

# Wrist angle estimation based on bilinear model using electromyographic signals from circularly-attached electrodes

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**Abstract:** This paper aims at estimating a joint angle from EMG signals. A bilinear model reflecting a muscle visco-elastic property changing with its activity is introduced as the dynamic equation. Learning parameters of the dynamical model will decrease the effect from the difference of human users. The signal separation techniques based on the principal or independent component analysis are adopted to solve a problem about noises and crosstalk in EMG measurements, by applying them to some signals detected from some numbers of electrodes attached around the body parts. Experiments on the hand dorsal extension/palmar flexion evaluates some estimation results of angle deviation in the actual hand movements.

**Keywords:** EMG signal, angle estimation, bilinear model, principal/independent component analysis, dorsal extension/palmar flexion

## 1. INTRODUCTION

Information technology based on computers are changing our daily life to get convenient. A typical example is found in the smart phone: Of course, the mobility of this device is one of the key technology, but, as we can easily guess, another important factor that has widely spread such a device is its human interface. This kind of interface with large display-panel enabling the acceptance of our input by direct finger touches is intuitive and friendly.

Near future, various kinds of devices will be developed. Some of them will have another type of interface and they may provide us with mechanical interactions: haptic devices [1] or powered suits [2] are good examples of them. The realization of these mechanical interactions needs some actuators with their controller: This kind of techniques consists of not only the information but also the robotic technologies. In order for these devices to be used by many peoples, the interface based on the robotic technology will also require the intuitive or friendly characteristics. Especially, many devices are supposed to be developed to possess many convenient, but complex, functions. Thus, to handle various functions smoothly, versatile interfaces have to be established.

Actually, there are some good commercialized interfaces to the mechanical systems: a keyboard, a joystick, a mouse, buttons operation or touch panels, a microphone and so on. Here, we focus attention on a bio-signal, especially, an electromyographic (EMG) signal, as a promising interface because of the following features. The EMG signals can be obtained easily, from everyone by just pasting the electrodes on the skin surface. Next, the signals are equivalent to the muscle activity related to the motor command: the analysis of the EMG signal will allow us to directly predict the human motions. Such prediction will

be available to assist some motions, hard labors for the healthy persons as well as the movement support for persons with disabilities. And, EMG signals are produced by our natural motions. If we can completely understand our intended motion from the EMG signals, and this intention is available for motor command to some devices, we do not have to learn some special operations for the devices.

From this point of view, the estimation of the human actual motion from the EMG signals will be one of the important problems to solve in order to apply them to the machine interface. Among human motions, complex hand motions would be a challenging and valuable target since the dexterous hand achieves several manipulations or operations that frequently used in our daily life. Therefore, we aim at estimating the hand motion from the EMG signals.

Actually, the hand posture estimation from EMG signal has been studied for a long time, mainly aiming at the application to the prosthetic hand [3, 4]. However, the measured EMG signals are different from person to person, which makes the practical application difficult.

In this study, regarding the hand motion, especially the dorsal extension/palmar flexion of the wrist, as the target motion, we will improve a angle estimation method in the following manner: Many electrodes are pasted around the forearm in the uniform intervals. Then the extensor/flexor components are extracted from multiple signals. Finally these components are inputted to the muscle dynamical model to obtain the angle estimation in the continuous time. The increase of the number of the electrodes will bring the robustness on the electrode position, while the parameter identification of the dynamical model for each operator will reduce the effect of the individual difference. Such a kind of pasting method of the electrodes, being proposed in [5], is not generally adopted. We here introduce it also because there is a possibility to ease

† Taro Keisoku is the presenter of this paper.

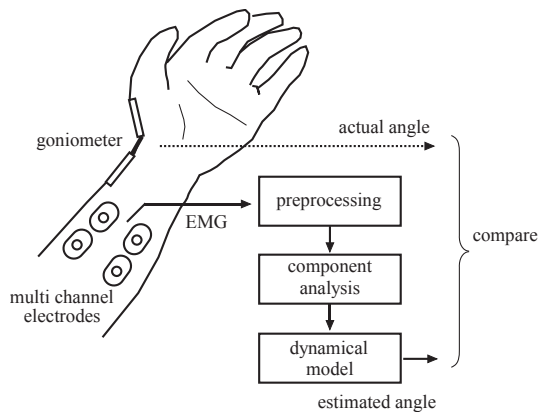


Fig. 1 Flow from EMG signal to angle estimation.

their attachment. The primary component analysis [6, 7] or independent component analysis [8, 9] has already utilized in many studies. Here, we will compare the results from two methods in this application. As for the muscle dynamical model, we will introduce the bilinear model whose effectiveness was reported in some studies [10].

