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Prediction of head-rotation movements using neck EMG signals for auditory tele-existence robot "TeleHead"

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Abstract— **A number of works have been reported on robot control using EMG signals. Control of robots, wheelchairs, and rehabilitation aids using the arms, hands or legs by EMG signals has been quite popular and effective. However, few works have dealt with head-movement control using neck EMG signals. We have built a model that estimates continuous human head movement from neck EMG signals. Our proposed model, which considered not only static but also dynamic effects, effectively suppressed the over/undershoot, and predicted head-rotation movements well. This result indicates that the proposed model has the potential to reconstruct the observed data from neck EMG signals properly.**

I. Introduction

A virtual reality provides various kinds of sensory information to make users feel that they are in a particular "place". The auditory tele-existence robot is one kind of the virtual auditory display systems and was built based on the concept that remote 3D sound space reproduction can be best achieved by using a steerable user-like dummy head that tracks head movement([1-3], Fig. 1). This robot quietly synchronizes with the user's head movements in real time, providing the user with a perfect 3-Dimentional virtual auditory space. Because, perfect dynamic binaural signals are presented at the user's ears.

In order to achieve a believable sense of reality, it is essential for the system to calculate and display sensory information fast enough to fool the senses. Current motion sensors (e.g. acceleration and magnetic sensors), which monitor the head movement of the user, have enough capability for capturing fast movements but have some temporal delay (Fig. 1(b)). However, time delay inevitably exits because of controlling the mechanical dummy-head robot. The total amount of the time delays is 100 ms, which is larger than the threshold of detecting the motion delay, i.e. 60 ms [4]. The delay could somehow deteriorate the reproduced virtual 3D auditory space.

For avoiding this problem, the use of electromyogram (EMG) is one of the alternative candidates for monitoring a user's head-rotation movements (Fig. 1(c)). Because EMG is observed about 100 ms before the onset of the muscle movement. A number of works have been reported on human-robot interface using EMG signals [5]. Control of robots [6-8], wheelchairs [9-11], and rehabilitation aids [12] using the arms, hands or legs by EMG signals have been quite popular and effective. Some studies have also dealt with head-movement control using neck EMG signals. For example, several head motions could be detected from characteristics of the neck EMG signals, and their motions are converted into operation commands [9] [11]. Head postures were estimated from neck EMG signals using the artificial neural network model [13]. These studies uncovered several motion patterns from the EMG signals. However, there are infinite numbers of spatio-temporal motion patterns, and it is impossible to recognize all types of head movements. For building a practical human-robot interface for "TeleHead", it is necessary to estimate the time series of head-rotation movements.

This paper proposes a simple and effective method for estimating continuous human head-rotation movements from neck EMG signals. Our proposed model, which considers not only static but also dynamic effects, effectively suppresses the over/undershoot, and predicts head-rotation movements well. This result indicates that the proposed model has the potential to reconstruct the observed data from neck EMG signals properly.

II. Methods

A. Subjects

Ten male subjects, aged 21-35 years old, participated in the experiment. All subjects participated in the three experimental tasks. The institutional ethics committee approved the experiment, and the subjects gave informed consent prior to participation.

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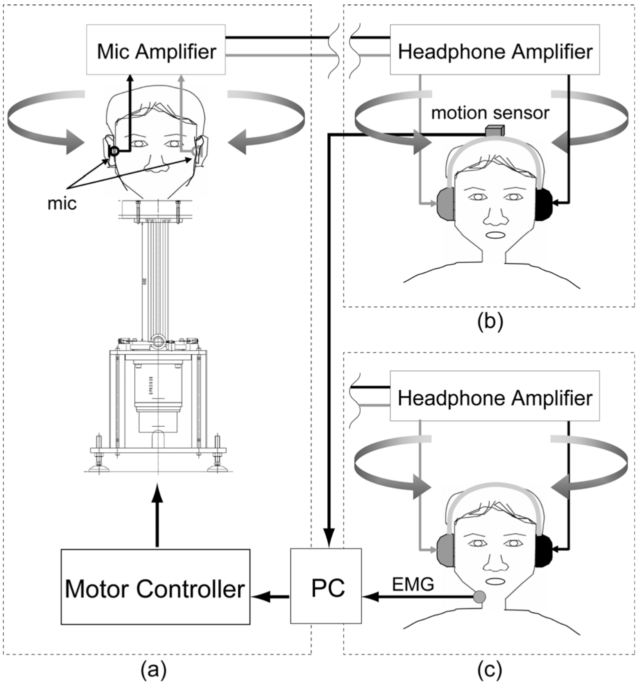

