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Analysis of Musculoskeletal System of Human during Lifting Task with Arm using Electromyography

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This paper aims to investigate movement prediction of lifting task on sagittal plane using EMG signals. We used surface EMG sensor on BILH and TRLH to measure the force and position sensor (Attitude Heading Reference System; AHRS) on wrist to measure the elbow joint angle corresponding to external coordinate of musculoskeletal system. The experimental task was lifting an object on the table which varied in weight and speed. The task was mainly analyzed in time-domain and divided in three phases; pre-lifting, lifting, and holding. First, we normalized EMG signals using holding-phase EMG actuation levels instead of conventional MVC. In sequence, weight and speed classification was applied on responses of prelifting and lifting phase. This was grounded on expected characteristics such as large initiating force to lift off. Speed was classified by increasing speed of TCL (total contraction level) of pre-lifting phase ($p<0.05$) and weight was classified by peak TCL of lifting phase ($p<0.05$). Lastly, we tried trajectory estimation for the next step. Trajectory estimations for each speed and weight conditions followed trend of trajectory change, even though we used a simple linear regression method. The correlations between the estimated and measured trajectories were about 82 percent in average.

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1. Introduction

Let us consider the operation that a robot and a man lift a heavy object together. It is possible to classify the robot-driven operation and human-driven operation depending on whether who is the initiator of the task, a robot or a man. For Robot-driven operation, it is sufficient for human to adjust the position and the strength flexibly to the movement of the robot as the same way people working with other people every day. However, in the case of human-driven operation, the robot should infer the human movement intention and perform a situation analysis to respond appropriately to unforeseen circumstances. It is believed that there are some limits still in intelligence level of the robot to operate reliably in unstable environments; mechanisms that transmit the information of human motion directly would be effective.

In the method of transferring the human intention to the robot, there is no way for human to instruct the movement information such as direction, speed, and force continuously and quantitatively. Therefore, sensing technology which can simultaneously measure the dynamic and kinematic parameters of human is required. However, common kinetic sensors are mostly huge and complex equipment. And there will be a problem if we perform a real-time interaction because of sensor delay. Alternatively, in this study, we propose the method to extract the human movement intention from EMG signal in time series, and use it as control parameter for robot.

Advantage of the EMG signal is a point that it is not the record of the movement appeared externally, to measure the movement of the internal occurring in muscular level. It is useful to figure out the movement intentions from EMG signals. Even though the external motions are same, we can distinguish them in more detail by checking muscles used or stiffness levels from EMG signal. In particular, it is important to measure the stiffness in time series for human interaction with the objects, closely related with compliance movements. In the past, stiffness was measured by the perturbation method using a 2-DOF manipulator on a horizontal plane.[1] This method was extended to measuring the mechanical impedance such as stiffness, viscosity, and inertia.[2,3] Such methods estimated through the displacements caused by the perturbations from manipulator in the course of fixed hand or point-to-point movement.

It is possible to estimate the stiffness along the position through a lot of trials, but it is difficult to measure in time series. Previous studies have shown that there are linear relationships between surface EMG and joint torque and stiffness.[3,4] Further, IMJC (index of muscle co-contraction around the joint) could be calculated from EMG and it is possible to use them to measure the joint elasticity during the motion.[5] IMJC is a total of tensions, but it is not the stiffness itself. Although, there are mathematical models to estimate stiffness and stiffness ellipse from surface EMG.[6]

Verification and estimation of human arm parameter through the EMG were mainly performed in the horizontal plane, and it was proceeded in a manner to compare the TCL (total co-contraction level) calculated from EMG and stiffness obtained from the manipulator perturbation. This corresponds to the situation such as pushing the things on the table. However, the usual object interaction of the human is lifting. It is constrained movement according to the weight, and differences on torque and stiffness characteristics are expected.

