

Improvement of Estimation Accuracy of Body Motion Based on Muscle Potential Signal

Yoshino Shingo¹, Hatakeyama Shoshiro¹, Iwase Masami¹ and Inoue Jun¹

¹ Dept. of Robotics and Mechatronics University of Science and Technology for Future Life, Tokyo Denki University, 5 Senju-Asahicho Adachi, Tokyo 120-8551, Japan

Email: yoshino@ctrl.fr.dendai.ac.jp

Abstract. The purpose of this research is to develop a man-machine interface that changes machine impedance based on surface myoelectric potential. The impedance model of the wrist joint is constructed from the measured data to derive the moment of inertia, viscosity coefficient and rigidity of the human's wrist joint, investigate the relationship between human joint impedance and electromyography (EMG), according to the change of EMG from the relationship, We have developed an interface to change the mechanical impedance of the robot arm. We investigate the relationship between human joint impedance and EMG, and apply the sparse modeling method to the modeling process. We have created an interface to change the mechanical impedance of the robot arm based on the model. As a result, myoelectric potential and force data have been acquired. Also, mechanical impedance has been acquired. In this study, we improve the estimation accuracy of physical motion by selecting characteristic parameters and terms using sparse modeling, which is considered to be feasible by estimating the force that occurs at the same time as the position at the time of physical movement.

1. Introduction

The purpose of this study is to improve the estimation of physical motion by EMG. The human body consists of various muscles, large and small, and the desired behavior is realized by the action of each muscle. Then, when the muscle is activated, an action potential called a EMG is generated. EMG have a feature called electrodynamic delay that occurs a few seconds earlier than the actual physical movement, such as the meaning of motion and information such as the size of the force. Therefore, by estimating the physical movement from the EMG, it can be used as an interface that mediates between the operator and the machine, such as power assist and teleoperation.

As a study of Man Machine Interface (MMI) using EMG, Hayashi and his colleagues have identified the Nonlinear Regression with EXogenous inputs (NARX) model, which inputs EMG and outputs the neck angle, and has built a system with excellent responsiveness and discretion [1]. However, since physical movement is caused by various muscle interactions, it is necessary to estimate the combined movement of multiple movements in order to cope with cases where multiple muscle groups such as fingers are involved. Hwang and colleagues use the least absolute shrinkage and selection operator (LASSO) for multiple degrees of freedom to extract the feature quantity for each channel obtained from the EMG [2]. Lasso can reduce the term by selecting characteristic parameters and terms and zeroing the other terms.



Using Lasso, Ono et al. constructed a model that considers the interaction of multiple muscle stomors and joint angles for multiple degrees of freedom of motion as a study of models considering muscle interactions, and analyzes the effects on single/complex operations [3]. As a result, Lasso reduces the model term and can estimate the degree of wrist angle with high accuracy. However, there is a problem that the estimation accuracy is low in that the operation is switched. In this study, we aim to improve the estimation degree of physical motion by selecting characteristic parameters and terms using sparse modelling. In addition, the estimation of position control only does not take into account the time of contact with the object. It is thought that it is possible to estimate a more precise physical movement by estimating the force which occurs at the same time as the position at the time of the body movement. In this paper, we report the method of angular degree estimation, force estimation, and future prospects at the time of palm flexion/back flexion of wrists, flexion/ shaku bending.

2. System identification based on EMG

This section describes sparse modelling of l_1 normalization, which simultaneously estimates the parameters of a model and sparses the terms. In addition, we describe a NARX model representing a nonlinear system between the EMG and the motion used in the previous study, and the sequential least squares method to estimate the model parameters.

2.1. Sparse modeling

In this study, the sparse modelling is used to select parameters and terms of the constructed model in order to improve the estimation accuracy of physical motion. By selecting characteristic parameters and terms using sparse modeling, it is thought that overfitting at the time of derivation of the estimated model can be eliminated, and the estimation accuracy is improved [4].

