angles. As a second stage, the optimization-process is proposed by using Lagrange multiplier method for the minimization of a given performance index. Finally, the processed signals are directly used for the real-time motion tracking of elbow joint, in other words, we suggest the real-time motion tracking simulation results which follow the flexion and extension motion of a human elbow joint well.

This paper is organized as follows; in section 2, the pre-processing method is proposed to obtain the pre-angle values; in section 3, the optimization problem and its solution are suggested; in sections 4 and 5, we show the experimental results and draw the conclusion, respectively.

2. Pre-processing of EMG Raw Signal

In this section, the pre-processing method is suggested to obtain the pre-angle which will be used in optimization process later. The pre-processing procedures consist of taking the RMS (root-mean-squares) in a given period of moving window, filtering noises out with LPF (low pass filter), and making polynomial interpolation about given a few data. And then, the pre-angle values are obtained kinematically for elbow joint angles. Before explaining the pre-processing, let us consider the kinematic characteristics of human elbow joint. The human elbow joint motion is defined as flexion and extension as shown in Fig. 1, also, the range of motion of elbow joint is known as about 0 ∼ 145°. Actually, there may be a hyperextension of about 0 ∼ −5° though it is different according to experimenters. In general, since the hyperextension is very small, we are to exclude the hyperextension for

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simplification of the algorithm development. Also, though the power source muscle of flexion motion is the biceps brachii and that of extension motion is the triceps brachii in the anatomical terminology, we will focus only on the biceps brachii because the signal of the triceps brachii is very weak comparing to that of biceps brachii. In addition, the attachment points of electrodes become very weak according to time progress (1024 samples = 1[s]). Although the EMG signal is sensitive to various environmental conditions, the attachment points of electrodes become very important for precise signal acquisition. So, we try to attach the electrodes to the center of motor point of biceps brachii. Also, we make use of Ag/AgCl (bipolar) one time electrodes which are widely used for the precise biomedical signal acquisition.

2.1 Taking RMS & LPF

First, we set the sampling frequency to 1024[Hz] for the fast EMG data acquisition. Fig. 2.(a) shows the raw EMG signal acquired from flexion first and then extension motion according to time progress (1024 samples = 1[s]). Although the maximum amplitude of EMG signal is different according to the experimenters and the gripping force of hand, here, it becomes about ±150[μV] at a natural status with no gripping force. As we can see in Fig. 2.(a), the sequential flexion and extension motions have something to do with the amplitude of signal. More concretely, the amplitude increases as the elbow joint angle increases, though they do not seem to be linear. Here, we take RMS (root-mean-squares) value with \( T \) samples moving window to obtain the average envelope information as following form:

\[
RMS[n] = \sqrt{\frac{1}{T} \sum_{k=n-(T-1)}^{n} EMG[k]^2} \quad \text{for} \quad n = 0 \ldots m
\]

where \( RMS[n] \) means the RMS value with \( r \) samples moving window and \( EMG[k] \) means the raw EMG signal at \( k \)-th sample with \( EMG[k] = 0 \) for \( k = -(T-1) \ldots -(T-2) \ldots -1 \), here, \( T = 64 \) was used for the RMS operation. As a matter of fact, the RMS value of signal includes the information of power as well as the envelope. As shown in Fig. 2.(b), the RMS values show the similar characteristics with positive envelope of EMG signal.

Second, we take the LPF (low pass filer) to RMS signal because the human elbow motion has the bandwidth of at most a few Hertz as following simple form:

\[
LPF[n] = \theta RMS[n] + (1 - \theta)LPF[n-1] \quad \text{for} \quad n = 0 \ldots m
\]

where \( LPF[n] \) means the low-pass-filtered signal at \( n \)-th sample with \( LPF[-1] = 0 \) and \( \theta \) is defined as follow:

\[
\theta \triangleq 2\pi f_c T
\]

where \( T \) is a sampling period of 1 1024[s] and \( f_c \) means the cutoff frequency in [Hz] for low pass filtering, here, \( f_c = 1 \). The corresponding LPF signals are shown in Fig. 2.(c). So, we can get the smooth signal for the flexion and extension motion of elbow joint. These LPF signals will be used for the generation of pre-angle as explained in following section.

