Electromyograph Discrimination of Six Hand-Actions for Twisting Manipulation

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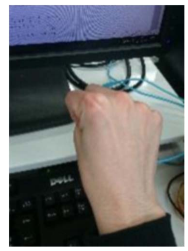
***Abstract*— This paper proposes a motion discrimination with electromyogram for twist manipulation, which is composed of flexion/expansion and pronation/supination. Instead of attaching a set of electrodes at the surfaces on each target muscle, we adopt a commercial arm-band-type electrodes array with focusing on wearability. A typical signal processing, IEMG, and a classifier, SVM, are employed to analyze eight channels of electromyogram for six hand actions. We experimentally investigate the accuracy of discrimination in real-time and interference of muscle fatigue. Since each pattern of electromyogram for a particular motion is changed by posture of upper limb, the interference of its noises are also investigated.**

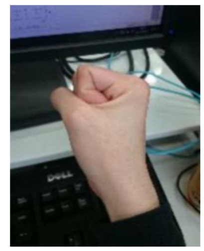
I. Introduction

Electromyogram (EMG) is a set of electrical signals which is activated by contraction of muscles. It can be observed not only inside of muscles but also on the surface skin, and the latter is called as surface EMG (SEMG). Since SEMG is easily measured with attaching electrodes to the skin, it is widely used to estimate preliminary motion of human body and to control myoelectric prostheses and orthoses, as [1]. As for arrangement of electrodes, each of them is generally attached near the target muscle as [2], [3], in order to reduce noises on measurement. On the other hand, some commercial devices of electrodes often focus on wearability on the forearm rather than precise measurement. For example, an arm-band-type product has electrodes arranged in a line [4] and another previous study [5]. In these cases, electromyogram retrieved by all the electrodes is statistically analyzed to classify several forearm and hand actions. Although precision and responsibility of electromyography is low, its easiness to use the device is a quite advantage for non-professional users.

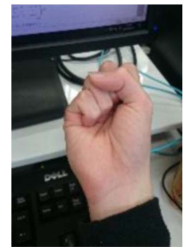
Multiple DOF (Degrees of freedoms) prosthetic hands controlled with electromyogram have been thoroughly investigated and developed based on the analyses of EMG processing to discriminate intention to make hand actions. Each target action is, however, often composed of SINGLE motion such as opening and closing fingers, twisting wrist called pronation/supination/flexion/extension [6], and gestures with finger(s) pointing [5]. On the other hand, our daily activities using arms and hands are more complicated and flexible. For example, when we try to unlock a door, it is needed grasping a key, inserting it into the lock, and turning it. This task requires not only multiple actions but also combination



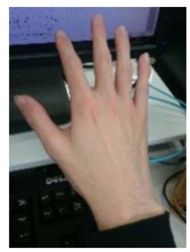
(a) PG: Pronation and grasp



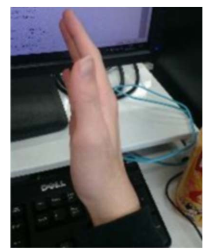
(b) NG: Neutral and grasp



(c) SG: Supination and grasp



(d) PO: Pronation and open



(e) NO: Neutral and open

(f) SO: Supination and open

Fig. 1. Target six actions: *Grasp* means flextion of all fingers; *Open* means the hand is relaxed, not concentrated

of single motions such as grasping and twisting. Hence those twisting manipulation by EMG prosthetic hands can be performed by EMG-based discrimination for combined actions.

In this paper, we adopt the arm-band with eight electrodes in a line in order to easily retrieve datasets of electromyogram and hand state. Each hand state is a combination of fingers closing and wrist twisting. Our discriminator of hand state with electromyogram is built with Support Vector Machine (SVM), a widely-used statistical method. The datasets for learning of the SVM include two components. One is electromyogram during hand motion, which is retrieved by the arm-band-type electrodes array. Another is the corresponding hand motion, which are automatically recognized by a device for Motion Capture, Leap Motion [7]. The trained SVM discriminator can perform high accuracy of recognition for six hand states, which is not lower than 80%. In addition, interference from fatigue of muscles and also from upper-limb motion are investigated.

II. Signal Processing and Classification of Electromyogram

Fig. 1 shows our target hand states, each of which is a combination of flexion/extension of fingers and prona-

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Fig. 2. Measurement setup: a subject lays their forearm on the table

tion/supination/neutral. In these cases, each corresponding pattern of electromyogram may be different from its components as SINGLE motions. To discriminate these signals, we adopt conventional processing methods: rectification, integral, normalization, and Support Vector Machine (SVM).