When the vector x of \mathbf{R}^n has many elements of 0, the vector is sparse. Sparse vectors have a small l_0 norm in (1). However, it is in the $|\text{supp}(x)| \triangleq i \in \{1, \dots, n: x_i \neq 0\}$.

$$\|x\|_0 \triangleq |\text{supp}(x)| \quad (1)$$

2.2. NARX model

In this section, we describe a method for constructing a NARX model that represents a nonlinear system between EMG and motion [5]. For the output signal shown in figure 1, a range is set around the output level y_l ($l = 1, 2, \dots, v, v + 1, \dots, V$) relative to 0. And, an ARX model is identified for each range of values. The ARX model near y_l is (2) when the number of input and output data is N , the input of the ARX model is ${}^l u[k]$ ($k = 1, 2, \dots, N$), the output is ${}^l y[k]$, the parameter is ${}^l a_f$ ($f = 1, 2, \dots, F$), ${}^l b_h$ ($h = 1, 2, \dots, H$), and ${}^l c$. However, the output level y_l is $y(k) \in y_l$ and $y_l = [{}^{l-1}y, {}^l y]$.

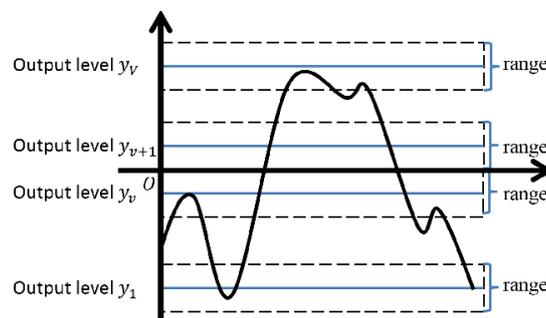


Figure 1. Schematic drawings of NARX model

$${}^l y = {}^l \theta {}^l \phi^T \quad (2)$$

From (2), the parameter vector ${}^l \theta$ of the ARX model is defined as (3), and the data vector ${}^l \phi$ of the input and output is defined as (4).

$${}^l\theta = [{}^l a_1, \dots, {}^l a_n, {}^l b_1, \dots, {}^l b_m, {}^l c] \quad (3)$$

$${}^l\phi = [-{}^l y(k-1), \dots, -{}^l y[k-n], {}^l u(k-1), \dots, -{}^l u[k-m], 1] \quad (4)$$

The set of ARX models for all sections is give in (5).

$$y(k) = \left\{ \begin{array}{l} {}^1\theta^T \varphi(k)^T \quad y(k) \in {}^1y \\ \vdots \\ {}^v\theta^T \varphi(k)^T \quad y(k) \in {}^vy \\ \vdots \\ {}^p\theta^T \varphi(k)^T \quad y(k) \in {}^py \end{array} \right\} \quad (5)$$

When $a_f(y)$, $b_h(y)$, and $c(y)$ are the interpolation functions, the NARX model is give in (6). However, $\hat{y}[k]$ is the output of the model.

$$\begin{aligned} \hat{y}[k] &= \sum_{f=1}^n (-a_f(y)y[k-f]) + \sum_{h=1}^m (b_h(y)y[k-h]) + c(y) \\ a_f(y) &= {}^l a_f y^r + {}^{l-1} a_f y^{r-1} + \dots + {}^1 a_f y + {}^0 a_f \\ b_h(y) &= {}^l b_h y^s + {}^{l-1} b_h y^{s-1} + \dots + {}^1 b_h y + {}^0 b_h \\ c(y) &= {}^l c y^w + {}^{l-1} c y^{w-1} + \dots + {}^1 c y + {}^0 c \end{aligned} \quad (6)$$

2.3. Sequential least squares

In this section, we describe the sequential least squares method, which is estimate model parameters. The parameter estimate ${}^l\theta$ from the data vector ${}^l\phi$ and the output ly is defined as (7).

$$\begin{aligned} \hat{\theta}(N) &= (\sum_{k=1}^N \varphi(k)\varphi^T(k))^{-1} (\sum_{k=1}^N \varphi(k)y(k)) \\ &:= \mathbf{P}(N)\mathbf{Q}(N) \end{aligned} \quad (7)$$

When the inverse matrix of $\mathbf{P}(N)$ is calculated and deformed, (8) is determined.