2.2 Pre-angle Generation

The pre-angle generation method is based on the curve-fitting using polynomial interpolation. In other words, for a given specific elbow joint angle, we get the averages of LPF values of (2) as following form:

\[
V_{LPF}[q_i] = \frac{1}{L+1} \sum_{k=0}^{L} LPF[k] \quad \text{for} \quad k = 0 \ldots L
\]

where \( V_{LPF}[q_i] \) means the average of LPF values at a specific joint angle \( q_i \) and \( i \) is the number of specific joint angle. At four specific joint angles of 0° 45° 90° and 125°, the averages of LPF values are obtained as shown in Fig. 3 with \( L = 512[samples] \) or 0 5[s]. For example, the first figure in Fig. 3 shows that the average of LPF values calculated at elbow joint angle of 0° is 5 2618[μV], and remaining figures show corresponding data as follows:

- at 0°: \( V_{LPF}[0] = 5 2618[μV] \)
- at 45°: \( V_{LPF}[45] = 10 4527[μV] \)
- at 90°: \( V_{LPF}[90] = 20 9107[μV] \)
- at 125°: \( V_{LPF}[125] = 42 6719[μV] \)

With four given data set, the polynomial interpolation can be implemented for third-order polynomial function as following form:

\[
q_i = a_0 + a_1 V_{LPF}[q_i] + a_2 V_{LPF}[q_i]^2 + a_3 V_{LPF}[q_i]^3
\]

where \( a_0 \) a1 a2 a3 mean the coefficients to be determined by using above given data set. Their coefficients are obtained as:

\[
\begin{align*}
a_0 &= -66 9660 \\
a_1 &= 15 0567 \\
a_2 &= -0 4703 \\
a_3 &= 0 0052
\end{align*}
\]

Now, the scaling function between the LPF value and pre-angle of elbow joint can be obtained as shown in Fig. 4. As a result, the pre-angle is generated in real-time by using above coefficients determined from polynomial interpolation as following form:

\[
x[n] = a_0 + a_1 LPF[n] + a_2 LPF[n]^2 + a_3 LPF[n]^3
\]
(a) EMG signal acquired from flexion first and then extension motion

(b) RMS signal taken through a given moving window of 64 samples

(c) Signal obtained using LPF with cutoff frequencies of 1[Hz]

Fig. 2. Signal obtained by taking RMS & LPF

Fig. 3. Averages after taking RMS and LPF for raw EMG signal measured at specific joint angles; first figure is obtained at elbow joint angle of 0°, second one at 45°, third one at 90° and fourth one at 125°. (In figures, the dotted lines are the averages of entire LPF values)

Fig. 4. Scaling function between pre-angle and LPF signal of Eq. (2)

where \( x[n] \) means the pre-angle of elbow joint calculated at \( n \)-th sample and \( LPF[n] \) is obtained by (2). This pre-angle is the resultant signal of pre-processing procedure and will be used as an input signal of the optimization process to minimize the tracking error in the following section. In addition, we should notice that the proposed processes can be implemented in real-time with \( T \) samples (64 samples or 62.5[ms]) delay.

3. Optimization Process

The pre-angle generation method suggested in the previous section can be directly used for real-time motion tracking of elbow joint, however, it does not guarantee the minimum error between the pre-angle and real elbow joint angle. In this section, we are to solve the optimization problem for error minimization with constraints. Here, we assume that the joint angle to be estimated has the following second-order dynamic relation with pre-angle obtained from the pre-
expressed as a vector form:

\[ q[n] = w(n)^T x(n) \]  

(7)

where \( q[n] \) is the elbow joint angle estimate, \( x[n] \) is the pre-angle obtained from (6) and \( w_k[n] \) means the tap-weights for \( k = 0 \ 1 \ 2 \) at \( n \)-th sample. Also, above equation can be expressed as a vector form:

\[ q[n] = w(n)^T x(n) \]