Fig. 1. Outline of "TeleHead" system. (a) Steerable dummy-head (b) Current interface using motion sensors. (c) EMG interface.

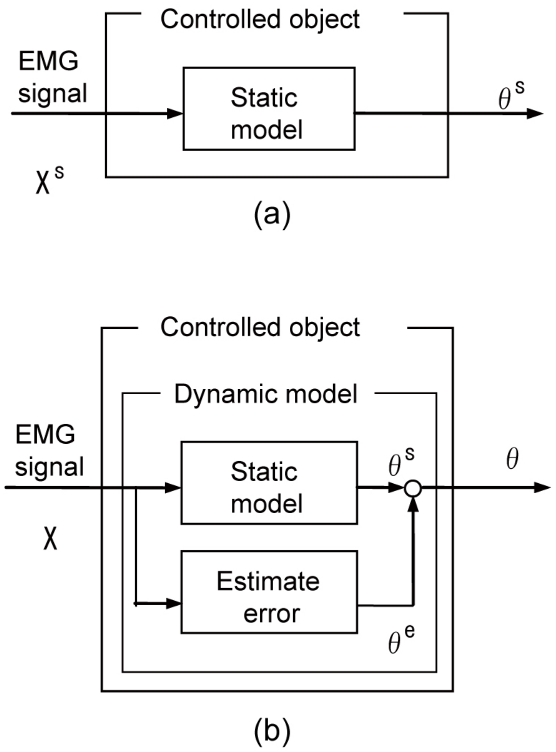

Fig. 2. Diagrams of estimation models. (a) indicates static model (b) indicate dynamic model, which considers not only static but also dynamic effects.

B. Experimental settings

Subjects sat on chairs, and their shoulders were fixed to the back of the chairs with a harness. Three LCD monitors were placed in front of the subjects, and gave the subjects the visual information about the movement tasks.

Head-direction angle was recorded using a motion sensor (Flock of Birds, Ascension Technology Corporation) and sampled at 35Hz. This motion sensor was horizontally attached to the head of the subjects with a headband (Katyusha).

Surface EMG activity was recorded from four main muscles for head-rotation movements: right and left sternocleidomastoid muscles and right and left trapezius muscles. EMG signals were recorded with pairs of silver-silver chloride surface electrodes in a bipolar configuration. Each signal was amplified by BioSemi Active-Two amplifiers (BioSemi, Amsterdam, The Netherlands) and sampled at 2048 Hz.

C. Head-direction angle estimate by EMG

1) Static model

Muscle activations produce tensile forces. Head-direction angle depends on the static balance between the left- and right-ward tensile forces. We assumed that the neck EMG signal, which reflects muscle activation levels, has some correlation with the head-direction angle. In order to estimate the head-direction angle from neck EMG signals, we used a linear regression model (Fig. 2(a)). This model is given by

$$\theta^s = \sum_{i=1}^{N} \beta^s X_i^s + E^s \,, \qquad (1)$$

where N is the number of channels (N=4). X_1^s, X_2^s, X_3^s, and X_4^s are static EMG signals of left and right sternocleidomastoid muscles and left and right trapezius muscles, respectively. β^s is partial regression coefficient, E^s is residual error for the static model, and θ^s is the estimated head-direction angle. The suffix "*s*" represents a parameter used by the static model.