A. Pre-processing of Retrieved Electromyogram

In this paper, we use only magnitude of electromyogram because of low sampling rate of EMG sensors. Since frequency of electromyogram usually distributes from 5 to 500 Hz, more than 1 kHz sampling rate of EMG is required to reconstruct and analyze. Nevertheless the employed commercial SEMG sensor has a sampling rate of 200 Hz, and it is insufficient to retrieve whole specification of frequency of electromyogram.

As general, measured SEMG from electrodes is processed with rectification, integral, and normalization. In this paper, rectified electromyogram, $R_{\text{emg}}(t)$, is calculate with Root Mean Square:

$$R_{\text{emg}}(t) = \sqrt{\frac{1}{n}\sum_{i=0}^{n-1} E_{\text{emg}}^2(t-i)}, \tag{1}$$

where $E_{\text{emg}}(t)$ represents electromyogram measured at the time of t.

As a magnitude index of electromyogram, IEMG is widely adopted for motion classification.

$$I_{\text{emg}} = \int_{t-\tau}^{t} R_{\text{emg}} dt, \tag{2}$$

where τ represents time constant, and here $\tau = 0.5$ [s]. The IEMG of each channel is normalized where its average and variance are equal to 0 and 1 respectively.

B. Classification of Hand State with Depth Images

In order to discriminate hand actions, datasets for SVM learning are required, which are composed of IEMG and motion (state) label of hand. Additionally, in order to evaluate accuracy of real-time classification, an estimated label has to be checked with its corresponding true label. Although it can be manually added, a motion capturing device gives the labels automatically. In this paper, we use Leap Motion (Leap Motion, inc. [7]), a depth sensor for hand tracking. The device can recognize hand shapes with estimating each joint of fingers and points on the palm. Every pointing vector, p_i of the twenty vectors is corrected, with taking relative posture between the device and the hand into consideration:

$$\boldsymbol{p}_{it} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos\theta & \sin\theta \\ 0 & -\sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} \cos\phi & 0 & -\sin\phi \\ 0 & 1 & 0 \\ \sin\phi & 0 & \cos\phi \end{bmatrix} \boldsymbol{p}_i \tag{3}$$

$$\boldsymbol{p}_{iu} = \frac{\boldsymbol{p}_{it}}{||\boldsymbol{p}_{it}||}, \tag{4}$$

where $||\cdot||$ means Euclidean norm. These corrected twenty vectors as 60 dimensional datasets are used as input of SVM (Support Vector Machine) learning to classify hand states. In our preliminary experiments, the classification of hand states shown in Fig. 1 has no errors.

III. Experiments and Results

A. Measurement setup

Fig. 2 shows our experimental setup. A subject sit down on the chair and lays their forearm down on the stage with 15 [cm] height from the table. A band of EMG sensors array, Myo band (Thermic inc.) is attached to an appropriate position on their forearm following its instruction. A infrared depth sensor, Leap Motion, on the table watches the subject's hand action and estimate its posture to retrieve datasets. Our proposed system uses SVM (Support Vector Machine) and Neural Network built with scikit-learn [8], a machine learning library for Python. The kernel of SVM is Radial Based Function with default hyper parameters.

We retrieve datasets of both hand actions and corresponding EMG for SVM learning with the following procedure:

Step 1. Lay down their forearm on the stage and relax.
Step 2. Form either of six motions shown in Fig. 1.
Step 3. Start to measure EMG and calculate IEMG after the value of EMG is in constant and keep the posture in 10 seconds.
Step 4. Repeat the above processes for every motion.

Since the sampling rate of the EMG measurement is 10 Hz, we can retrieve 100 datasets per a motion.

B. Experimental results

1) Offline discrimination: To verify our proposed system to discriminate the six combined motions, we examined for three non-amputee 20-years-old people in offline. As Sec. III-A, we retrieved three amounts of datasets, and merge them. Then 10 percent of the datasets, thus 180 datasets are used for SVM learning and the rest are to be classified by the discriminator.

