Power Assist Control based on Motion Estimation of Wearer's Forearm using Motion Sensor

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***Abstract*—Powered exoskeletons are becoming popular especially in fields of nursing care and agriculture. We have been developing a powered exoskeleton that is supposed to be used in case of a nuclear hazard. Conventional powered exoskeletons typically use electromyographs (EMG), force switches, or force sensors on the wear's feet. Unfortunately, the former suffers from the decline in measuring accuracy or slips of EMG sensor by sweating. The force-switch-based assist control method has a difficulty in speedy assist control of walk because it needs a few steps of a walk for the recognition. The force-sensor-based assist control method realizes a rapid assist control but the assistive motion is defined beforehand in general. We propose a new approach for power assist controller based on user motion prediction using 9 axis motion sensor. The motion sensor detects the angle and angular velocity of the wear's limb and estimates the appropriate angle of the powered attachment according to the estimated motion. This report conducts experiments with one degree of freedom powered arm to evaluate the proposed method by EMG sensors and a force sensor.**

I. Introduction

Powered exoskeletons attract attentions especially in the fields of nursing care, transportation and agriculture because workers in those fields need heavy lifting. We are also developing powered exoskeletons for a case of hazard at a nuclear plant. The powered exoskeleton is to be active at the time of the nuclear disaster since a worker wears a protective suit which weight is about 40 [kg].

Almost conventional methods of power assist control are based on electromyography (EMG)[1], [2], force switches, or force sensors on feet. EMG can detect an electrical signal that is generated 50 [ms] before a muscle starts its contract so that the power assist control based on the EMG amplifies the wear's motion rapidly. However, EMG is not suitable for our purpose because it is weak with sweat. The worker has to stand high temperature and high humidity wearing a radiation protection suit in the hazard nuclear plant[3]. The situation makes the worker a lot of sweat. An electromyograph must be attached the wear's skin directly so that it is sensitive to movement of the probe or conditional change of the surface of the skin.

The force-switch-based assist control method [4], [5] uses force switches on feet to estimate wear's walking intention. Unfortunately, it has a difficulty in speedy assist control of walk because it needs a few steps of a walk for the recognition. The force-sensor-based assist control method [6] realizes a rapid assist control but it often supports only one specific motion, for example, walk, even though a wearer takes a variety of motions wearing the powered exoskeleton. Furthermore, repeated impacts against the ground break the force sensors or force switches on the feet easily so that they are not reliable for long-term usage.

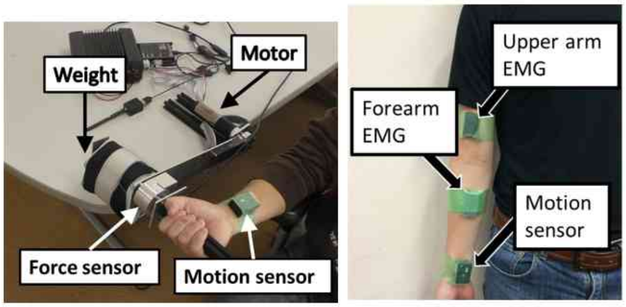
We propose an assist control method using 9-axis motion sensors. A motion sensor measures wearer's limb motion in severe working conditions such as high temperature and high humidity. The motion sensor is attached to the human limb so that it avoid the breakdown by the repeated impacts from the ground. Murata et al.[7] also had a study of assist control using a motion sensor and used Kalman filter to predict Human's motion, however, it supports only short-term motions. Our proposed method aims at assist control for long-term motions based on a motion database. In order to investigate the validity of our proposed approach, this report conducts a simple experimental task using a single-degree-of-freedom assist device. The proposed assist control estimates human forearm motion based on K-nearest neighbor algorithm (KNN) and the motion database, then, assists the motion appropriately.

II. Experimental Setup

Figure 1 shows the experimental setup. Figure 1(a) shows the single-degree-of-freedom forearm assist device. A subject grabs the handle of the assist device and attaches his/her elbow at the armrest that is fixed during the experiments. 2 [kg] weight is fixed to the opposite end of the handle of the assist device. The rotation axis of the subject's elbow is aligned to the rotation axis of the arm of the assist device. A motion sensor is attached to the wrist of the subject. The motion sensor has 3-axis accelerometer, 3-axis gyroscope, and 3-axis magnetometer. It provides the posture of the subject arm using Madgwick's IMU algorithms[8]. A force sensor is attached to the handle to measure the force of the hand. It is only used by evaluation of the assist performance. Two EMG sensors are attached to the subject arm as shown in Figure 1(b). One is on the forearm and the other is on the upper arm. The EMG records are used for evaluation of assist performance since the amplitude of EMG is related to the tension of muscle.