To estimate human intention from EMG, human characteristics should be investigated first. In human body, both internal and external coordinate exist. Therefore, relationship between these coordinates should be examined. Because the internal coordinate has high DOFs (degree of freedoms), various correlations with the external coordinate are made. Thus, investigation of the correlations is complicated. We tried to observe human intention through EMG during lifting tasks. To examine the relationship between internal and external coordinate which reveals the characteristics of human, we observed the reproducibility of movement in external coordinate using EMG information.

Regarding EMG processing, several techniques including pattern recognition, force estimation, and angle estimation are practiced to predict human intentions. Among them, the force estimation needs calibration procedure. Through simple modeling, we estimated weight level and force level to observe parameters for investigation of external coordinate by using only EMG and thus found the proper coordinate correlation.

We tried to estimate the intention and the rough trajectory in the periodic lifting task on sagittal plane in previous studies.[7,8] In this investigation, we found that TCL varies depending on the weight and it could be able to classify through the TCL. In this study, we normalized the EMG signals using weights, and single point-to-point lifting tasks were performed, and task speeds and weights were classified. In addition, we estimated the rough trajectories by applying a simple regression method for each condition, to test the feasibility of the integrated model that condition classifier and trajectory estimator are combined. Condition classifier predicts weights and velocities through EMG signal on pre-lifting motion whereas trajectory estimator works by using coefficients applied to linear model that the condition classifier predicted according to the condition.

EMG signal as a human intension predictor is noisy, personal, and easily influenced by the environment so it is not a highly reliable sensor. However, the origin of EMG signal is action potential which contracts a muscle, so the signal is valuable information which can replace various nonverbal communications when human cooperates with others. EMG based integrated model, which this study aims at, will be useful to make robots decide its reaction after recognizing human action or to realize compliance motion.

In this study, we investigated characteristics of the lifted object, magnitude of load on joints, trajectory during lifting exercise, and features of the movement from EMG signals (internal coordinate). We used a very simple regression due to the chronic calibration problem of EMG. Through experiment, the feasibility of the simple estimation was examined for applications.

2. Methods

2.1 EMG signal processing

Surface EMG signals were recorded from two muscles. For the flexion and the extension of the elbow joint, the biceps long head (BILH, flexor) and the triceps long head (TRLH, extensor) were measured. The amplitude of EMG signal reflects the muscle tension. Raw EMG signals from the CNS contain high frequency, which needs rectification and low-pass filtering to get the amplitude.'BagnoliTM Desktop EMG Systems' of Delsys Inc. measured the raw EMG signals. The bandwidth of the system was 20~450 Hz and rolloff was 80 dB/decade. The sampling rate of the DAQ was 1 kHz with a 16-bit resolution. In previous study, second order low pass filter is enough to estimate muscle tension from EMG signal. The signals were digitally rectified and filtered with the following frequency response Eq. (2).[9]

$$q(t) = \sum_{j=1}^{m} h_j EMG(t-j+1) \tag{1}$$

$$h(t) = 6.44 \times (e^{-10.80t} - e^{-16.52t}) \tag{2}$$

The filtered signal was called quasi-tension since it showed high correlation with the actual muscle tension. In an arithmetic operation, we converted the filter to a digital filter by applying a bilinear transformation.

2.2 Estimation of joint torque and joint stiffness

Joint torque is generated by the difference in flexor and extensor EMG signals, and can be determined by Eq. (3) using muscle i acting on joint j is similar to actual muscle tension.

$$\tau_j(u,\theta) = \sum_i a_{ji} T_i(u,\theta) \tag{3}$$

($a_{ji} > 0$ ($i = 1, 2, \ldots; j = s, e$) is the length of the moment arm)

A constrained optimization method was applied to estimate the parameter a_{ji}. Since the quasi-tension is similar to actual muscle tension, joint torque can be estimated using quasi-tension. Joint torque is generated during movements, and movement trajectory can be estimated from the joint torque using numerous mathematical models such as Least Square Fitting and neural networks.[9,10]

Joint stiffness, or total co-contraction level (TCL), is the summation of effective muscle stiffness, and can be expressed as Eq. (4).