2) Dynamic model

Unbalanced tensile forces between left- and right-ward neck muscles cause a head-rotation movement.

We assumed that muscle activations consist of two components. The first is a static effect that contributes to holding the current posture. The latter is a dynamical effect that contributes to accelerating or decelerating the head-rotation movements.

In general, EMG signals have a correlation with movement acceleration. Angle acceleration is assumed to be expressed as follows:

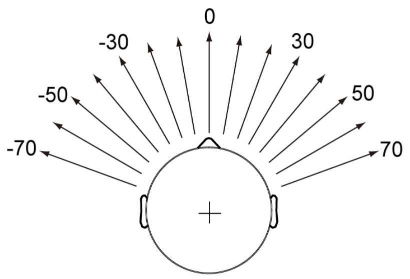

Fig. 3. Task setting (Experiment I).

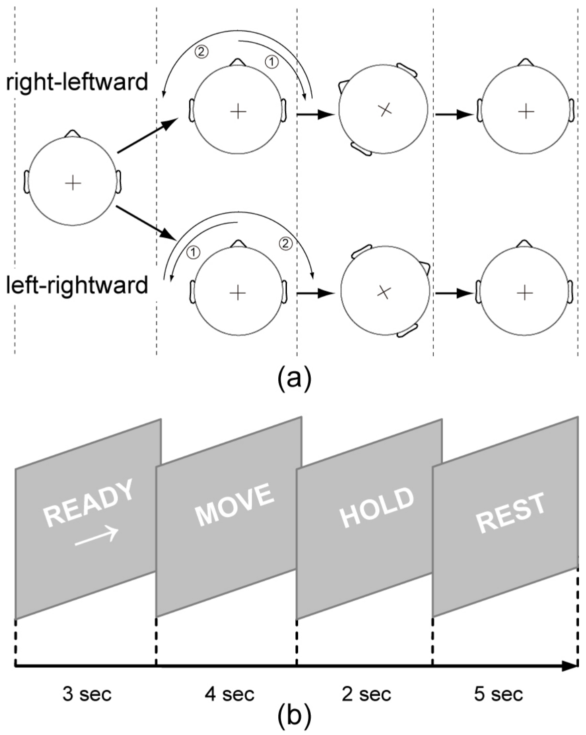

Fig. 4. Schematic illustration of a trial sequence (Experiment II).

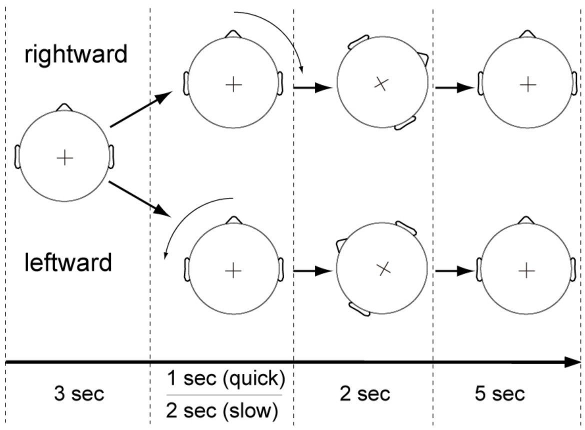

Fig. 5. Schematic illustration of a trial sequence (Experiment III).

$$\theta^e(t) = \theta''(t) = \sum_{i=1}^{N} \beta^e X_i\,(t-d) + E^e, \quad (2)$$

where d means time delay between the EMG and realized rotation angle. The suffix "e" represents a new parameter used by the dynamic model.

To compensate for the effect of dynamics, estimated head-direction angle $\theta(t)$ is expressed as follows:

$$\theta(t) = \theta^s(t) + \theta^e(t) = \sum_{i=1}^{N} (\beta^s + \alpha\beta^e) X_i\,(t-d) + E\ , \quad (3)$$

where N=4, X_i is EMG signal, β^e is partial regression coefficient, and E is residual error for the dynamic model. Here, α is a constant number. This model represents the dynamical effects as a parameter β^e, thus giving it the ability to estimate the effect of dynamics properly.