## 2. ANGLE ESTIMATION FROM EMG SIGNALS

### 2.1. Problems and solutions

To detect some meaningful information on the motion from the EMG signals, we should paste the electrode directly on the agonist of the target motion. However, to find the adequate point for EMG detection sometimes requires a special medical or bio-mechanical knowledges as well as lots of experiences. Even if the positions of the electrode for EMG signal are well-selected, the signals are often affected from some kinds of noises or contains the activities of other muscles. In addition, the physical parameters of muscles, size or weight, differ from person to person, which also gives the difference in sensitivity at the actual measurement of the EMG signals. These factors make the EMG signal changeable and do not work to obtain the stable and consistent ones from all the persons.

There, about the electrode-placement problem, we got an idea that the paste of some electrodes circularly around the arm regardless of the agonist position will reduce the deviation effect of the electrode positions. We can also expect the simple attachment of the electrodes by making a kind of band with the electrodes placed in equal intervals in advance.

At the next step, we introduced the processes of the signal component analysis. To circularly paste the electrode has some disadvantages: The electrodes are not always pasted on the agonist and some of the circularly-placed electrode may cover the multiple muscles or pick up the signal from uninterested muscles simultaneously. Therefore we introduced the signal component analysis so as to find the related component to the agonist. This process will reduce the effect of the noises and crosstalk of the muscle activities.

Finally, we adopted a dynamical model to estimate the

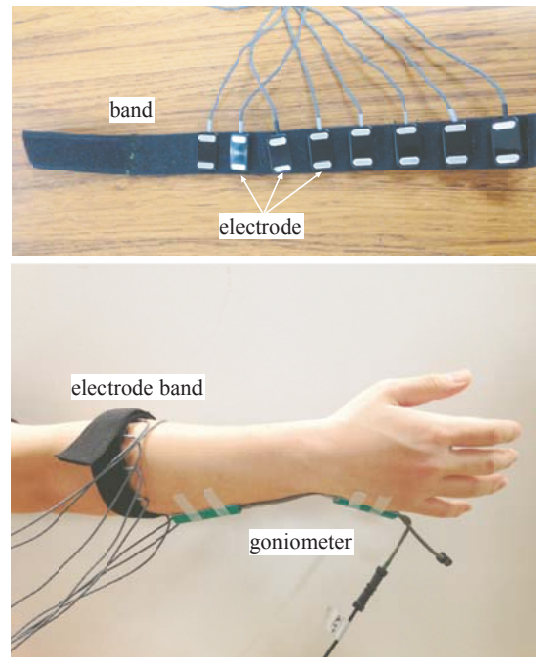


Fig. 2 An electrode band and its attachments.

magnitude of the joint angle continuously from the EMG signals. This model should be based on the mechanical dynamics describing the physical movement of the hand as well as reflecting the elasticity and the viscosity of the muscles. But, these properties are different in persons. Therefore, we took an approach that identifies such parameters for respective operators. In fact, we will introduce the learning phase in which such parameters are estimated from the simple movement pattern in some off-line operations.

Figure 1 shows the processes of the angle estimation from EMG signals that we propose in this study. A bilinear model is adopted as the dynamical model of the muscle-skeletal system because it reflects the variation of the muscle elasticity and viscosity in relation to the activity of the muscles themselves. In the practical use of the bilinear model, we have some unknown parameters, the identification of which will be formulated in the section 2.3. Next, although the joint motions are generated by many muscles, the bilinear model presumes only two muscles: the agonist and the antagonist. Thus, the extraction of the agonist/antagonist components from the multiple electrodes is discussed in the section 2.4.

### 2.2. A dynamical model for angle estimation

The agonist and antagonist are cooperatively acting in the joint motions. The force balance between them determines the actual joint angle. However, the joint impedance is also adjustable without changing the joint angle. At this time, the muscle elasticity and viscosity give an influence to the joint impedance: they get large as the muscle activities are increasing. The muscle model should have this property to enhance the estimation accuracy.