$$R_{jk}(u,\theta) = \sum_i a_{ji}^2 (k_0^i + k_1^i u_i) \tag{4}$$

Assuming that muscle activation is proportional to the EMG level, we can estimate the stiffness directly using Eq. (4). When the movement velocity increases in multi-joint movement, the joint stiffness also increases.[9,11]

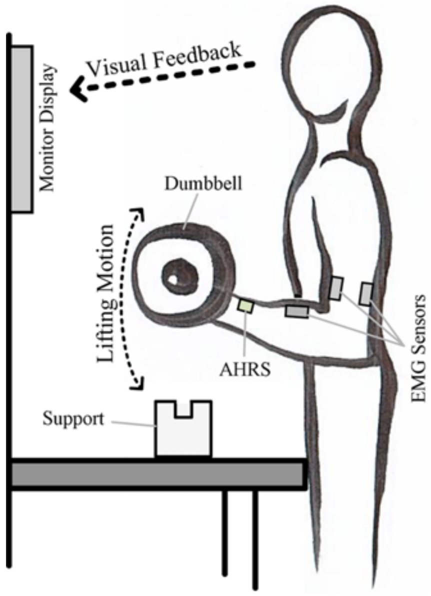

Fig. 1 Experimental setup: A subject stands front of the table and holds the dumbbell on the support. According to the lifting cue, the subject lifts the dumbbell in instructed speed. The speed guide and the target position are displayed on the screen. Force sensors were attached on the support to catch the lifting time of the dumbbell

2.3 Joint angle measurement and linear regression

To test the feasibility of trajectory estimation, the elbow angle was estimated from the quasi-tensions using linear regression expressed as Eq. (5). The reference angle is measured with AHRS (altitude heading reference system) sensor which has the bandwidth of 100 Hz. The sensor was attached on the wrist to move together with the forearm.

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$$\underbrace{\begin{bmatrix}\theta_1\\ \theta_2\\ \dots\end{bmatrix}}_{Y}=\underbrace{\begin{bmatrix}q_{f1}\,q_{e1} & 1\\ q_{f2}\,q_{e2} & 1\\ \dots\ \dots & \dots\end{bmatrix}}_{H}\underbrace{\begin{bmatrix}c_f\\ c_e\\ c_o\end{bmatrix}}_{X} \tag{5}$$

Where, Y: measured angle, H: quasi-tension, X: linear coefficients.

The linear relationship between the quasi-tension and the angle derived from above regression is presented in Eq. (6). The equation was also used to calculate the trajectory after coefficients were estimated on each condition.

Joint torque and joint stiffness were calculated from EMG.[6] Joint angle estimation is possible through the calculated joint torque and joint stiffness with a proper moment arm parameters. However, the trajectory estimation in this study was conducted through the linear relationship between EMG and angle to verify the possibility of simple model for applications.

$$\theta = c_f q_f + c_e q_e + c_o \tag{6}$$

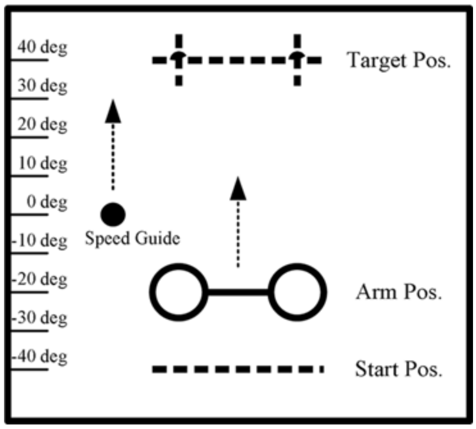

Fig. 2 Monitor display during the tasks: The subject should maintain the elbow angle tracer to be overlapped with the target

3. Experiment

3.1 Experimental setup

A support for the object (dumbbell) was placed on the table. Force sensing resistors (FSR 402) were attached on the support to check when the object was lifted. The object was placed on the support before the task started. The object can provide various weights (0.5~6.5 kg). While the subject lifts the object, visual feedback such as joint angle, speed guide is displayed on the screen.