III. Assist Control based on Motion Prediction

We propose the assist control system based on motion prediction. Figure 2 shows the outline of the proposed power assist controller. The motion sensor measures sequential angles



(a) Assist devise (b) Measuring the position of the EMG

Fig. 1. Experimental landscape

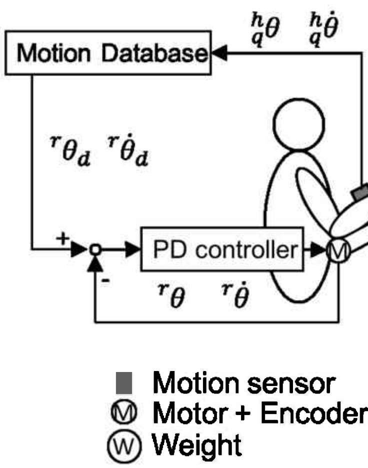


Fig. 2. Schematic diagram of assist control with motion sensor

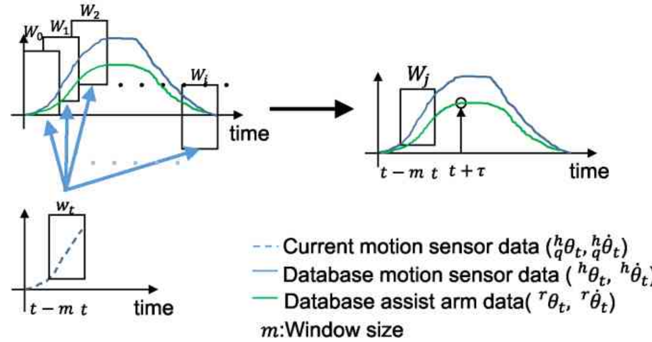


Fig. 3. Motion prediction

and angular velocities of the subject's forearm and assist device arm. ${}^h\theta$ and ${}^h\dot{\theta}$ indicate the angle and angular velocity of the subject's forearm, respectively. ${}^r\theta$ and ${}^r\dot{\theta}$ indicate the angle and angular velocity of the assist device arm, respectively. The sampling rate is 100[Hz]. It estimate appropriate angle and angular velocity of the assist device arm, ${}^r\theta_d$ and ${}^r\dot{\theta}_d$, from the sequence of ${}^h\theta$ and ${}^h\dot{\theta}$ based on a motion database. ${}^r\theta_d$ and ${}^r\dot{\theta}_d$ are supposed to assist the subject's motion. A PD-controller controls the motor according to ${}^r\theta$ and ${}^r\dot{\theta}$, ${}^r\theta_d$ and ${}^r\dot{\theta}_d$.

The motion database is composed of subject's motion, that is, sequences of the angle and angular velocity of the subject's forearm, ${}^h\theta$ and ${}^h\dot{\theta}$, the corresponding angle and angular velocity of the assist device arm, ${}^r\theta$ and ${}^r\dot{\theta}$, and motion classes c corresponding to the subject's motion. The data for the database is collected beforehand while the subject moves his/her arm without the weight attached to the end of the handle. The motion the subject demonstrated without the weight is supposed to be the desired motion with the weight and the power assist. Upper right figure in Figure 3 shows how to build the motion database. The acquired motion sequential data is divided with the window size $m+1$. One datum in the motion data $\boldsymbol{W}_i$ consists of sequential motion sensor data, $({}^h\theta_{t-m}, {}^h\dot{\theta}_{t-m}, \cdots, {}^h\theta_t, {}^h\dot{\theta}_t)$, the corresponding arm motion at time $t+\tau$, $({}^r\theta_{t+\tau}, {}^r\dot{\theta}_{t+\tau})$, and the motion class c. m is size of the sequence window size. The motion class c is defined by four classes; arm stop motion at right angle, stretching motion, arm stop motion horizontally, and flexing motion.

