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Continuous Estimation of a sEMG-Based Upper Limb Joint

Dongdong Bu[1], Shuxiang Guo[1,2*], Wenyang Gao[1]
[1] *Key Laboratory of Convergence Biomedical Engineering System and Healthcare Technology, The Ministry of Industry and Information Technology, School of Life Science, Beijing Institute of Technology, No.5, Zhongguancun South Street, Haidian District, Beijing 100081, China*
[2] *Faculty of Engineering, Kagawa University, 2217-20 Hayashi-cho, Takamatsu, Kagawa 760-8521, Japan*
E-Mails: {budongdong & guoshuxiang &gaowenyang} @bit.edu.cn;
* Corresponding author

***Abstract*-The more hidden information from surface electromyography (sEMG) should be extracted for the continuous estimate of the human motion intention based on sEMG. Since feature selection is very important to generalize an estimate model. In this work, the time-domain features (TF), and corresponding time-delayed features (TDF) of sEMG were extracted to estimate human upper limb joint motion. Considering execution time and measure accuracy, Random Forests (RF) algorithm is applied to estimate the joint motion based on the multi-features of sEMG. The difference between the actual angle and the estimated angle were calculated to verify the performance of proposed estimate model. Moreover, the average time of motion estimation is also calculated and the significance of each feature was quantized. Finally, the results showed that the TDF features of sEMG perform well for estimating the joint motion.**

Index Terms - continuous estimation. surface EMG. feature selection. joint motion.

I. INTRODUCTION

Currently, the increasing people affect neuromuscular insults, such as stroke, which may cause the loss of upper limb motion function for many patients. However, the upper limb motion function plays an important role to perform activities of daily living (ADL). Clinical researches indicate that hemiplegia is usually caused due to the inappropriate treatment of neurological impairment after stroke frequently [1], [2]. The delay of Intervention therapy will affect patient's functional capability restoration and increase rehabilitation duration [3]. The rehabilitation robots are usually applied to rehabilitate the limb movement function in practical clinical application [4]. Currently, surface electromyographic (sEMG) as the control source has been widely used to patient's functional rehabilitation training in order to realize friendly human-machine interaction [5]. And many sEMG-based motion recognition algorithms are also presented to measure limb motion. However, the limb motion of many ADLs is continuous and the existing recognition algorithms are not available to realize the continuous estimation of limb joint. Feature extraction and estimate methods of the continuous limb motion are important to motion estimation. The effectiveness of feature selection can extract more available information from sEMG thus improving the estimation accuracy of motion estimation.

The raw sEMG is low-SNR and its energy mainly is concentrated at 13~500 Hz [6]. Since the available feature selection and motion estimation methods are vital. Generally, the feature signals of sEMG involve time-domain features, frequency-domain features and time-frequency domain features [7]. The time-domain features mainly involve integrated electromyogram (IEMG), mean absolute value (MAV), waveform length (WL), and zero crossing (ZC), difference absolute standard deviation value (DASDV), slope sign changes (SSC), and so on. The frequency-domain features mainly involve auto-regressive coefficients (AR), power spectrum (PS), mean frequency (MF), median frequency (MDF), frequency ratio (FR), and so on. The time-frequency domain features include short time Fourier transform (STFT), wavelet transform (WT), and so on [8], [9]. The joint angle is usually applied to estimate the upper limb motion. Generally, the estimation methods like Hill muscular model is usually used to establish the biomechanical model to reveal the relevance between sEMG signal and the limb joint movement [10], [11]. Due to the poor performance of above model, some common machine-learning models are proposed to replace the biomechanical models including radial basis function (RBF) neural network, back propagation (BP) neural network, random forests (RF) and support vector machines (SVM) [12], [13]. The time-delayed features of sEMG were extracted to perform the motion assessment [14]. And an artificial neural network with time-delayed (TDANN) was established to measure the rhythmic clenching movements based on sEMG by Hadi Kalani [15]. In addition, the sEMG signals were processed (rectifying and smoothing) through the average slide window. In [16], two different neural networks with time-delayed were applied to estimate elbow and shoulder torque based on MAV features of sEMG for the exoskeleton. However, only less features of sEMG and their corresponding time-delayed features were considered in above studies. Therefore, much available information may lose for the low-pass filtering sEMG signal. More available information of limb motion should be obtained based on the time-delayed signal of sEMG.