$$\begin{aligned} \mathbf{P}^{-1}(N) &= \sum_{k=1}^{N-1} \varphi(k)\varphi^T(k) + \varphi(N)\varphi^T(N) \\ &= \mathbf{P}^{-1}(N-1) + \varphi(N)\varphi^T(N) \end{aligned} \quad (8)$$

As in (8), $\mathbf{Q}(N)$ is represented by terms from 1 to $N-1$ and N is an (9).

$$\mathbf{Q}(N) = \sum_{k=1}^{N-1} \varphi(k)y(k) + \varphi(N)y(N) \quad (9)$$

(8) and (9) is assigned to (7), $\hat{\theta}(N)$ can be represented by a $\hat{\theta}(N-1)$ as in (10).

$$\begin{aligned} \hat{\theta}(N) &= \mathbf{P}(N)(\sum_{k=1}^{N-1} \varphi(k)y(k) + \varphi(N)y(N)) \\ &= \hat{\theta}(N-1) + \mathbf{P}(N)\varphi(N)\{y(N) - \varphi^T(N)\hat{\theta}(N-1)\} \end{aligned} \quad (10)$$

By using the idea of inverse matrix lemma here, It is possible to represent $\mathbf{P}(N)$ as shown in (11) by the value $\mathbf{P}(N-1)$.

$$\mathbf{P}(N) = \mathbf{P}(N-1) - \frac{\mathbf{P}(N-1)\varphi(N)\varphi^T(N)\mathbf{P}(N-1)}{1+\varphi^T(N)\mathbf{P}(N-1)\varphi(N)} \quad (11)$$

(11) from $\mathbf{P}(N)\varphi(N)$ is represented by $\mathbf{P}(N-1)$ as shown in (12).

$$\mathbf{P}(N)\varphi(N) = \frac{\mathbf{P}(N-1)\varphi(N)}{1+\varphi^T(N)\mathbf{P}(N-1)\varphi(N)} \quad (12)$$

When (12) is assigned to (10), it becomes e (13). However, the prediction error is $\varepsilon(N)$.

$$\hat{\theta}(N) = \hat{\theta}(N-1) + \frac{\mathbf{P}(N-1)\varphi(N)}{1+\varphi^T(N)\mathbf{P}(N-1)\varphi(N)} \varepsilon(N) \quad (13)$$

$$\varepsilon(N) := y(N) - \varphi^T(N)\hat{\theta}(N-1)$$

(11), (13) is a new time-to-time formula used in the sequential least squares method. However, γ is a positive constant and the initial value of the parameter estimate $\hat{\theta}$ and the covariance \mathbf{P} is (14), (15).

$$\hat{\theta}(0) = \hat{\theta}_0 \quad (14)$$

$$\mathbf{P}(0) = \gamma \mathbf{I} \quad (15)$$

3. Measurement of the movement of the hand joint

We construct a model from the EMG, wrist angle, and contact force at the time of palm flexion and back bending, and evaluate the estimation accuracy of wrist movement. To measure the EMG that occurs during movement and operation of the hand joint when the hand is not in contact with the object and the EMG that occurs during the operation and operation of the hand joint during the operation and operation of the hand during the operation and operation of the hand.

3.1. Measurement of hand joint motion when non-contact to object

Here, we show the wrist movement and the measurement environment of the EMG and the experimental task when the hand is not in contact with an object.

3.1.1 Measurement environment. In this bar, we describe the method of measuring the EMG and wrist angle at the time of palm flexion/back flexion and tibia flexion/shaku flexion and signal processing method. figure 2 shows the measurement environment. We show the EMG obtained by a dry wireless electromyography sensor of in Table 1 ch1 to ch4.