The appropriate angle and angular velocity of the assist device arm ${}^r\theta_d$ and ${}^r\dot{\theta}_d$ are estimated based on the motion database using KNN. Figure 3 shows the overview of the calculation. KNN compares the current sequential data obtained from the motion sensor, $\boldsymbol{w}_t = ({}^h_q\theta_{t-m}, {}^h_q\dot{\theta}_{t-m}, \cdots, {}^h_q\theta_t, {}^h_q\dot{\theta}_t)$, and sequence of the data included in the motion database $\boldsymbol{W}_j$ according to euclidean distance between them. KNN chooses the most similar K sequences of the motion data. The appropriate angle and angular velocity of the assist device arm ${}^r\theta_d$ and ${}^r\dot{\theta}_d$ are calculated as average angle and angular velocity of the assist device arm ${}^r\theta_{t+\tau}$ and ${}^r\dot{\theta}_{t+\tau}$ of the selected K motion data.

Here, we have two issues applying the KNN for calculating ${}^r\theta_d$ and ${}^r\dot{\theta}_d$. One is how to handle the different units, angle and angular velocity, simultaneously. One possible solution is to merge them with weights to calculate the euclidean distance as follows:

$$d = \sum_{t-m}^{t} \left(k_a \left| \frac{{}^h\theta_t - {}^h_q\theta_t}{\sigma_a} \right| + k_\omega \left| \frac{{}^h\dot{\theta}_t - {}^h_q\dot{\theta}_t}{\sigma_\omega} \right| \right) \tag{1}$$

where σ_a and σ_ω are standard deviation of angle and angular velocity of the subject's arm, k_a and k_w are weight, respectively. Another solution is to apply KNN methods to angle and angular velocity, separately. ${}^r\theta_d$ is calculated based on only angle sequence, $({}^h\theta_{t-m}, \cdots, {}^h\theta_t)$ and ${}^r\theta_{t+\tau}$. ${}^r\dot{\theta}_d$ is calculated based on only angular velocity sequence, $({}^h\dot{\theta}_{t-m}, \cdots, {}^h\dot{\theta}_t)$ and ${}^r\dot{\theta}_{t+\tau}$. This solution assumes that the sequence of joint angle is independent of the one of angular velocity and does not need to tune weight parameters trial and error.

The other issue is how effectively the clustering of the motion work for the power assist. The estimation of future angle and angular velocity of the assist device arm, ${}^r\theta_{t+\tau}$ and ${}^r\dot{\theta}_{t+\tau}$, should be better if the database is categorized into predefined classes because the motion database without clustering includes all motion of the subject's arm and it affects worse so that it includes unnecessary motions for the estimation. This paper investigates the issue, too. Four motion classes, arm stop motion at right angle, stretching motion, arm stop motion horizontally, and flexing motion, are defined as follows: “arm stop motion at right angle” is defined as the arm angle is smaller than 45 [deg] and the absolute value of the arm angular velocity is smaller than 10 [deg/s]. “stretching motion” is defined as the arm angular velocity is larger than 10 [deg/s]. “horizontal stop motion” is defined as the arm angle is larger than 45 [deg] and the absolute value of the arm angular velocity is smaller than 10 [deg/s]. “The flexing motion” is defined as the arm angular velocity is smaller than -10 [deg/s].

Once the desired angle and angular velocity of the assist device arm, ${}^r\theta_{t+\tau}$ and ${}^r\dot{\theta}_{t+\tau}$, is calculated, the PD controller controls the input to the motor u based on Eq.2.

$$u = -k_p({}^r\theta - {}^r\theta_d) - k_d({}^r\dot{\theta} - {}^r\dot{\theta}_d) + k_c \qquad (2)$$

where k_p and k_d indicate proportional and differential gains, respectively. k_c consists constant current.

IV. Experiment

In this experiment, a subject bends and stretches his/her arm intermittently while he/she keeps gripping the handle. The 2 [kg] weight is fixed the tip of the assist arm. The performance of the power assist system is evaluated with the EMG sensor and the force sensor. The EMG sensors are attached on biceps brachii muscle and flexor carpi radialis muscle as shown in Fig.1(b). When the subject bends the elbow, the biceps brachii muscle flexes. When the subject bends the wrist, the flexor carpi radialis muscle flexes. The force sensor measures the load on the hand.