D. Movement tasks

1) Experiment I (postural maintenance)

The first task was to hold an instructed head-direction angle for a brief period (about seven seconds). Fifteen head-direction angles were prepared (0°, ±10°, ±20°, ±30°, ±40°, ±50°, ±60°, and ±70°, Fig. 3). The instructed and observed angles were displayed on the LCD monitors. Subjects were requested to hold each instructed head-direction angle while watching the monitors. Ninety trials (15 directions × 6 sessions = 90 trials) were recorded and used for analysis. Subjects were allowed to take a brief rest after each session.

2) Experiment II (rotating movements)

The second task was to rotate the head direction slowly. Subjects performed two types of movements: right-leftward and left-rightward head rotational movements (Fig. 4(a)). Three seconds before the movement start cue, visual information about the task type was presented on the screen ("→" for right-leftward and "←" for left-rightward movement tasks). After the start cue, subjects began to rotate their head direction for four seconds and maintain their angles for two seconds (Fig. 4(b)).

One session consisted of thirty repetitions of a trial for two movement patterns. Each subject carried out 60 trials (2 types × 15 trials × 2 sessions = 60 trials). Two types of the tasks were presented in a pseudorandom order.

3) Experiment III (different speed movements)

The third task was to execute head-rotation movements of two different rotation speeds: quick and slow. In the quick movement, subjects rotated their heads from the front to an instructed direction for one second. In the slow movement task, subjects rotated them for two seconds. After the movement, subjects maintained their angles for two seconds

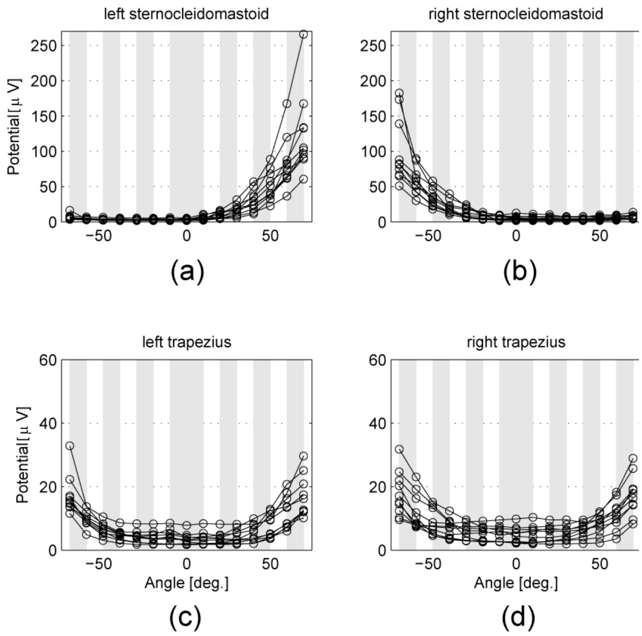

Fig. 6. Mean rectified EMG of each muscle for each subject and head-rotation angle. (a)-(d) indicate mean rectified EMG of left and right sternocleidomastoid, and left and right trapezius muscles, respectively. Open circles indicate the observed value for each head-rotation angle. Gray areas indicate the angular range of ten degrees.

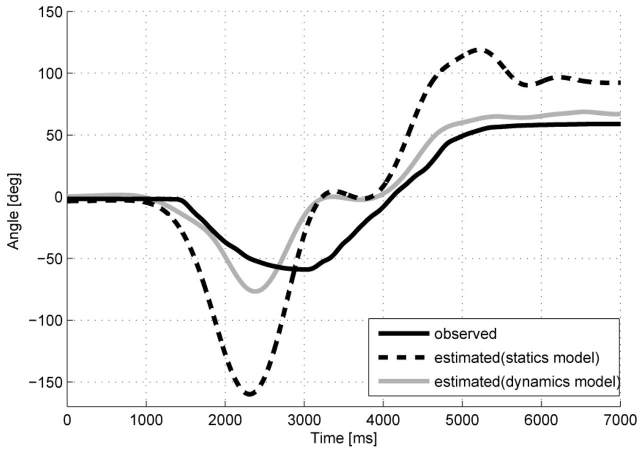

Fig. 7. Example of observed and estimated angle data (left-rightward movement). The black line indicates the observed angle data. The dashed and gray lines indicate the estimated angle data using static and dynamic models, respectively.