In our previous research, the multiple scale entropy and sliding-window were applied to describe correlation between the elbow joint and the biceps muscle sEMG signals by Zhenyu Wang [17]. In order to improve the estimation performance, an improved weighted peaks method was presented and a linear-fitting method was applied to measure the elbow movement information by Zhibin Song [18]. A novel ensemble empirical mode decomposition (EEMD) algorithm was proposed by Xuan Song to estimate the continuous motion of elbow joint [19]. Songyuan Zhang proposed a novel bilateral rehabilitation system with coordinative motion of the limbs. And the affected and unaffected limbs performed the same movements synchronously and independently based on the virtual training model [20]. In this paper, to involve more details from sEMG, multiple features and some corresponding time-delayed features (TF&TDF) are extracted to improve the estimation accuracy for motion estimation. Considering execution time and estimation accuracy of learning model, Random Forests (RF) algorithms is applied to generate the learning model to estimate the continuous joint motion. The time-delayed features of sEMG are verified that they can perform good availability for the motion continuous estimation from the experiment results.

II. Methods

A. Feature selection of sEMG

In this section, multiple time-domain features including IEMG, MAV, WL, ZC, DASDV, SSC and corresponding time-delayed features of sEMG are extracted, which are calculated through the sliding window function. Actually, these features of sEMG were extracted to generate learning model. And in this paper, the semg_k, semg_{k-2}, semg_{k-1}, and semg_{k+1} are defined as the raw sEMG at time k $k-2$, $k-1$, and $k+1$ respectively in $Equation(1) \sim Equation(12)$. And i, n, and N denote the time-delayed coefficient, the times of time delay, and the sliding-window width respectively. Hence, the time-domain features and corresponding time-delayed features of sEMG are described as [21]:

1) Integrated Electromyogram (IEMG):

$$IEMG(m)=\frac{1}{N}\int_{m-N+1}^{m}|semg_k|\,dk \tag{1}$$

$$IEMG(m-ni)=\frac{1}{N}\int_{m-ni-N+1}^{m-ni}|semg_k|\,dk, n=1,2... \tag{2}$$

where $IEMG(m)$ and $IEMG(m-ni)$ denote the integrated absolute value and corresponding time-delayed feature of sEMG respectively.

2) Mean Absolute Value (MAV):

$$MAV(m)=\frac{1}{N}\sum_{k=m-N+1}^{m}|semg_k| \tag{3}$$

$$MAV(m-ni)=\frac{1}{N}\sum_{k=m-ni-N+1}^{m-ni}|semg_k|, n=1,2,... \tag{4}$$

where $MAV(m)$ and $MAV(m-ni)$ denote the mean absolute value and corresponding time-delayed feature of sEMG respectively.

3) Zero-Crossing (ZC):

$$ZC(m)=\frac{1}{N}\sum_{k=m-N+2}^{m}\mathrm{sgn}(-semg_k semg_{k-1}) \tag{5}$$

$$ZC(m-ni)=\frac{1}{N}\sum_{k=m-ni-N+1}^{m-ni}\mathrm{sgn}(-semg_k semg_{k-1}), n=1,2,... \tag{6}$$

where $ZC(m)$ and $ZC(m-ni)$ denote the zero-crossing feature and corresponding time-delayed feature of sEMG respectively.