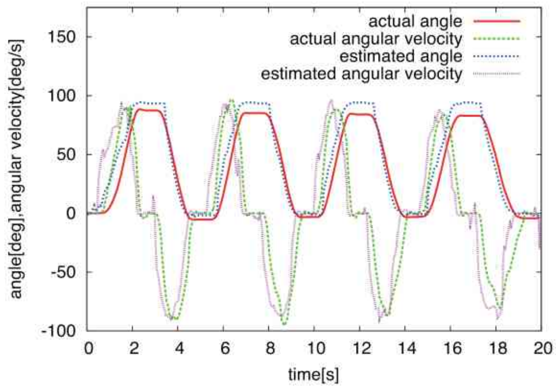
We set the window size m in Figure 3 30 in the experiments below. The window size was adjusted by hand and we found the window size 30 shows better performance than 10, 20, or 40.

A. Motion Prediction Evaluation without Assist Control

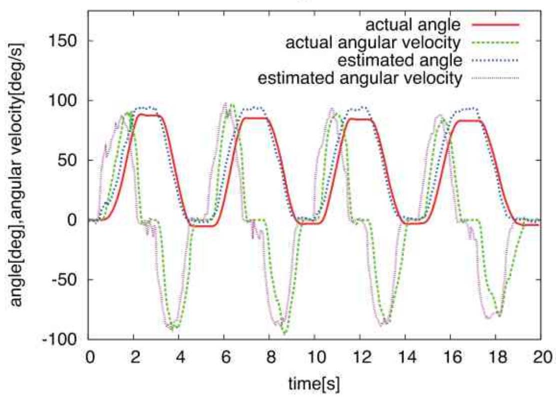
This experiment was carried out to verify prediction by KNN. It uses a motion database with one kind of the subject’s arm angle and angular velocity. Figure 4 shows motion prediction without motion clustering. Figure 4(a) shows separate KNN prediction of angle and angular velocity. Figure 4(b) shows unified KNN prediction of angle and angular velocity. Unified KNN prediction means that it uses Eq.(1) for distance calculation. k_a and k_ω are set to 1, here. Figure 4 shows that the both cases do not estimate the angular velocity very well.

Figure 5 shows motion prediction results with motion clustering. Figure 5(a) shows separate KNN prediction of angle and angular velocity. The prediction becomes better than that without motion clustering, however, it still has impulse shape noise on the estimated angular velocity at the change of the motion. Figure 5(b) shows unified KNN prediction of angle and angular velocity. k_a and k_ω are set to 1, too. It shows better estimation result of angular velocity than the others so far. However, it still has impulse shape error of the estimated angle at the change of the motion, sometimes.

The weights for the distance calculation are tuned by hand as $k_a = 1.0$, $k_\omega = 10.0$. We have tested various set of the weights, the parameter set above shows the best performance to predict the given motion. Figure 6 shows the motion prediction result with motion clustering and the weights. It shows that it estimates the motion without impulse shape noise on the angle and angular velocity of the arm. It realizes smooth motion prediction so that we adopt the weight for the assist control. Hereafter, the weights are used for the following experiments.



(a) individual prediction



(b) Unified prediction, $k_a = k_\omega = 1.0$

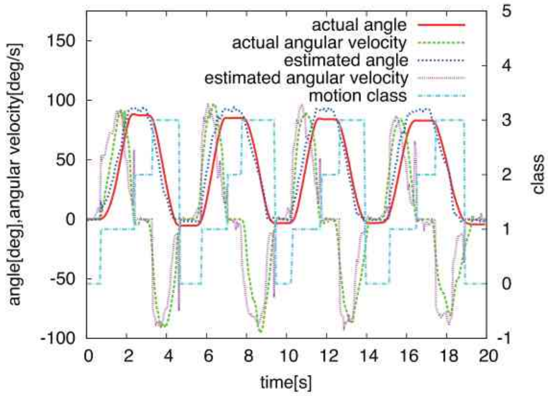
Fig. 4. Motion prediction without clustering