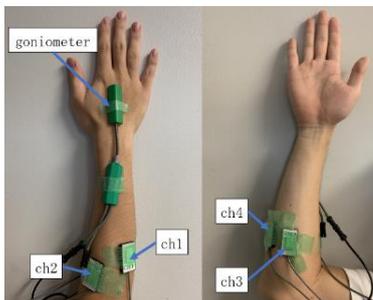


Figure 2. Measurement environment

Table 1. EMG measurement location.

| sensor | Measurement point |
|--------|--|
| ch1 | Short-tibia lateral carpal elongus |
| ch2 | Long tibia lateral carpal esotusmuscle |
| ch3 | flexor carpal muscle |
| ch4 | flexor carpal muscle |

Get the wrist angle by attaching a goniometer to the back of your hand. In this work, we obtain EMG and wrist angular velocity both at a sun-pling time of 1 ms. Then, the measured signal is the operation characteristic is extracted by the processing shown in figure 3, and it is an input signal for the same constant. The cut-off frequency of the EMG is 5 Hz. In addition, the cut-off frequency of the low frequency component of the wrist angle is 0.05 Hz, and the number of cut-off frequencies of the high-frequency component at 5 Hz. In the smoothing of figure 3, a low-pass filter of equation (16) is applied to the EMG. For wrist angle, the bandpass filter of equation (17) is applied. For wrist angle, the bandpass filter of equation (17) is applied.

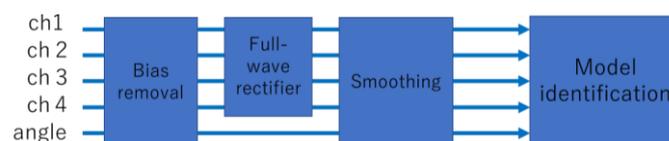


Figure 3. Method of the signal processing

$$G_l(s) = \frac{w_l^2}{(s+w_l)^2} \quad (16)$$

$$w_l = 2\pi f_l \quad f_l = 5 \text{ Hz}$$

$$G_b(s) = \frac{sw_b^2}{s^2 + (w_b1 + w_b2)s + w_b1w_b2} \tag{17}$$

$$w_b1 = 2\pi f_b1 \quad w_b2 = 2\pi f_b2 \quad 2f_b1 = 0.05 \text{ Hz} \quad f_b2 = 5 \text{ Hz}$$

3.1.2 *Experimental tasks.* In this experiment, the wrist is repeated alternately by the operation of the palm flexion / back bending while the hand does not come into contact with the object as in figure 4, and the angular displacement θ of the hand neck obtained from the EMG and the goniometer at the time of operation is measured. In addition, the angular displacement θ of the wrist obtained from the EMG and the goniometer at the time of operation is repeated alternately as at the time of palm flexion / back bending as at the time of flexion / shaku bending as figure 5.

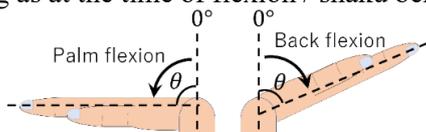


Figure 4. Palm bending / back-bending operation when non-contact

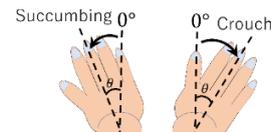


Figure 5. Deflection / shakubutting operation when non-contact

3.1.3 *Experimental results.* It shows the measurement result of the wrist movement and myoelectric position signal in the state where the hand is not in contact with the object. The EMG of ch1, ch2 are at the time of palm flexion / back bending in figure 6 and figure 7, the ch1, ch2 at the time of succumbing / back bending, the wrist angle at the time of palm flexion / back bending in figure 8, the EMG of ch1, ch2 at the time of tibia bending / shaku bending in figure 9 and figure 10 to tibia / shaku flexion , showing the wrist angle at the time of flexion / succumb in figure 11. Since the EMG is positive and negative, the EMG of ch1, ch3 is converted to a negative value to make it easier to see the graph after the signal processing. We design an estimation model based on this measurement data.