4) Waveform Length (WL)

$$WL(m)=\frac{1}{N}\sum_{k=m-N+2}^{m}|semg_{k+1}-semg_k| \tag{7}$$

$$WL(m-ni)=\frac{1}{N}\sum_{k=m-ni-N+2}^{m-ni}|semg_{k+1}-semg_k|, n=1,2... \tag{8}$$

where $WL(m)$ and $WL(m-ni)$ denote the waveform length feature and corresponding time-delayed feature of sEMG respectively.

5) Slope Sign Changes (SSC)

$$SSC(m)=\sum_{k=m-N+3}^{m}\mathrm{sgn}\left[-(semg_k-semg_{k-1})(semg_{k-1}-semg_{k-2})\right] \tag{9}$$

$$SSC(m-ni)=\sum_{k=m-ni-N+3}^{m-ni}\mathrm{sgn}\left[-(semg_k-semg_{k-1})(semg_{k-1}-semg_{k-2})\right], n=1,2... \tag{10}$$

where $SSC(m)$ and $SSC(m-ni)$ denote the slope sign changes feature and corresponding time-delayed feature of sEMG respectively.

6) Difference Absolute Standard Deviation Value (DASDV):

$$DASDV(m)=\sqrt{\frac{1}{N}\sum_{k=m-N+2}^{m}(semg_{k+1}-semg_k)^2} \tag{11}$$

$$DASDV(m-ni)=\sqrt{\frac{1}{N}\sum_{k=m-ni-N+2}^{m-ni}(semg_{k+1}-semg_k)^2}, n=1,2... \tag{12}$$

where $DASDV(m)$ and $DASDV(m-ni)$ denote the difference absolute standard deviation feature and corresponding time-delayed feature of sEMG respectively.

B. Random Forests

Random forests (RF) algorithms is used to measure the continuous wrist joint movement due to the good ability of avoiding over-fitting and anti-noise. The RF consist of a set of decision trees. These decision trees are generated based on classification or regression kernel function. Considering the generalization ability of estimation model, splitting feature sequence is selected randomly, and the splitting nodes of decision tree each time is selected based on the Gini coefficient. In addition, the importance of each evaluation feature can be sorted through the RF algorithm. Considering the bootstrapping, about 36% of the original training sets will not be sampled, which are used as out-of-bag estimate. The four-channels features importance from sEMG of wrist joint motion will be evaluated by RF algorithms. The M defined as number of decision trees and M_t defined as the number of input feature properties randomly are two main parameters for a RF. In general, M_t should be far less than M and the parameter M should be set reasonably. The execution time and complexity of the RF will be increased if M is set too large.

III. EXPERIMENT AND RESULTS

A. Experiment setup

To verify the availability of time-delayed features, three healthy subjects (named as A-C, 22-30 years old) were recruited. Before the experiment, the subjects should remain the upper limb relaxed, thus avoiding the signals offset due to muscle tension. The wrist joint motion including flexion and extension are considered to perform in this paper. According to [22], [23], the flexion/extension motion range of wrist joint is -80$^{\circ}\sim$80°. In this work, the flexion/extension motion range of wrist joint was defined as -50° ~ 50°. The wrist joint flexion/extension is mainly associated with the Flexor Carpi Radialis, Flexor Carpi Ulnaris, Flexor Digitorum, Flexor Pollicis Longus, Extensor Carpi Radialis, Extensor Carpi Ulnaris, Extensor Digitorum, Extensor Pollicis Longus. As shown in Fig.1, Considering the computational complexity, the Flexor/Extensor Carpi Radialis and Flexor/Extensor Carpi Ulnaris were considered as the main muscles for this paper [14].