B. Motion Prediction Evaluation with Assist Control

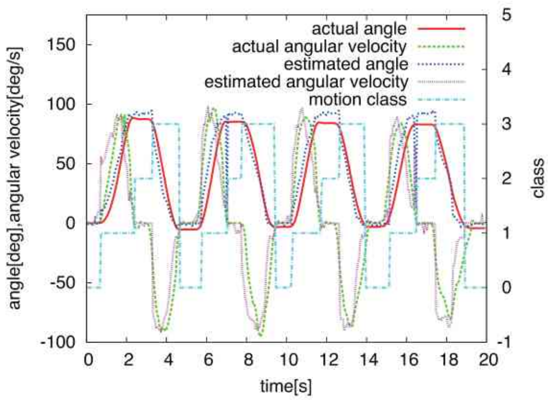
This experiment evaluates the prediction methods under the assist control. Figure 7 shows prediction result without motion clustering. The individual prediction of angle and angular velocity has relatively big noise, especially on the angular velocity. The unified prediction shows the better result than the individual one. Figure 8 shows prediction result with motion clustering. The result shows that the motion clustering is effective because both predictions are better than the last one. The individual prediction shows slightly better result than the unified one.

C. Evaluation of Assist control using Motion Prediction

Forearm EMG and upper arm EMG sensors measure surface myoelectric potential biceps brachii muscle and radial flexor muscle of wrist, respectively. Force at the handle is also measured for the evaluation.



(a) Individual prediction



(b) Unified prediction, $k_a = k_\omega = 1.0$

Fig. 5. Motion prediction with motion clustering

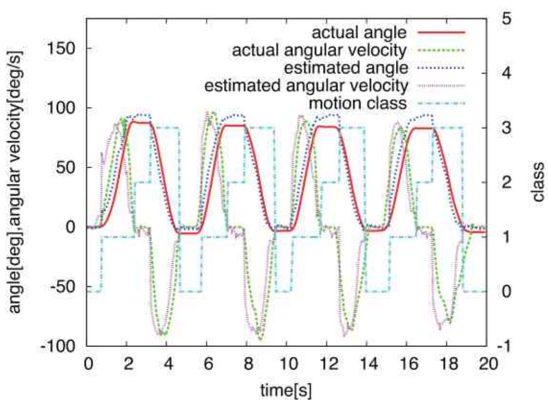
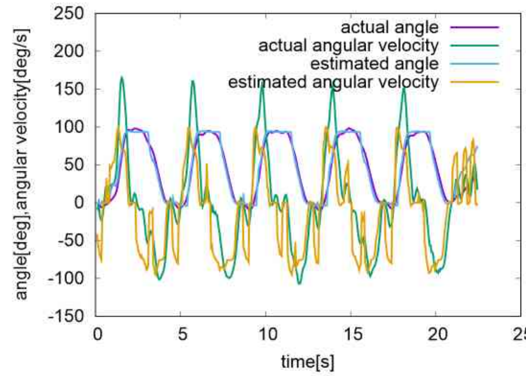


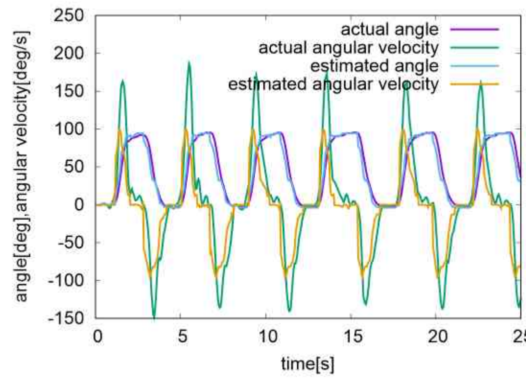
Fig. 6. Motion prediction with clustering and weights $k_a = 1.0$, $k_\omega = 10.0$ for distance calculation

Figure 9 shows a sequence of assist device arm angle, forearm and upper arm EMG signals, and force to the handle in case of no assist control. Figure 10 shows the ones under the proposed assist control methods. All assist controllers reduce the forearm and upper arm EMG signals. There is little significant difference in force sensor value between the assist controllers and no assist control although the force value at the motion "arm stop motion at right angle" tends to be smaller.