3.2 Experimental procedure

The subject waited for start instruction holding the object. The initial position (joint angle) was about -40 deg. When a target appeared on the screen, the subject lifted the object. In the case that lifting speed was given, a speed guide moved at a speed of 40, 80, or 160 degrees per second. After the subject lifted the object to the target, the subject was instructed to maintain the position of the object. After a while, the subject put down the object on the support. It is the end of a cycle.

The subject was asked not to move his wrist and shoulder. Only using the muscles of upper arm was recommended to lift the object. Weights of the object were 0.5 kg, 2.5 kg, 4.5 kg, and 6.5 kg. The experiment was done at the four kinds of lifting speed conditions (Free, 40 deg/s, 80 deg/s, 160 deg/s). The lifting speed 160 deg/s, 80 deg/s, and 40 deg/s were selected to make lifting time to be 0.5, 1, and 2 seconds respectively. The lifting speeds were designed not to force the subjects to follow visual feedback but to voluntarily distinguish slow, medium, and fast speeds. The experiment was done four times in each condition. One subject tried that 64 times in total.

4. Result

We divided the lifting task into 3 phases. First phase was called pre-lifting phase, as it represented the period during the moment from the quasi-tension activated to the object lifting. Second phase was called lifting phase, and it represented the period that the transition section of point-to-point movement. Third Phase, maintaining the height, was called holding phase. Before the lifting, the quasi-tensions were activated in

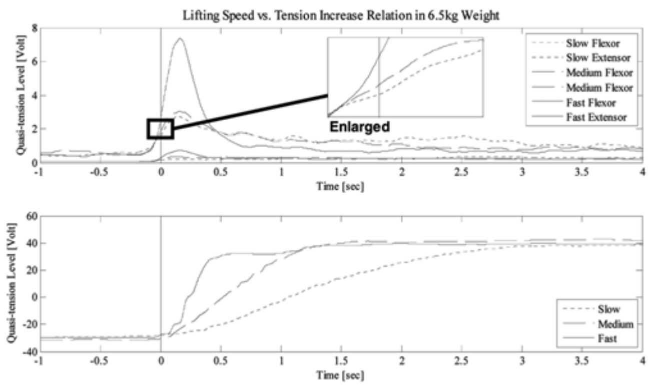

Fig. 3 Lifting speed vs. Quasi-tension increase: There are different tension slope in pre-lifting phase depend on lifting speed

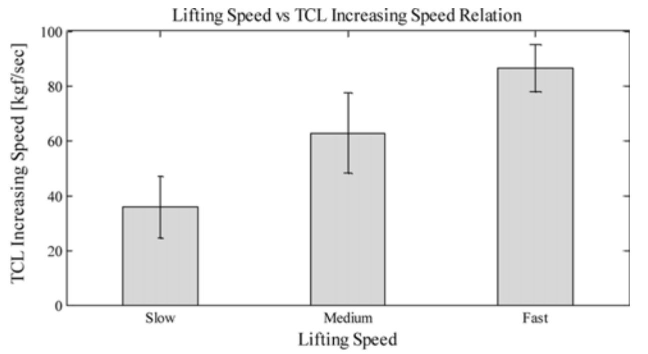

Fig. 4 Lifting speed vs. TCL increasing speed: There is clear distinction of TCL increasing speed between lifting speeds in pre-lifting phase