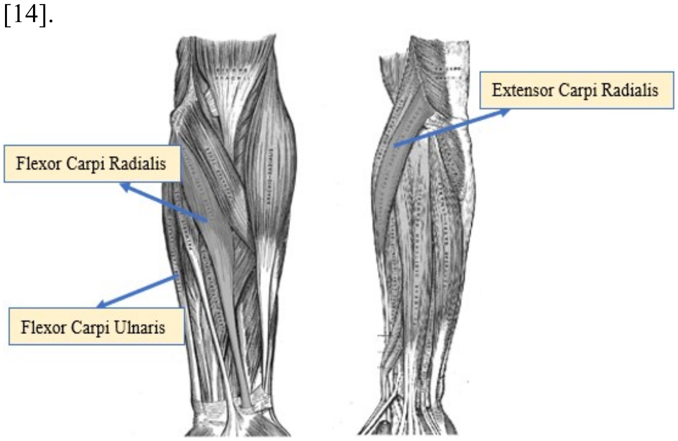


Fig. 1. The main muscles of wrist joint flexion/extension

B. Data acquisition and Signal processing

As shown in Fig.2, the raw sEMG were obtained through the superficial electrodes (FREEEMG 300 manufactured by Italian BTS Company), and the spacing between reference electrodes and measuring electrodes is about 20 mm. The device transmits the collected raw sEMG signal by wireless transmission. The collected raw sEMG signals were filtered by the band-pass filter with bandwidths at 13 ~ 500 Hz, trapped at 50 Hz, and sampling frequency of the sEMG acquisition device was set at 2048 Hz.

Fig. 2. The sEMG acquisition system

To avoiding the slight movement of the upper arm during experiments, single channel sEMG acquired by the sEMG sensor attached on the upper limb, was insufficient to estimate the wrist joint flexor/extensor angle. In this work, 4-channels sEMG were obtained and four sEMG sensors were attached on the thickest part of the forearm (about 5cm from the elbow), forming an equidistant circular configuration respectively in Fig.3. The subjects are asked to perform two types wrist gesture: flexion (0$^{\circ}\sim$-50°)/extension(0$^{\circ}\sim$50°). Each subject was required to perform wrist flexion/extension in the range of 0$^{\circ}\sim$-50$^{\circ}\sim$50$^{\circ}\sim$0° slowly which was defined as a group. A group sample is acquired in 15 seconds, and will be performed 20 times repeatedly for each subject. There were 5 minutes to rest between each experiment.

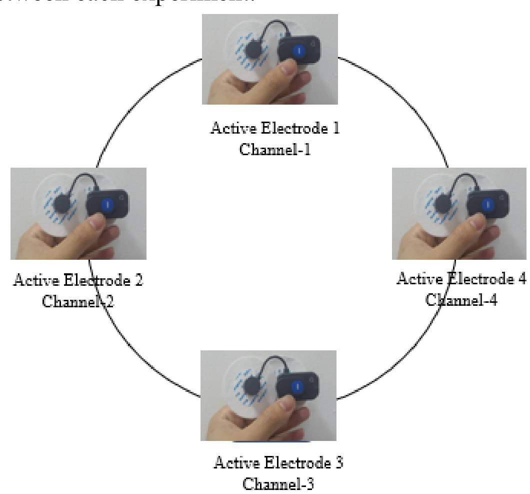


Fig. 3. Electrode placement configurations

C. Estimation Model

The structural diagram of the RF based on more details features of sEMG is illustrated in Fig. 4. In this figure, the training process of the estimation model is described as the blue areas and the red areas denote the verification process of the estimation model. The time-domain and of sEMG including IEMG, MAV, WL, ZC, SSC, DASDV and their time-delayed features including TD_IEMG, TD_MAV, TD_WL, TD_ZC, TD_SSC, TD_DASDV will be extracted. These above features of sENG will be defined as X_{train} that is the input variables of RF and the Y_{pre} is defined as the estimation angle of RF.