The bilinear model is one of this kind, which defines

dynamics of one joint movement as follows.

$$M/\ell \cdot \ddot{\theta} = u_e - u_f - (u_e + u_f)(k\theta + b\dot{\theta}) \quad (1)$$

Here,  $M$  is the moment of inertia of the end-effector,  $\ell$  denotes the moment arm,  $\theta$  is the joint angle from the natural length of the extensor/flexor and takes positive if the joint is extended.  $k$  and  $b$  are positive constants representing the muscle elasticity and viscosity, respectively.  $u_f$  and  $u_e$  denotes the contracting force of the muscles in the range,  $0 \leq u_f \leq u_{fmax}$  and  $0 \leq u_e \leq u_{emax}$ , respectively, where  $u_{fmax}$  and  $u_{emax}$  are the maximal force of the flexor and extensor.

### 2.3. Unknown parameter identification

The muscle elasticity and viscosity as well as the moment of inertia differ in persons and are difficult to measure. This is why we treat them as the unknown parameter in the muscle dynamics. Instead of the actual measurement, they are acquired as the coefficient parameters in the dynamic equation based on the regressor consisting of the EMG signals and the actual joint angle.

The actual data we will obtain are not continuous but discrete. Accordingly, we replace eq. (1) with the difference equation. Using the backward difference with the sampling period  $\Delta t$ , the derivatives of  $\theta$  are expressed as

$$\dot{\theta}(n) = \frac{\theta(n) - \theta(n-1)}{\Delta t} \quad (2)$$

$$\ddot{\theta}(n) = \frac{\theta(n+1) - 2\theta(n) + \theta(n-1)}{(\Delta t)^2}. \quad (3)$$

Substituting them in (1), we obtain the following difference equation:

$$\theta(n+1) = AX(n) \quad (4)$$

where  $A$  is the unknown constant vector and  $X(n)$  is the regressor, a computable vector obtained from the past and current values of the measured data, which are respectively given as

$$A = \begin{bmatrix} 2 \\ -1 \\ \ell(\Delta t)^2/M \\ -\ell(\Delta t)^2/M \\ -\ell(k(\Delta t)^2 + b\Delta t)/M \\ -\ell(k(\Delta t)^2 + b\Delta t)/M \\ \ell b\Delta t/M \\ \ell b\Delta t/M \end{bmatrix} \quad (5)$$

$$X(n) = \begin{bmatrix} \theta(n) \\ \theta(n-1) \\ u_e(n) \\ u_f(n) \\ u_e(n) \cdot \theta(n) \\ u_f(n) \cdot \theta(n) \\ u_e(n) \cdot \theta(n-1) \\ u_f(n) \cdot \theta(n-1) \end{bmatrix} \quad (6)$$

We will identify this unknown constant vector recursively.

### 2.4. Component analysis of EMG signal

The bilinear model describing the relation from muscle activities to the joint angle assumes the contribution from only two muscles, extensor and flexor. The actual joint motions are, however, produced from the cooperative contractions of many muscles, and actually-measured signals from the pasted electrodes also contain the information of the muscle activities other than them. Namely, we should extract the main component that gives large effects to the joint motion from the EMG signals containing many information about various muscles.

Based on this idea, we take the following approach: the muscle activities are widely measured from not only the agonist/antagonist but also a lot of synergists around the electrodes. Next, the components that act as the extensor and the flexor,  $u_e$  and  $u_f$  in eq. (1), are extracted from lots of signal information using the signal analysis techniques. Then, these components are utilized to estimate the joint angle continuously based on the bilinear dynamics.

Here, either the principal component analysis (PCA) or independent component analysis (ICA) will be applied as this component analysis: we will compare the results of the two methods by the experiments.

#### 2.4.1. Application of PCA

The PCA is a method for reconstructing the data set by finding new synthetic variables in order so that they contain as much amount of information on the original signals as possible.

The application of PCA to the EMG signals obtained from the electrodes pasted circularly around the forearm will provide the same number of the signal components as the electrodes. If we restrict the joint motion into one degree of freedom of motion, we can expect that the activities corresponding to the extensor and flexor are detected as the first and second primary component. Accordingly, the primary score of the first and the second primary component in the result of the PCA is regarded as the activities of the extensor or flexor for the input of the muscle dynamics.

#### 2.4.2. Application of ICA

If there are multiple signal sources, a sensor sometimes catches many of them as the mixed signal. The ICA is a method to separate the original signals from the mixed measurement data based on the independence of the signals, when the mixed signals are measured by the multiple sensors.