(Fig. 5). Either one of the rightward and leftward directions was randomly presented on the screens (the same protocol as *Experiment II*).

We recorded 30 trials for each speed and each direction. One session consisted of thirty repetitions of a trial for two movement directions. Altogether, 120 trials were obtained (2 speeds × 2 directions ×15 trials ×2 sessions= 120 trials).

E. Data Analysis

Angle data were digitally filtered by a third-order Butterworth filter with an upper cutoff frequency of 5 Hz. Derivatives of the angle data were computed by applying a three-point local polynomial approximation.

The noise signals of the angle sensor (Flock of Birds) were removed using the band-stop filter 201-213 Hz. Each EMG signal was digitally filtered at 20 Hz (high-pass) and 1,000 Hz (low-pass) to remove some of the noise component. The filtered EMG signals were full wave rectified and then smoothed using a moving average technique that averaged every 101 points of data.

Estimated angles using Eqs. (1) and (3) were smoothed by a third-order low-pass Butterworth filter at 1Hz cut-off.

III. Results

A. Relationship between head-rotation angle and neck EMG signals

First, we investigated the relationship between the head-rotation angle and neck muscle activation levels. In the rightward rotation task, mean EMG signals of left-sternocleidomastoid and right-trapezius muscles were increased (Fig. 6(a) and (d)). In the leftward rotation task, the activation levels of right-sternocleidomastoid and left-trapezius muscles were increased (Fig. 6(b) and (c)). The intensity of the sternocleidomastoid muscles had a tendency to be larger compared to that of the trapezius muscles. A higher variance was present at large angles among the subjects (e.g. ±70°).

B. Estimation of head-direction angle from neck EMG signals

We estimated head direction angles from neck EMG signals. The first step in data analysis was a multiple linear regression using the model of Eq. (1). This analysis yielded coefficients for each EMG signal using the least square method. Next, predicted angles were computed by Eq. (1). The quality of the prediction was quantified by calculating the *R*-square coefficient between actual and predicted data. Finally we carried out cross-validation analysis to evaluate the robustness of the results. The trial data of the six sessions were equally divided into three data sets, and two of them were used for the calculation of weighting coefficients as training data sets. Then the angle predictions were computed for the other one-third as a test data set.

The *R*-square coefficients between the actual and predicted angles were high (first one-third of the data set: R^2 = 0.87 ± 0.06 [mean±SD], second one-third: R^2 = 0.86 ± 0.08, final one-third: R^2 = 0.86 ± 0.06).

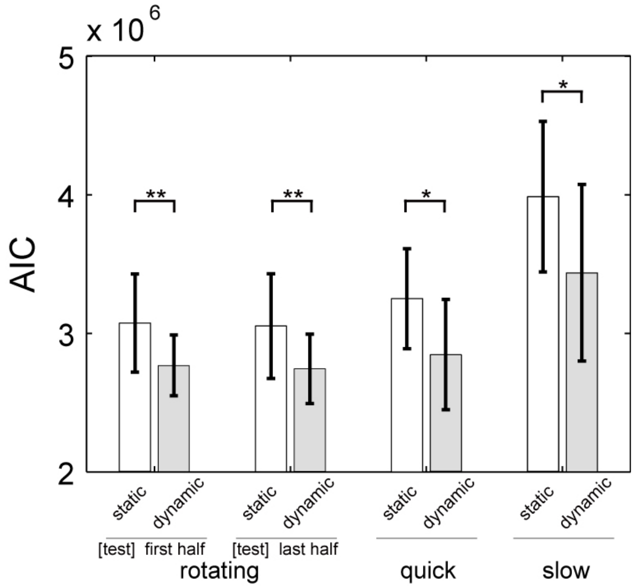

Fig. 8. Comparison of AIC for each test data set. Data represent means ± SD. To evaluate the two models, paired t-test was conducted for each test data set. * and ** denote significant levels p<0.01 and p<0.001, respectively.