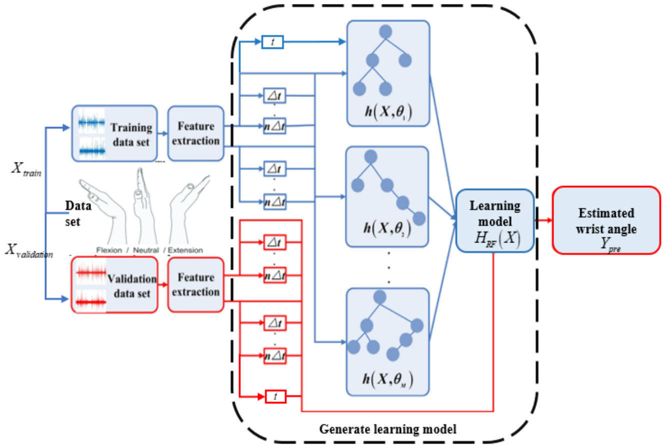


Fig. 4. The structural diagram of the RF based on time-domain and time-delayed features of sEMG

The delayed-time variable $\Delta t = i/2048$ and the parameter n will be set later. And then Using the training data set $D_{train} = \left(X_{train}, Y_{train\_angle}\right)$ to establish the learning model $H_{RF}\left(X\right)$. The learning model $H_{RF}\left(X\right)$ is described by:

$$H_{RF}\left(X\right) = \frac{\sum_{i=1}^{M} h_{rf}\left(X, \theta_i\right)}{M} \tag{13}$$

The $\theta_i\left(i = 1,2,...\right)$ denotes model parameter obtained by model training algorithm; The parameter M_t denotes the number of possible splitting directions at each leaf node of each decision tree. The X_{test} will be applied to test the estimation performance of the learning model, and the estimation value y_{pre} will be described by:

$$y_{pre} = H\left(X_{test}; \theta_1, ...\theta_M, D_n\right) = \frac{1}{M}\sum_{i=1}^{M} h\left(X_{test}; \theta_i, D_n\right) \tag{14}$$

In this work, the root mean square deviation ($RMSD$) between actual angle and forecasting angle is calculated to estimate the performance of learning model. To estimate time delay between the actual and forecasting angle. the cross-correlation is calculated as defined by [21]:

$$RMSD = \sqrt{\frac{\sum_k\left(\left(y_{pre} - y\right)^2\right)}{\sum_k\left(y\right)^2}} \tag{15}$$

$$\tau_{delay} = \frac{1}{f}\arg\max\left(\frac{\sum_i\left[\left(y(i) - \mu_y\right)\left(y_{pre}\left(i+\tau\right) - \mu_{y_{pre}}\right)\right]}{\sqrt{\sum_i\left(y(i) - \mu_y\right)^2}\sqrt{\sum_i\left(y_{pre}\left(i+\tau\right) - \mu_{y_{pre}}\right)^2}}\right) = \frac{1}{f}\arg\max\left(r\left(\tau\right)\right) \tag{16}$$

where μ_y and $\mu_{y_{pre}}$ are denote the mean of actual value and the forecasting value of wrist joint motion, respectively. And $r\left(\tau\right)$ represents the cross correlation series between actual value y and forecasting value y_{pre}, and parameter $\tau = -\left(S_d - 1\right), ..., -1, 0, 1, ..., S_d - 1$, where S_d represents the number of predicted angle series and f denotes the sampling frequency; τ_{delay} represents the index of the maximum. The seven parameters about the RF in this paper should be set, including the number of training samples N_t, the number of trees in the forest M, the number of input variables randomly chosen at each split node M_t, the time-delayed coefficient i, delayed-time variable Δt, and the times of time delay n. The values of these parameters are defined as shown in Table I, and the learning model will have good generalization ability based on these the values of parameters.

TABLE I
THE OPTIMAL VALUES OF PARAMETERS

Parameters	Values
i	300
N_t	15000*20
M	300
M_t	24
N	512
Δt	300 / 2048
n	2

IV. RESULTS

A. The performance estimation of learning model

To estimate availability of the time-delayed features from 4-channels sEMG for motion estimation of continuous joint, the machine learning methods RF are used to generate the learning model to estimate wrist joint movement. The train data of RF involves time-domain features of sEMG and their time-delayed features. As shown in Fig.5 and Fig.6, a group of the 4-channels raw sEMG and one-channel features data of sEMG involving time-domain and time-delay features from subject A are descried.