Table I shows a confusion matrix that represents each motion to be classified by the SVM discriminator with measured IEMG and its result. To evaluate discriminators, we usually use *F-measure*, which is harmonic mean calculated with classification precision and recall rate as (5). Precision means a rate which each classification result matches that of true class. Recall means a rate which the discriminator successfully detects cases in target true class.

$$(F-measure) = \frac{2(Precision)(Recall)}{(Precision)+(Recall)} \tag{5}$$

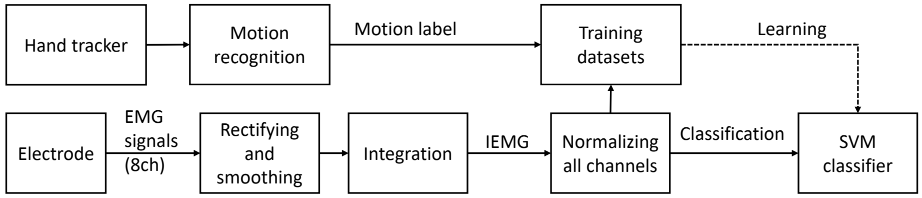


Fig. 3. A classification diagram for the six hand states

TABLE I

A RESULTANT CONFUSION MATRIX

		Estimated class						
		PG	NG	SG	PO	NO	SO	F-measure
Actual class	PG	.978	.004	0	0	0	0	0.978
	NG	0	.996	0	0	0	0	0.996
	SG	.003	.003	.996	.998	0	0	0.994
	PO	.004	0	0	.998	0	0	0.998
	NO	.032	0	0	0	.932	.012	0.931
	SO	0	0	0	0	.096	.944	0.942
							Mean	0.973

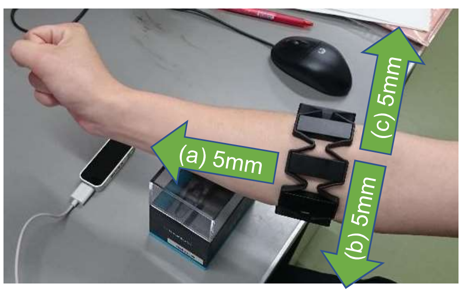


Fig. 4. Offset of sensors alignment

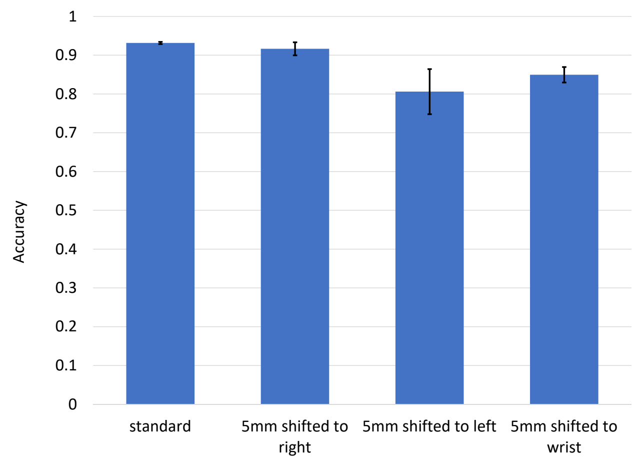


Fig. 5. Location changing interfere with classification accuracy

The confusion matrix (Table I) shows that the average of F-measure is 97.3 % and the worst case is for NO motion with 93.1 % rate. This may be caused by the errors in SO classification where 10 % of datasets are wrongly classified as NO motion. Our results of classification rate for combined motion are sufficient since a similar score for single motions is reported in a previous study [3].

In addition, our datasets for SVM learning are retrieved from three people and they are merged. Thus individual differences from each other are successfully absorbed.

C. Interference by offset of sensors alignment

When the band of EMG sensor array used in this paper is attached to a subject's forearm, it is difficult to align the sensor precisely at same location in every time. Thus differences of sensors alignment may occur in iterated measurement and interfere the values of measured EMG. In this section, we investigate the interference of sensors alignment as follows.

The band is usually attached to a subject's forearm at 7 cm far from their elbow toward the wrist. And an LED embedded in the band determines the angle of the attached band. With this standard position, we shift the band alignment with 5 mm for each direction as Fig. 4. Datasets for SVM learning are retrieved when the band is located at the standard position. After that datasets from misaligned sensors are examined whether they can be appropriately classified by the discriminator leaning on the standard position.

As a result shown in Fig. 5, each classification rate by the misaligned sensors is decreased up to about 15 % at the worst cases. Considering that 5 mm misalignment is actually too large in usual uses with suitable attachment, decrease of classification rate will become smaller.