(7)

where

\[ w(n) \triangleq [w_0[n] \ w_1[n] \ w_2[n]]^T \]

(8)

\[ x(n) \triangleq [x[n] \ x[n-1] \ x[n-2]]^T \]

(9)

with \( x[-1] = x[-2] = 0 \). Also, as we can see in Fig. 5, the error between the elbow joint angle estimate of (7) and the real angle measured from the tilt sensor attached to the wrist can be defined as following form:

\[ e[n] = q_d[n] - q[n] = q_d[n] - w(n)^T x(n) \]

(10)

where \( e[n] \) is the error and \( q_d[n] \) the real elbow joint angle. In addition, the minimization for the rate of tap-weight change is required to avoid the numerical instability, here, we are to suggest the performance index as following form:

\[ J = [w(n) - w(n-1)]^T [w(n) - w(n-1)] + \alpha E[e(n)^2] \]

(11)

where \( E[e(n)^2] \) is the expectation operator and \( \alpha \) means the ratio between the change rate of tap-weight vector and error, and \( E[e(n)^2] \) has the following form:

\[ E[e(n)^2] = E[q_d[n]^2] + w(n)^T x(n) x(n)^T w(n) - 2q_d[n]^T x(n)^T w(n) \]

\[ = E[q_d[n]^2] + w(n)^T E[x(n) x(n)^T] w(n) - 2E[q_d[n] x(n)^T] w(n) \]

\[ = E[q_d[n]^2] + w(n)^T R(n) w(n) - 2p(n)^T w(n) \]

(12)

with the definitions of auto-correlation matrix and cross-correlation vector as following forms:

\[ R(n) \triangleq E[x(n) x(n)^T] \in \mathbb{R}^{3 \times 3} \]

\[ p(n) \triangleq E[q_d[n] x(n)] \in \mathbb{R}^3 \]

With above definitions, we are to suggest the Lagrangian function with the constraint \( (q_d[n] = w(n)^T x(n)) \) as following form:

\[ \mathcal{L}(w(n) \ \lambda) \triangleq \frac{1}{2} J + \lambda (q_d[n] - w(n)^T x(n)) \]

(13)

where \( \lambda \) means a Lagrange multiplier. And then, by taking the derivatives with respect to \( w(n) \) and \( \lambda \), we can get the followings:

\[ \frac{\partial \mathcal{L}}{\partial w(n)} = w(n) - w(n-1) + \alpha R(n) w(n) - \alpha p(n) \]

\[ - \lambda x(n) = 0 \]

\[ \frac{\partial \mathcal{L}}{\partial \lambda} = q_d[n] - w(n)^T x(n) = 0 \]

Now, let us rearrange above equations, then we can get the following matrix-vector equation:

\[ \begin{bmatrix} I + \alpha R(n) & x(n)^T & 0 \\ x(n)^T & 0 & -\lambda \\ W(n) - W(n) x(n) x(n)^T W(n) & W(n) x(n) y(n) & 1 - y(n) \end{bmatrix} \begin{bmatrix} w(n) \\ w(n-1) + \alpha p(n) \\ q_d[n] \end{bmatrix} \]

(14)

where \( I \in \mathbb{R}^{3 \times 3} \) is an identity matrix. This kind of matrix is referred to as a “bordered gramian matrix”. The inverse of bordered gramian matrix has the following form:

\[ \begin{bmatrix} I + \alpha R(n) & x(n)^T & 0 \\ x(n)^T & 0 & -\lambda \\ W(n) - W(n) x(n) x(n)^T W(n) & W(n) x(n) y(n) & 1 - y(n) \end{bmatrix} \]

\[ \begin{bmatrix} (I + \alpha R(n))^{-1} \\ x(n)^T W(n)^{-1} \\ y(n) \end{bmatrix} \]

(14)

with the following definitions:

\[ W(n) \triangleq [I + \alpha R(n) + x(n) x(n)^T]^{-1} \]

\[ y(n) \triangleq [x(n)^T W(n) x(n)]^{-1} \]