In the extension and flexion of the joint, the extensor and flexor usually works in a complementary way. However, they can adjust the joint impedance by their co-activations at the same instant. This fact indicates that the activities of the extensor and flexor are not always in antiphase, that is to say, their activities contain the in-phase variations. As a result, the activities of extensor and flexor can be regarded as independent of each other in a sense that one activity cannot be estimated from another. Based on this idea, we apply the ICA to the EMG

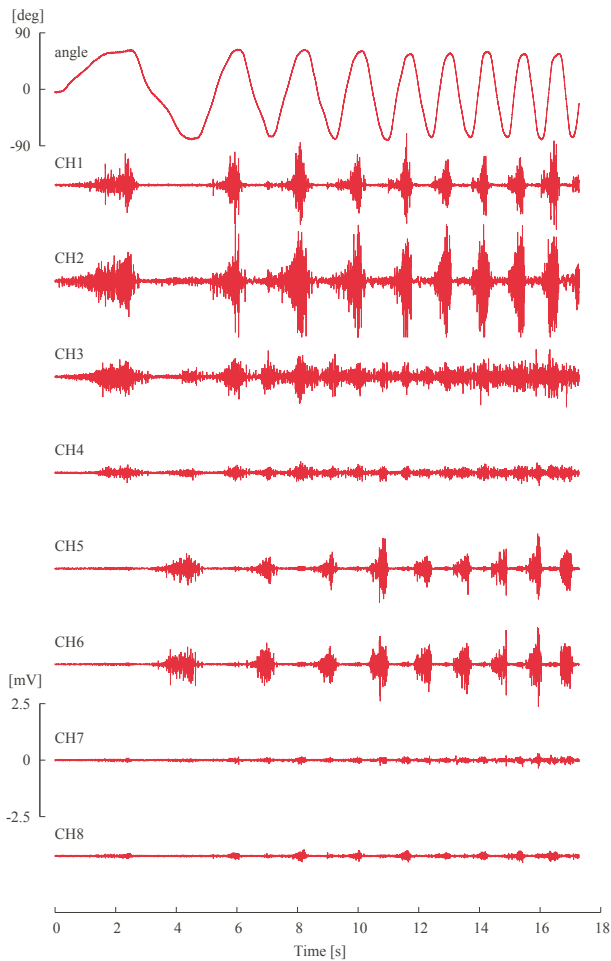


Fig. 3 EMG signals and wrist angle deviation for motion pattern 0 of Subject 1.

signals from the circularly-pasted multiple electrodes so as to get the components of the extensor and flexor.

### 3. EXPERIMENTS

#### 3.1. Setups

In the experiment in this section, we apply the method shown in the Fig. 1 to estimate the joint angle from the EMG signals. The experiments were designed for the angle estimation of the wrist, especially of the dorsal extension/ palmar flexion, from the surface EMG signal obtained from the electrode on the forearm.

The EMG signals were measured by use of the EMG measuring equipment and its accompanying software. The sampling period was 3kHz and, at the data acquisition, the second order bandpass filter from 5Hz to 999Hz as well as 1000 times amplification were applied automatically. At this time, the integral EMG signals, which were obtained by 4 times amplification of the rectified signals filtered by the 2nd order butterworth filter with 4.8Hz cut-off frequency, can be obtained simultaneously.

To assess the estimation result of the joint angle as well as the parameter identification of the muscle dynamical model, the actual angle was measured by the goniome-

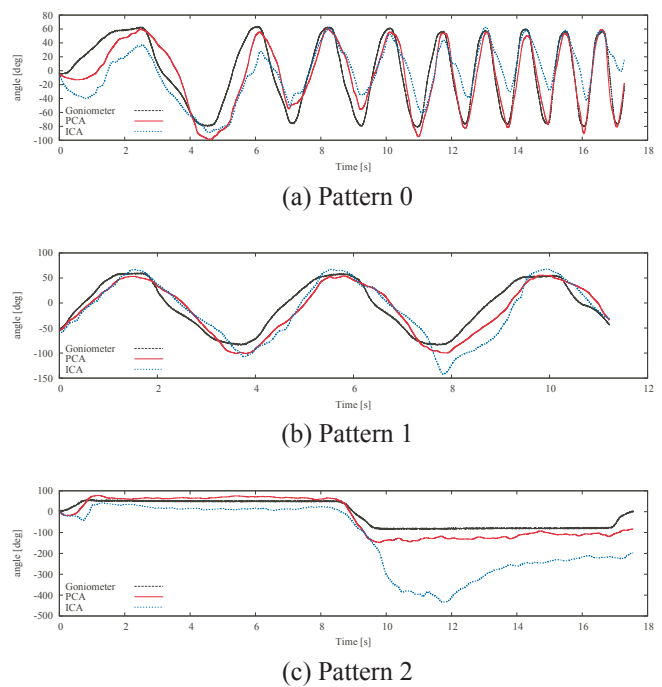


Fig. 4 Angle estimation results from Subject 1.

ter. The signal from the goniometer obtained as the electric voltage are inputted to the other channel of the EMG equipment. Thus, the synchronization is ensured between the EMG and goniometer signals.