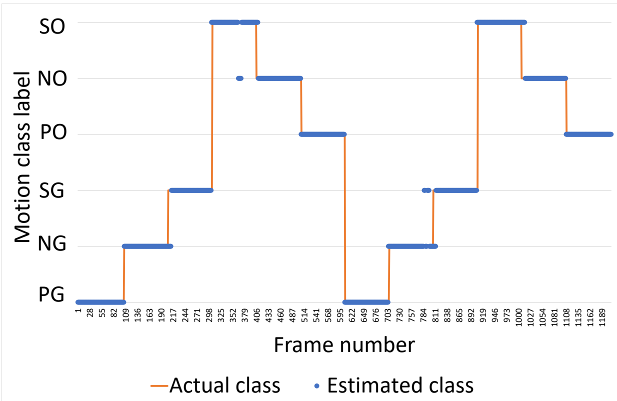
D. Real-time classification

To consider daily uses to operate electromyographic prostheses, real-time classification is essential and is expected to be with high success rate. Then we have to avoid a response time lag from actual motion (or willingness to move) to the end of classification. Additionally wrong classification caused by impulse EMGs may occur during a shift from a certain motion to another motion.

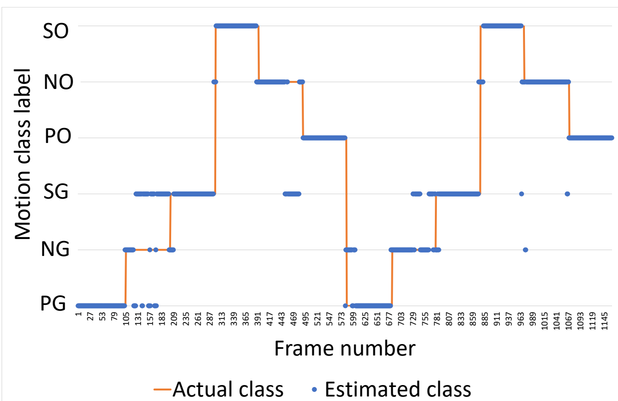
In this section, we examine a real-time classification for a continuous shift of motion: PG -> NG -> SG -> SO -> NO

TABLE II
ACCURACY OF REAL-TIME CLASSIFICATION

	PG	NG	SG	PO	NO	SO	Mean
Trained User	0.99	0.94	0.94	0.99	0.95	0.94	0.96
Inexperienced User	0.91	0.57	0.72	0.99	0.84	0.95	0.83



(a) Performed by a trained subject



(b) Performed by a non-experienced subject

Fig. 6. Real-time classification of six hand postures (Fig. 1): (a) a person who has trained for EMG measurement many times, (b) a person who is a beginner for EMG measurement.

-> PO, with three subjects. Each motion is kept 10 seconds. Judgment of classification depends on the estimation by Leap Motion, a hand tracking system with infra-red depth sensor, and its accuracy of classification of the target motions is almost 100% in our pre-experiments. Each SVM discriminator has been built and learned with 100 datasets per a motion (totally 600 datasets) retrieved from each single person.

Experimental results are shown in Fig. 6 and Table II. Performances of a trained person are well discriminated with high classification accuracy of 95.9%, and the result by a non-experienced person is quite smaller with the rate of 83.0%. Classification delay appeared with 0.17 seconds in average and up to 0.9 sec. Our presented classification system can be used in real time although its accuracy depends on the user's experiences on measuring electromyography.

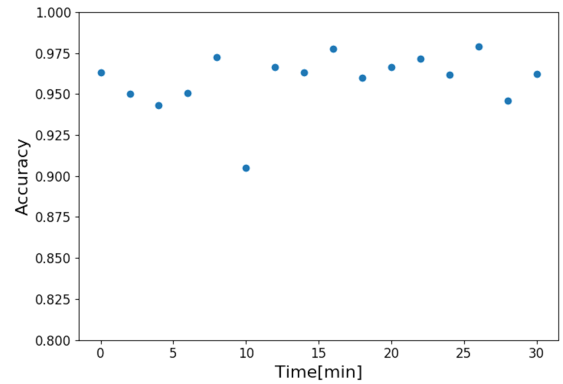


Fig. 7. Classification accuracy during a continuous motion

E. Interference of Muscular Fatigue

Continuous muscular contraction causes reduction of both length and contraction of muscles, and the resultant muscular strength will become smaller. And then measured IEMG will be also smaller even if the subject acts the same motion. In this section, we investigate the effect of muscular fatigue for measuring electromyogram and its classification. The following results are executed by the above trained person.