TABLE I shows the average EMG signals of the flexor carpi radialis and biceps brachii muscles during each motion



(a) Individual prediction



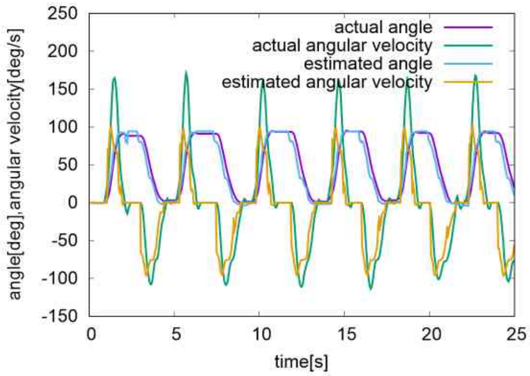
(b) Unified prediction

Fig. 7. Motion prediction without motion clustering

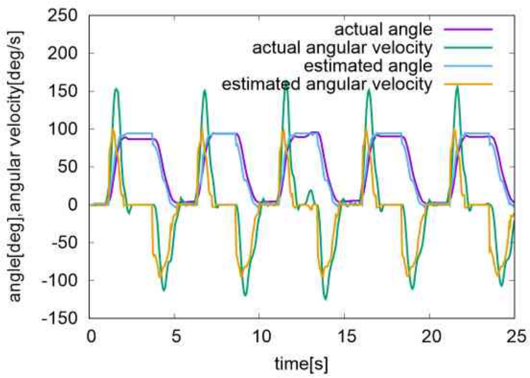
with/without the proposed four power assist methods. All power assist controls successfully reduce the EMG signals. Especially, the power assist control based on the angle and angular velocity individual prediction with motion clustering shows the best performance among them.

Figure 11 shows the average and standard deviation of EMG signals with/without the proposed power assist control during the whole motion. It shows the all power assist systems successfully reduce the activities of the arm muscles. The power assist systems based on motion clustering are better than the ones without motion clustering. The power assist system based on the angle and angular velocity individual prediction reduces the EMG signals of the upper arm most while the one based on unified prediction reduces the EMG signals of the forearm most although the difference between them is small. The reason seems to be that the individual databases of angle and angular velocity offer more recorded data similar to the query data than the unified database, but, this should be verified more precisely in future.

Figure 12 shows the average and standard deviation of the force subjected to the handle of the arm during the whole motion. It shows there are no significant differences among them somehow. It is one of the future work to find the reason why there are no significant differences even though EMG signal powers reduce.



(a) Individual prediction



(b) Unified prediction

Fig. 8. Motion prediction with motion clustering

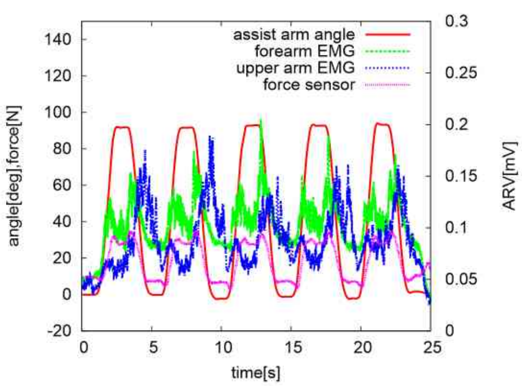
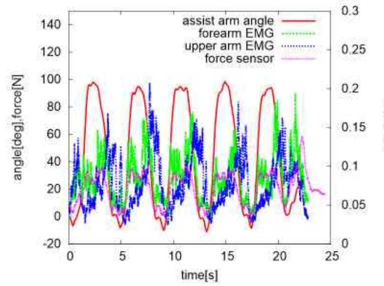
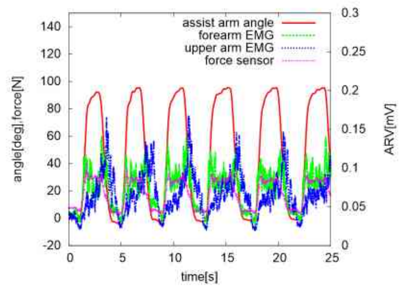


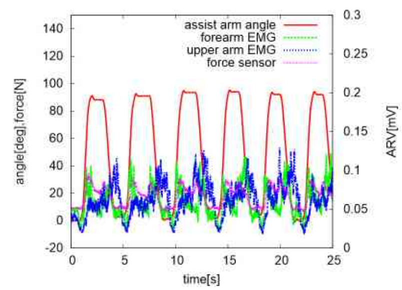
Fig. 9. Sequence of assist device arm angle, forearm and upper arm EMGs, and force to the handle in case of no assist control