The Support Vector Machine (SVM) was applied to identify the unknown parameter in the dynamical model based on the regression calculation after the EMG measurements. The function `ksvm` in the 'R' software package 'kernlab' was utilized for this calculation.

#### 3.2. Method

The motion pattern containing various frequency components, so-called 'rich input signal', is preferable for the parameter identification of the dynamical model. From this point of view, we selected a about 17-second repeated motion whose speed was gradually increased with keeping the moving range (Pattern 0), as the learning data for the parameter identification. the repeated motion with a constant period and a constant amplitude without stopping (Pattern 1), and the joint position fixation at the two different positions (Pattern 2). To produce almost the same motion for comparison, we show the subjects a computer-graphic image in which a bar moves left and right. The subjects were instructed to extend and flex the wrist in front of the body in synchronization with this bar. The bar movement in Pattern 0 was sinusoidal whose angular frequency was gradually increased from 0 rad/s, with the constant rate, 0.2 rad/s per second. The movement of Pattern 1 was sinusoidal with constant frequency 0.25 Hz, and that of Pattern 2 was discrete motion with a 7s extension and then a 7s flexion. We also asked them to extend and flex the wrist as much as possible.

Three subjects were recruited. All of them are male, age from 22-23 and have no disease. Eight electrodes

Table 1 Error evaluation for PCA based separation

(a) RMS

	sub1	sub2	sub3	Ave.
pattern0	22.2	17.8	9.6	$16.5 \pm 6.4$
pattern1	21.1	17.1	38.6	$25.6 \pm 11.4$
pattern2	34.8	40.5	58.1	$44.5 \pm 12.2$
Ave.	26.0	25.1	35.4	$28.9 \pm 15.2$

(b) Maximum

	sub1	sub2	sub3	Ave.
pattern0	58.4	52.7	40.7	$50.6 \pm 9.0$
pattern1	43.0	35.3	118.7	$65.7 \pm 46.1$
pattern2	84.8	92.6	115.2	$97.5 \pm 15.8$
Ave.	62.1	60.2	91.6	$71.3 \pm 32.3$

were pasted around the forearm using a electrode band as shown in Fig. 2, in which eight dry electrodes are stuck to the surface of a rubber band 26cm in length with 1.5cm interval.

We attempt at extracting the agonist component of the extensor and flexor from the EMG signals obtained from these eight electrodes on the basis of the PCA or ICA. The target motion was restricted to the dorsal extension/palmar flexion of the wrist, and other simultaneous motions such as radial/ulnar deviation of wrist and the finger extension/flexion were prohibited in order to extract pure muscle activities for this target motion.

Because the integrated EMG signals correspond to the contraction forces to drive the joint motion, we considered that we could get the force component of the extensor/flexor if we analyze the integrated EMG signals. Therefore, the integrated EMG signals were used for PCA. The first and second score of them was inputted to the muscle dynamical model as the contraction forces of the extensor and flexor.

On the other hand, it would be natural that the independence of the signal should be assumed to the original EMG signals free from any processings such as integral operation. Accordingly, the pure EMG signals were utilized in the ICA: after two independent signals were extracted by means of ICA, they were processed in the same integral operation as the measurement software, as mentioned in section 3.1, and then they were inputted to bilinear muscle dynamics model.

To assess the joint angle estimation, the root-mean-square value (RMS) and the maximal error were calculated.

### 3.3. Results

Fig. 3 depicts the wrist angle deviation as well as the EMG signals from eight electrodes pasted on the subject 1's forearm during the pattern 0 movement. The signals from CH1 and CH2 seems to be activated to maintain the extended posture, i.e, the positive angle, whereas the signals from CH5 and CH6 does when the hand was being

flexed. The CH3 and CH4 seems to contain both components of extension and flexion.