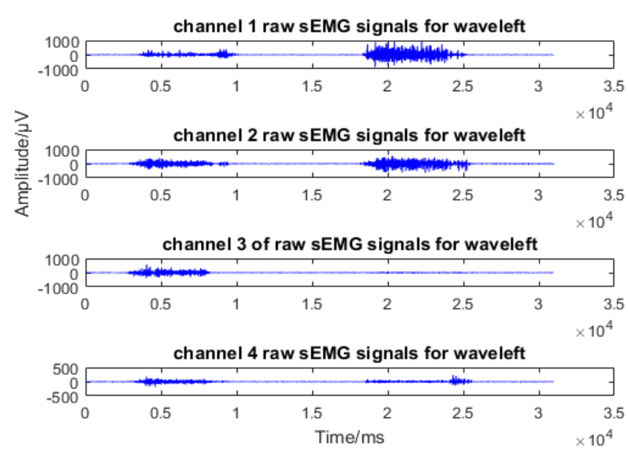
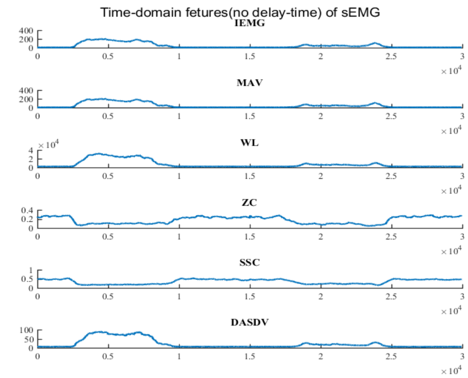
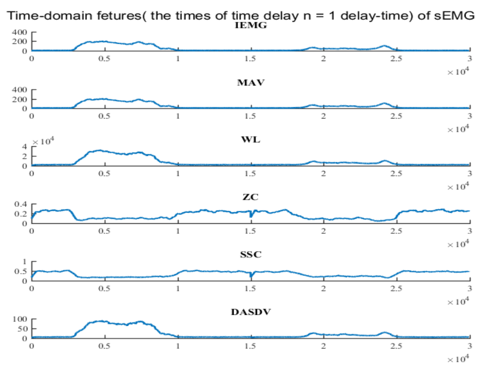


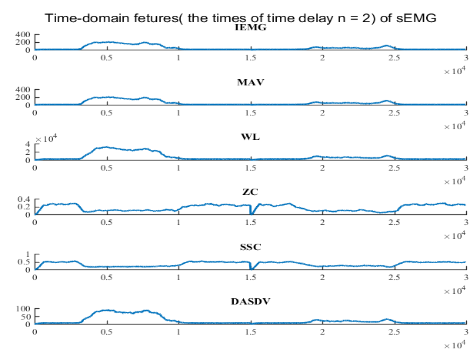
Fig. 5. The 4-channels raw sEMG from subject A



(a) The time-domain features of sEMG



(b) The delayed-time features (n=1) of sEMG



(c) The delayed-time features (n=2) of sEMG

Fig. 6. Features data of sEMG involving time-domain and time-delay features from subject A

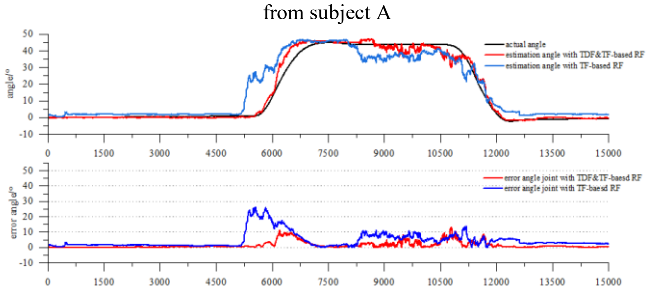


Fig. 7. The performance and the error between the actual and measured angle of wrist extension