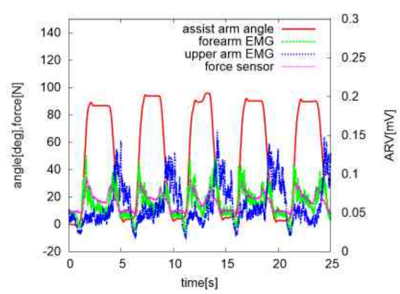
(a) Angle and angular velocity individual prediction without motion clustering



(b) Angle and angular velocity unified prediction without motion clustering



(c) Angle and angular velocity individual prediction based on motion clustering



(d) Angle and angular velocity unified prediction based on motion clustering

Fig. 10. Sequence of assist device arm angle, forearm and upper arm EMGs, and force to the handle under assist controls

V. Conclusion and Future work

We proposed a new approach for power assist controller based on user motion prediction using 9 axis motion sensor. The motion sensor detects the angle and angular velocity of the wear's limb and estimates the appropriate angle of the powered attachment according to the estimated motion. Experiments are conducted with one degree of freedom powered arm to evaluate the proposed method by EMG sensors and a force sensor. The experimental results show that the proposed method reduces the power of the EMG signals successfully although it does not reduce the force to the hand as expected.

One of the future work is to sophisticate the user motion prediction based on the motion sensors and assist the power more efficiently. Another one is the application to the powered exoskeleton to support various motions including walk, squat, stair stepping, and so on.

TABLE I
AVERAGE EMG SIGNAL POWER DURING EACH MOTION

motion	flexor carpi radialis muscle [mV]	biceps brachii [mV]
No assist control		
stop at right angle	0.078	0.077
flexing	0.113	0.074
stop horizontally	0.120	0.083
stretching	0.111	0.125
Individual prediction without clustering		
stop at right angle	0.057	0.065
flexing	0.085	0.049
stop horizontally	0.093	0.073
stretching	0.094	0.115
Unified prediction without clustering		
stop at right angle	0.062	0.060
flexing	0.0668	0.051
stop horizontally	0.066	0.051
stretching	0.067	0.043
Individual prediction with clustering		
stop at right angle	0.041	0.041
flexing	0.072	0.053
stop horizontally	0.057	0.068
stretching	0.066	0.084
Unified prediction with clustering		
stop at right angle	0.046	0.053
flexing	0.081	0.049
stop horizontally	0.063	0.049
stretching	0.068	0.100

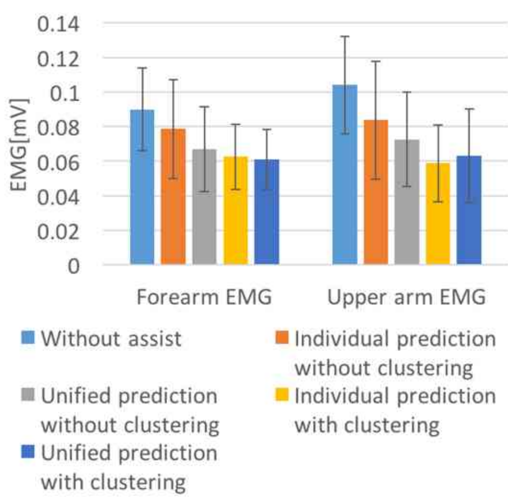


Fig. 11. Average and standard deviation of EMG signals

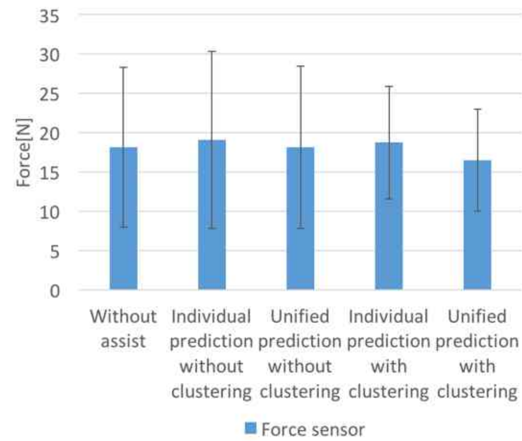


Fig. 12. Average and standard deviation of force to the handle

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