Now, we can get the exact solution of (14) by using above inverse matrix. Solving this equation gives

\[ w(n) = [W(n) - W(n) x(n) x(n)^T W(n)] x(n) + \alpha p(n) \]

\[ w(n-1) + \alpha p(n) \]

(15)

Also, by rearranging above equation, we can get the following:

\[ w(n) = x_w(n) + T q_d[n] + [I - x_w(n)^T x(n)^T] W(n) [w(n-1) + \alpha p(n)] \]

(16)

with the following definition:

\[ x_w(n)^T \triangleq W(n) x(n) y(n) \]

\[ = W(n) x(n) [x(n)^T W(n) x(n)]^{-1} \]

As a result, the tap-weight vector is updated by (16) in order to minimize the performance index of (11). After updating the tap-weights, the elbow joint angle estimates are obtained by using (7) with static tap-weights. In the follow section, the experimental results are suggested to show the effectiveness of the proposed pre-processing and optimization-process.
4. Experimental Result

The suggested EMG signal processing algorithms are summarized as shown in Fig. 6. Firstly, the scaling function is obtained from the pre-processing and then the pre-angles can be calculated in real-time. Second, the tap-weights are obtained from the optimization-process and then the elbow joint angle estimates are calculated in real-time through entire signal processing. In order to acquire the surface EMG and real elbow joint angle, the QEMG-4(manufactured by LAXTHA Co.) and EZ-TILT-2000 rev-2(manufactured by Advanced Orientation Systems, Inc.) were utilized in experiments, respectively. The electrodes are attached to the biceps brachii of experimenter and the tilt sensor is equipped with a wrist of experimenter in order to acquire the real elbow joint angle. Also, the suitable GUI (graphic user interface) module was developed by using OpenGL and Visual C++ version 6.0. At first, the initializations are required to implement the suggested algorithm; the initialization includes obtaining scaling function for pre-angle generation and updating tap-weights for elbow joint angle estimate.

4.1 Initialization

The surface EMG signal is very sensitive according to the environmental conditions, the physical conditions of experimenter and the electrode attachment points. So, we have to obtain the scaling functions in advance for pre-angle generation. These procedures have been explained in the previous section 2.2. By using the pre-angle and real elbow joint angle, the optimal tap-weights have been updated by using (16) with $\alpha = 1$ as shown in Fig. 7.

4.2 Real-time Experiment

After updating tap-weights in the optimization-process, we could get the experimental results as shown in Fig. 8. In Fig. 8.(a), we can see that the elbow joint angle estimate $q[n]$ tracks the real angle $q_d[n]$ better than pre-angle $x[n]$. The error between real angle and angle estimate is smaller than the error between the real angle and pre-angle as shown in Fig. 8.(b). Also, in order show the performance improvement by optimization quantitatively, we have suggested the $L_2$-norm values as shown in Table 1. The data in the table has said that the tracking performance by using optimization is improved almost two times than the tracking performance without optimization.

Also, we have suggested the snapshots captured from the experimental video as shown in Fig. 9. From these snapshots, we can know that the virtual arm of GUI module follows the elbow joint motion of experimenter well. Also, we could confirm the similar experimental results by repetitive

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Table 1. $L_2$-NORM COMPARISON

<table>
<thead>
<tr>
<th>Error before optimization</th>
<th>Error after optimization</th>
</tr>
</thead>
<tbody>
<tr>
<td>$e_{x[n]} = q_d[n] - x[n]$</td>
<td>$e_{q[n]} = q_d[n] - q[n]$</td>
</tr>
<tr>
<td>4.3548</td>
<td>2.1228</td>
</tr>
</tbody>
</table>

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5. Concluding Remarks

This paper has suggested the real-time extraction method for a human elbow joint angle by using the EMG signal processing. The pre-processing and the optimization process were proposed in detail based on the assumption that the measured EMG signal is quasi-stationary with no gripping force of hand. Finally, we showed the effectiveness of the suggested algorithm through experiments. In the future, we will try to apply the suggested algorithms to the robotic and prosthetic machine for a lower arm amputee.

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