1) Muscular Fatigue by a Continuous Motion: Considering iteration of routine motion for a long time, we investigate variance of classification accuracy in an experiment where the real-time classification presented in Sec. III-D is executed in 30 minutes. Fig. 7 shows the experimental results, in which each plot represents classification rate in each divided time period of 2 minutes. For every period, each classification rate is higher than 90% with some variance. Hence muscular fatigue by a continuous motion has few influence to classification accuracy in our experimental system.

2) Muscular Fatigue by a Large Load in Short Time Period: Considering applying a large load to muscles, for example when a user bring up a heavy baggage. As a large load to muscles in short time period, push-up exercise and continuous opening and closing of hand are performed. Table III shows our experimental setup and results. The row of A represents that classification rate of 85.6% was performed after 20 times push-up. And the row of C represents 88.8% rate of performance after 40 times push-up and next 100 times opening and closing of hand. This experimental results implies that heavy loads applied to muscles cause reduction of classification rate, comparing with the fatigue by a continuous motion reported in Sec. III-E.1. Note that the results does not validate a correlation between load magnitude and accuracy rate because the most highest accuracy rate of

TABLE III

CLASSIFICATION ACCURACY AFTER APPLYING A LARGE LOAD

	Number of loading [times]		Accuracy rate
	push-up	opening and closing	
A	20	0	0.856
B	40	0	0.902
C	40	100	0.888
D	40	200	0.933

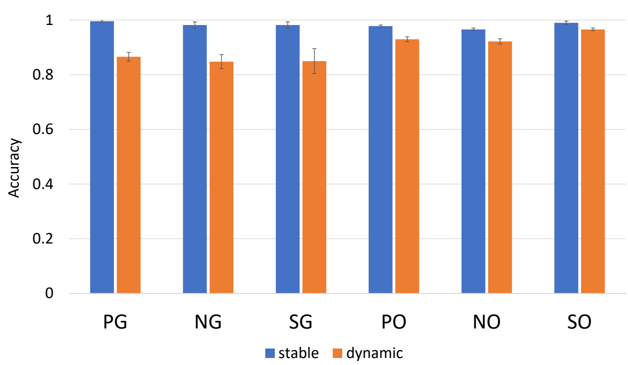


Fig. 8. Dynamic motion of upper limb interferes motion classification

motion classification is performed under the condition D with largest muscular load. It can be assumed that the subject has been experienced at the latter of experiments.

F. Interference of Upper Limb Posture

The above experiments were executed under the condition that the subject lays their upper limb on the table with keeping a particular posture shown in Fig. 2. On contrast in daily life, people often use their hands and fingers with upper limb motion, which is actuated by corresponding muscles' electromyography (EMG). The EMG for upper limb's motion interferes as noises above classification of hand's motion, and decreases classification accuracy as Fig. 8.

Hence we propose an improved classification diagram with correction, shown in Fig. 9. The EMG arm band used in this paper has internal gyro sensors and obtains its orientation. When a upper limb and a hand move together, obtained EMGs are as integrated EMGs for both the upper limb's motion and the hand's. Thus we remove the components of EMG for the upper limb's motion from the integrated EMGs with using a single Neural Network. The spatial range for the upper limb's motion, which can be observed, is limited to $400 \times 300 \times 400[\mathrm{mm}]$ from the hand tracker, Leap Motion.

Orientation of object is expressed with quaternion (q_0, q_1, q_2, q_3), and the input layer of the neural network has 12 dimensions: $q_i, \frac{dq_i}{dt}, \frac{d^2q_i}{dt^2}$ $(i = 0, 1, 2, 3)$. The output layer of the network has 8 dimensions corresponding the number of channels of the EMG sensor. Measuring EMG signals and the quaternion for only upper limb's motion without hand actions, the output of the neural network is tuned as IEMGs of the motion.

The neural network is built as follows. We retrieve sets of IEMG and quaternion during the upper limb's motion without hand action as flexion, pronation and supination. Note that we remove error values which are out of the range for 1σ. The number of datasets for neural network learning is about 30,000. Each of two mid layers has 500 nodes and other parameters are set as default. To compare the modified classifier (Fig. 9) with the previous method without correction (Fig. 3), the following classification experiments for the hand's motion with upper limb's motion are verified.

Step 1. 500 datasets of each of six motions in Fig. 1, which are with random motion of upper limb, are retrieved. Each dataset is composed of IEMGs from 8 channels of the arm band, quaternion representing orientation of the arm band, and motion label recognized by the hand tracker.