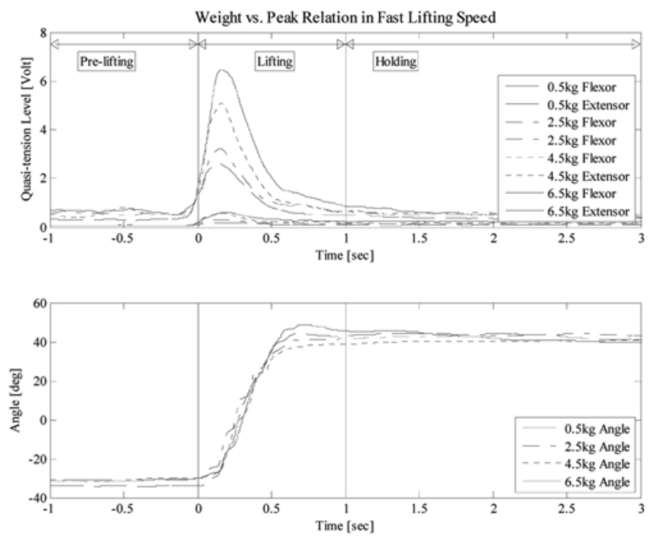

Fig. 5 Object weight vs. Quasi-tension increase: There are different peak levels in early lifting phase depend on object weights

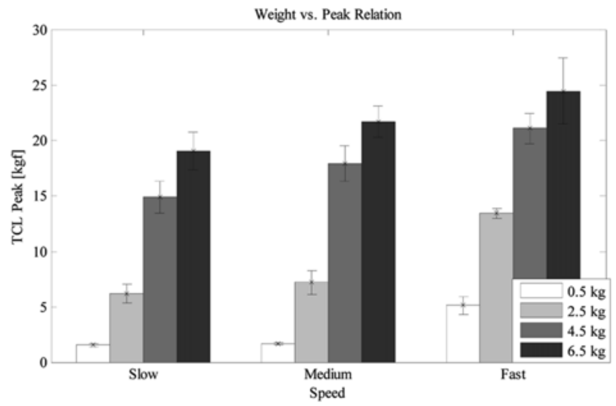

Fig. 6 Object weight vs. TCL peak level: There is clear distinction of TCL peak level between the object weights in equal speeds

the pre-lifting phase. After quasi-tension peaked in the lifting phase, it started to decrease and it converged smoothly to the level of the holding phase. The TCL was activated only enough to carry the object in the holding phase.

4.1 Lifting speed classification

Fig. 3 is an example of quasi-tension according to the lifting speed in the condition of the 6.5 kg of the weight. It seems that the quasi-tension increasing speed depends on the lifting speed in the same weight. Fig. 4 represents the average of the slope of the normalized TCL in accordance with the lifting speed (p<0.05). Lifting speed can be classified in accordance with the TCL increasing speed in data of each subject. Therefore, we expect a speed classification model could be realized.

4.2 Weight classification

Fig. 5 is an example of quasi-tension according to each weight in the condition of the fast speed. It seems that the peak value of quasi-tension is depending on the weight in the condition of the same lifting speed. In the case of the fixed lifting speed, we can classify the weight, using the peak value of quasi-tension. Fig. 6 represents the average of the peak value of the normalized TCL in accordance with the lifting speed in the lifting phase (p<0.05). We can classify the weight using this peak value of TCL. If we observe the peak value after the speed classification through the TCL increasing, both the lifting speed and the object weight could be classified.

However, the variance is not negligible. All of the subjects did not comply with suggested lifting speed exactly because they were not forced to follow the visual feedback and also the speeds were impossible to perfectly match. If subjects matched the lifting speed, the variance would have been negligible.

4.3 Trajectory estimation

Using the data of the first trial in the each condition of the experiment, we performed regression analysis through linear combination model. And, we calculated correlation factor by applying determined coefficients to the rest of the trial. Fig. 7 is the result of the estimation when the lifting speed is slow and the weight is 6.5 kg. Table 1 shows the correlation between the measured data and the estimated data.