Based on these data, dynamical model parameters for angle estimation are computed after the extraction of the extensor and flexor components. The joint angle estimated from the bilinear model is illustrated in Fig. 4(a). A black line, which is the same trajectory as the top of the Fig. 3, denotes the measured angle, while the red and blue lines are estimated one by means of the PCA and ICA respectively.

In addition, this bilinear model whose parameters are estimated from the Pattern 0 motion are applied to compute the angle in two other motions, Pattern 1, and Pattern 2, performed by the same subject 1. These results are depicted in Fig. 4(b) for the pattern 1 and Fig. 4(c) for pattern 2.

To evaluate the accuracy as well as the applicability of this method to the other persons, the same estimations are conducted for two more subjects, and the RMS and the maximal value of the error between the actual and estimated signals are calculated. These results are summarized in Table 1 and Table 2, obtained by means of PCA and ICA, respectively.

### 3.4. Discussion

The same data as used for the parameter identification are utilized for the angle estimation for pattern 0. Thus, the errors are smaller than the other two patterns in average, as summarized in Table 1 and Table 2. However, errors about 15 degree in average are still observed in the PCA-based method, and those about 25 degrees are found in the ICA-based method. For the subject 1, as shown in Fig. 4, the red lines denoting the PCA-based method, gradually approached to the black line denoting the desired trajectory, though they did not match well at the start of the movement. Namely, the better estimations seem to be resulted from the PCA based-method than ICA-based method denoted by the blue line. This effect is numerically shown in Table 1 and Table 2: both RMS and the maximal errors are smaller in the PCA-based method. The ICA can extract the independent component, but then the information of the signal amplitude are lost. This might not have some good effects on our estimation method.

The result in Fig. 4 indicates that, although the positive extended angle are well estimated, the negative flexed angle are not so good. This tendency is noticeable in the blue line: there are some deviations in the latter part of the experiment in the Pattern 0, and quite large error are generated in the Pattern 2. Especially, in the Pattern 2, the blue lines are always under the black line. This reason might come from the fact, that the activation of the flexor such as CH5 and CH6 is relatively smaller than those of extensor, CH1 and CH2 in the data set for the parameter identification shown in Fig. 3. Then the dynamical model calculated from such data will be easy to flex by the small flexor activation. Actually, in the pattern 2, not so larger signal than the extensors was generated, before the large flexion at around 8 s. This estimates more than 100 de-

Table 2 Error evaluation for ICA based separation

(a) RMS

	sub1	sub2	sub3	Ave.
pattern0	35.7	17.9	27.0	26.9 ± 8.9
pattern1	30.2	41.4	20.4	30.7 ± 10.5
pattern2	154.1	25.7	88.6	89.5 ± 64.2
Ave.	73.3	28.3	45.4	49.0 ± 44.7

(b) Maxmum

	sub1	sub2	sub3	Ave.
pattern0	88.6	47.6	70.9	69.0 ± 20.6
pattern1	78.3	104.2	48.7	77.1 ± 27.8
pattern2	353.2	75.1	160.0	196.1 ± 142.5
Ave.	173.4	75.6	93.2	114.1 ± 95.8

grees large flexion in both the red and blue lines. It is the same as the subject 3 whose result contains the similar large errors, but it is not a case as the subject 2 where the magnitude of the EMG signals are balanced in both the extension and flexion. It indicates that the detection of the similar magnitude of the EMG signal is necessary to improve the estimation from the method that we proposed here. Accordingly, the attachment of the electrode band should be selected at least to obtain the balanced EMG signal.

#### 4. CONCLUDING REMARKS

This paper considered the wrist angle estimation from EMG signals obtained by multiple electrodes that pasted around the forearm of the subjects. To select the extensor and flexor component from the signals obtained by multiple electrodes, the signal separation algorithms, the PCA and ICA were adopted. In addition, the introduction of the dynamics, i.e., bilinear model, allows us to estimate the continuous movement. To remove the difference in the EMG signals among subjects, the parameters of the bilinear model are estimated from the template motion pattern. The obtained model are applied to the estimation in the other motor patterns. As a result, the estimation still contained at least 15 degree errors in average for every test pattern.

The required accuracy will be different from application to application. Thus, we should begin with selecting an appropriate motion pattern for the parameter estimations to our application. But the correction from the deviation that have once happened seems to be difficult due to the continuous nature of the dynamics. An introduction of a kind of error correction mechanism, maybe it will have discrete property such as a reset operation, might solve this problem in the actual application.

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