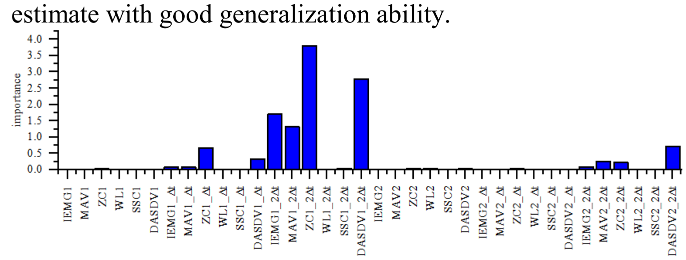
The performance and the error between actual angle and estimated angle of motion estimation model is described. As shown in Fig. 7, the blue curve represents the actual angle, and red curve represents the measured angle. The black curve denotes the error between actual angle and measured angle of motion estimation model. The estimation performance of TF&TDF-based RF method is much better than the RF's and other methods

TABLE II
THE AVERAGE ESTIMATION PERFORMANCE OF EACH LEARNING MODEL

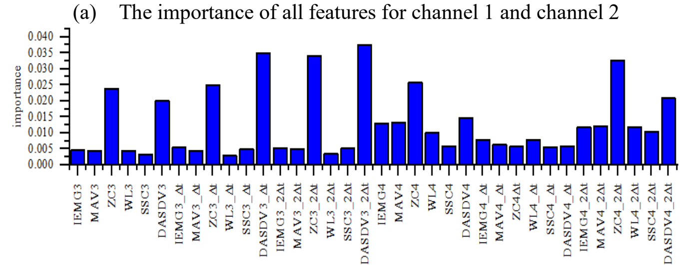
Methods	RMSD	τ_{delay}
RF (TF-based)	0.1378	0.00048
RF (TF&TDF-based)	0.2786	0.00047

B. *The importance comparison of all features based on RF*

Based on experiment results, the time-delayed features are verified that they are available for the performance improvement applied for the continuous limb joint estimation. And the mean *RMSD* and τ_{delay} of TF&TDF-based and TF-based RF methods estimation results of 10 groups test data are described in Table II respectively. The average execution time of TF&TDF-based RF method is about 0.40s, which is slightly longer than that of TF-based RF (0.30s). But the learning model of TF&TDF-based RF has better the estimate performance than that of the TF-based RF. The mean *RMSD* for the learning model of TF&TDF-based RF, is about half than that of the TF-based RF as shown in Table II. And the importance of all features during the model generation is listed from subject A in Fig. 8. The larger the histogram value corresponding to each feature, the more important it is in the process of motion estimation. When the value of a feature histogram is extremely small, the influence of the feature can be ignored. Because RF algorithm can automatically eliminate unimportant features and shorten execution time, RF algorithm is applied for the basic algorithm in this paper. The results show that the time-delayed features of sEMG is available and they can be used to perform limb join estimate with better performance. Therefore, the learning model of TF&TDF-based RF is available and also can perform well in motion estimate with good generalization ability.



(a) The importance of all features for channel 1 and channel 2



(b) The importance of all features for channel 3 and channel 4

Fig. 8. The importance of all input features based on RF

V. CONCLUSIONS

In this work, the availability based on the multi-time-delayed features from sEMG for the continuous estimate of limb joint was verified. Considering execution time and measure accuracy, the RF based on the TF&TDF of sEMG was used to generate the learning model for the continuous joint motion. The experiment results demonstrate that the estimation performance and robustness of the RF based on the TF&TDF work better. But the estimate performance may be affected when the wrist joint of subjects performs rapidly due to the reason that the features are described with a fixed width sliding window function. To solve above problem, the adaptive width sliding window function can be used in the future study. In general, the speed of the wrist joint motion in daily life is slow. According to mean *RMSD* and τ_{delay} from Table II and Fig. 7, multiple time-delayed features are good for estimating the continuous upper limb joint motion with high performance and the RF based on TF&TDF is available and also can perform well in motion estimate.

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