Table 1 shows correlation results in each experimental condition. For lighter weight and faster speed, a low correlation appears whereas a high correlation is calculated for heavier weight and slower speed. In

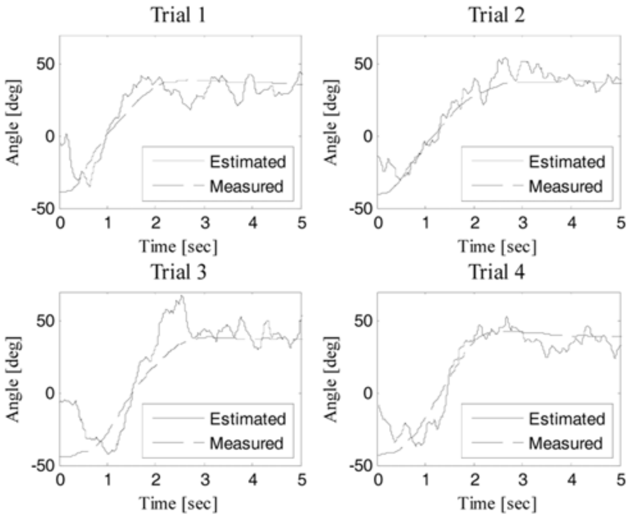

Fig. 7 Rough trajectory estimation: The arm trajectory was roughly calculated by linear combination of the quasi-tensions (flexion and extension)

Table 1 Correlation of Estimated Trajectory for Each Condition[%]

	Free	Slow	Medium	Fast
0.5kg	78.2±7.1	72.5±4.2	76.8±5.7	69.8±3.3
2.5kg	83.5±0.5	79.0±6.2	84.3±2.4	83.9±3.1
4.5kg	88.5±1.7	85.0±5.0	86.4±3.2	80.8±5.2
6.5kg	88.0±2.0	92.0±1.8	90.1±2.1	84.4±5.2

trajectory estimation, first trial of each condition was taken for learning reference, and we investigated whether the coefficient from first trial can describe the relationship between EMG and joint angle in other three trials. Therefore, low correlation means that factors from unintended movements except for the angle are included in EMG signal, and the proportion of joint movement on sagittal plane of tension by action potential is low. One of the effective causes is the unrestrained movement of shoulder joint since participants were able to exercise the lifting task in other directions other than the sagittal plane. Experiment design was quite inappropriate for the trajectory estimation.

The experiment was conducted to examine the feasibility of fast and simple estimation based on the assumption of simplification on learning procedure. It was performed to assure that a trajectory of the object can be estimated in the each lifting condition using only the flexor and the extensor. However, since the correlation during the lifting exercise with light object and fast speed was lower than expected, suggesting other parameters is necessary to improve the experiment. In further study, additional EMG channels on the shoulder should be considered, thus increasing the DOF measured to resolve the limited 1-DOF analysis of the lifting task. Then, comparing results between the past and future experiments under the same speed and weight conditions will confirm the reliability of the coefficients obtained using only EMG.

5. Conclusion

In this study, constrained single lifting task was experimented by using an arm in the sagittal plane, and EMG signals were measured to extract features. Raw EMG signals were converted into the quasi-tension by signal processing, and each quasi-tension was normalized by the weight through TCL in the holding phase of lifting task. We divided the weights into 0.5 kg, 2.5 kg, 4.5 kg, and 6.5 kg, and the speeds into slow, medium, and fast, and executed lifting tasks for each condition. As a result, features for classification could be extracted from the EMG signals. First, speed instructions were distinguishable by the TCL increasing speed in pre-lifting phase.

Weights were distinguishable by peak values of the TCL in each speed condition. Considering the EMG signals in terms of a control command transferred to the muscle, the TCL rapidly increased for muscle that prepared the stiffness to start lifting for fast convergence to the target speed. The peak value of the TCL appeared depending on muscle tension to reach the target speed and overcome the constraints.

Designing the condition classification model through the feature extraction is to estimate the trajectory of the forearm in the lifting task. We used regression and found coefficients of linear combination model and applied it to assure feasibility of trajectory estimation in EMG signals. Correlation was acceptable. Using speed and weight classification, if we design a model that compensates errors with quasi-tension in motion after rough trajectory is made, arm movement reproduction will be possible by using only EMG signals.

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