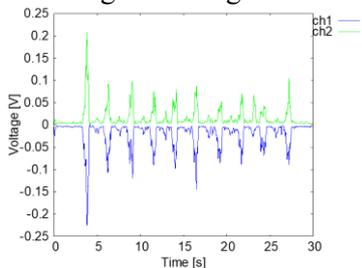


Figure 6. EMG signal during palm flexion / dorsiflexion of ch1 and ch2

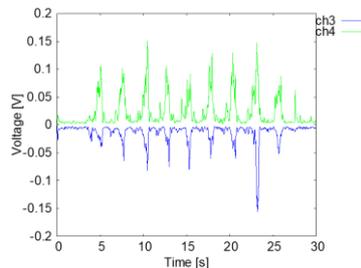


Figure 7. EMG signal during palm flexion / dorsiflexion of ch3 and ch4

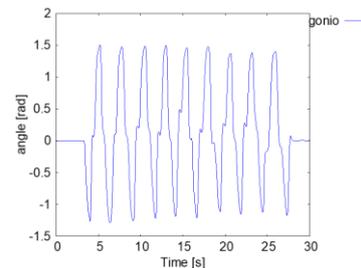


Figure 8. Angle during palm flexion / dorsiflexion

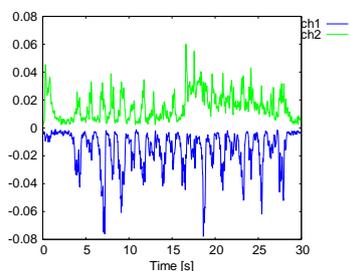


Figure 9. EMG signal during cramped / crouch of ch1 and ch2

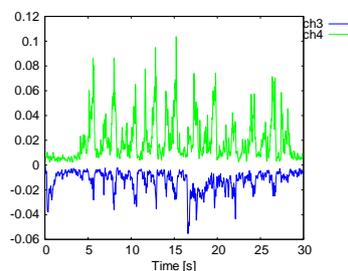


Figure 10. EMG signal during cramped / crouch of ch3 and ch4

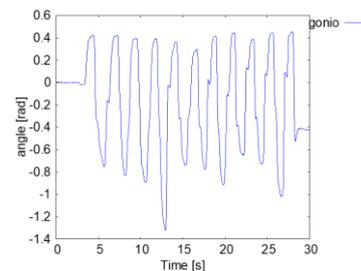


Figure 11. Angle during cramped / crouch

3.2. Measurement of the movement of the hand joint when in contact with an object

We show where wrist movement and measurement environment of EMG and experimental task in the state where the hand is in contact with an object.

3.2.1 Measurement environment. We describe the measurement method and signal processing method of EMG, wrist angle, contact force at the time of palm flexion/ back flexion and tibia flexion/ shaku bending when contacting an object. We constructed a measurement environment of figure 12. The mounting position of the muscle potential sensor and the goniometer, the sampling time of the sensor, and the signal processing method are the same as when measuring at the time of non-contact. The contact force of the hand is measured by contacting the hand to the force measuring instrument when the hand is operated.

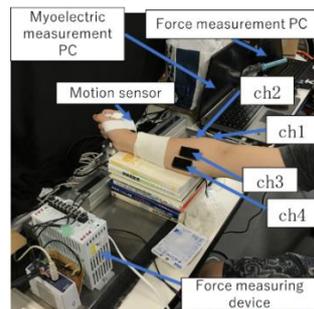


Figure 12. Measurement environment

3.2.2. Experimental tasks. In this experiment, as shown in figure 13, with the hand in contact with the object, the wrist was alternately repeated with palm flexion / dorsiflexion, and the wrist angular displacement θ obtained from the myoelectric signal during movement and the goniometer θ Measure the contact force F of the hand. Also, as shown in figure 14, during buckling / scale bending, as with palm flexion / dorsiflexion, buckling / scale bending is repeated alternately, and the wrist angular displacement obtained from the EMG signal and goniometer during operation. Measure θ and hand contact force F .

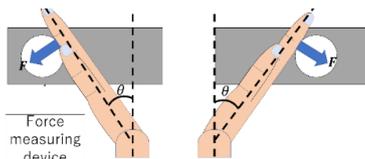


Figure 13. Palm bending / back-bending behavior at the time of contact

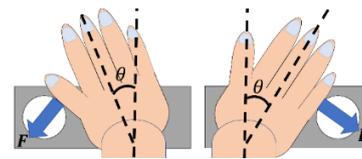


Figure 14. Deflection / shakubutting operation at the time of contact

4. Conclusion

The purpose of this study is to improve the accuracy of the estimation of physical motion by EMG. In this paper, we describe sparse modeling, NARX model, and actual test task used to identify the system of EMG. In the future, we will measure using these and analyze the estimation of physical motion from EMG.

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