Step 2. each 50 datasets for learning are randomly selected (amount of 300 datasets), and the rest are used for classification tests.

Step 3. The classifier built with SVM learns with the selected datasets and classify the rest datasets.

Step 4. Comparing each result of classification with the recognized motion label, accuracy rate of the experiment is calculated.

The above procedure is iterated 5 times to obtain average and standard deviation of accuracy rate.

The experimental results are shown in Fig. 10. Except NG and SG motion, every classification rate can be improved by correction attributed to upper limb's motion (Fig. 10(a)). On the other hand, we let the SVM classifier learn with each 100 datasets per motion (amount of 600 datasets), and obtained improved classification accuracy, particularly classification without correction. The results imply that increase learning datasets of six hand actions with upper limb movement facilitates to classify the motions, though correction considering EMG noises attributed to upper limb movement also contributes to classification accuracy.

IV. CONCLUSION

In this paper, we study on motion estimation using Surface electromyogram (SEMG), where combination of finger closing and wrist twisting. Our proposed discriminator is built with Support Vector Machine for recognition of electromyogram. The datasets for learning are retrieved by using a arm-band-type electrodes array and a motion capture device. The discriminator can perform high accuracy of recognition of electromyogram during combination state of single motions. In addition, we also investigated whether muscular fatigue and and upper limb motion interfere in measuring electromyogram and its discrimination. As a result, muscular fatigue seldom interferes the accuracy of classification in our experiments. As for upper limb motion, its effect cannot be

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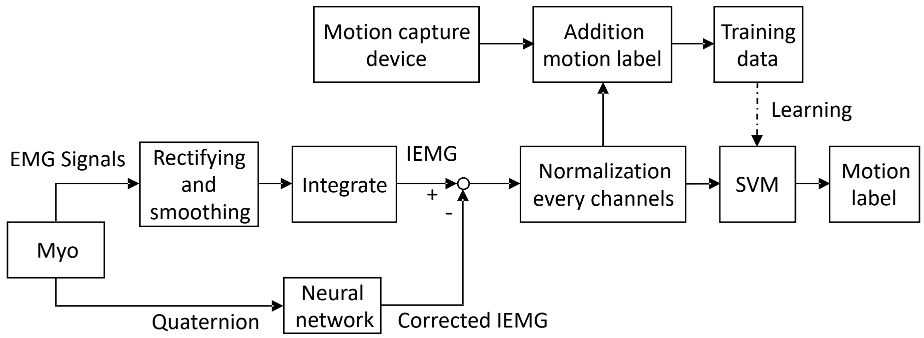
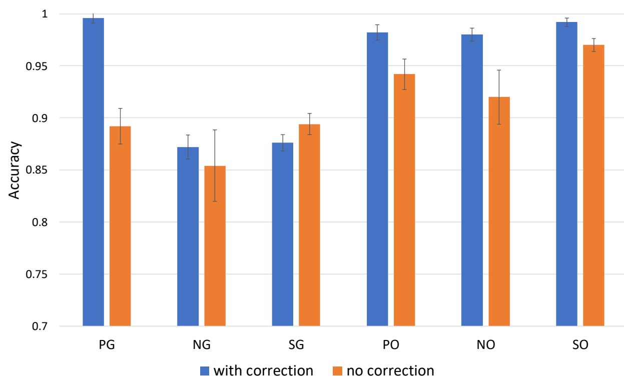
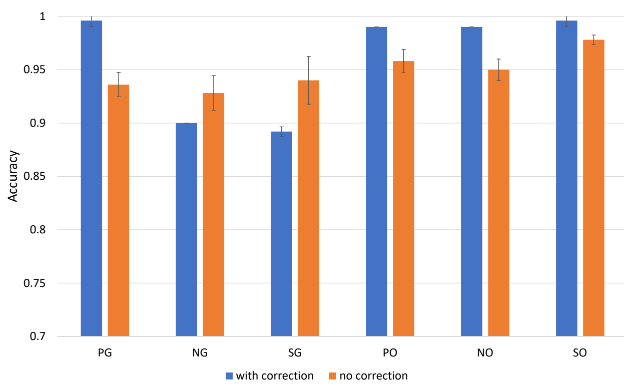


Fig. 9. A correction diagram for upper limb posture



(a) With 50 learning datasets



(b) With 100 learning datasets

Fig. 10. Classification result with correction

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