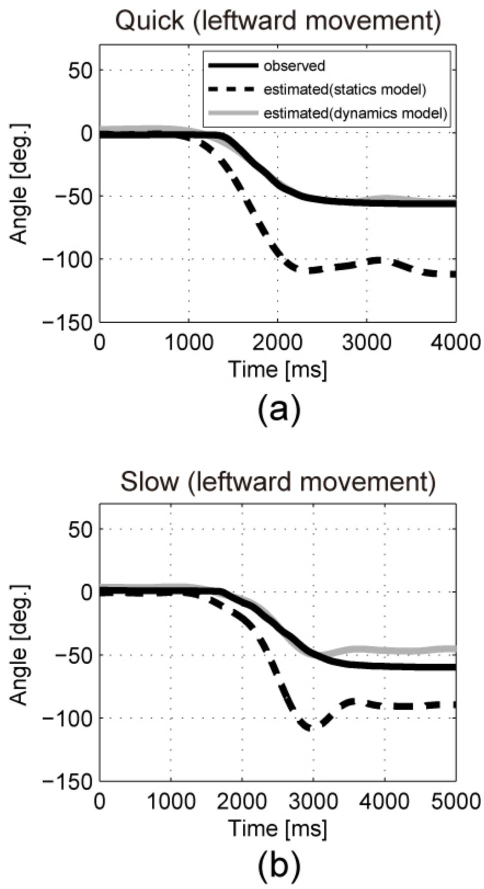

Fig. 9. Examples of observed and estimated angle data. (a) and (b) indicate the results of the quick and slow movement tasks, respectively.

We investigated whether there were any differences among the *R*-squares calculated from the three test data sets. A randomized block ANOVA could not find any significant differences among them ($F(2, 18) = 1.06$, $p = 0.39$).

These results indicate that, in this static task, a simple linear regression model can adequately predict head-direction angles with robustness from neck EMG signals.

C. Reconstruction of head rotation movement from neck EMG signals

When we rotate our heads, it requires a larger force to accelerate or decelerate the head-rotation movements. These movements inevitably involve dynamics to overcome the viscous-inertial load. If reconstructing the head-rotation movement information from neck EMG signals, it is necessary to compensate for the effect of dynamics.

In general, the mean levels of muscle activations have a tendency to increase with movement acceleration. This paper assumes that estimation errors of Eq. (1) arising from the dynamical effect have a correlation with movement acceleration and deceleration, and thus we derived Eq. (3).

This method concerning the effect of dynamics was applied to estimation of the time series of head-rotation movement. Figure 7 shows typical trial data from a single subject. The black line shows the observed data. The dashed line shows the estimated data using the static model, while the gray line shows the estimated data using the dynamic model.

When using the static model, estimated angle data have a tendency to overshoot and undershoot at movement onset and offset, respectively (Fig. 7, dashed line). When using only the static model, the observed data were unable to reconstruct the movement information correctly.

In contrast, the dynamic model, which considered not only the static but also the dynamic effects, effectively suppressed the over/undershoots. This result indicates that the proposed model has the potential to reconstruct the observed data from neck EMG signals properly.

In small head-rotation angles, errors between the observed and estimated angles using the both models were large because these angles require less muscle activations for head-rotation movements.

For the efficient model discrimination methods, Akaike's information criterion (AIC) was calculated [14]. The AIC of the dynamic model was significantly smaller than that of the static model ([first half] paired t-test: $t(9) = 4.56$, $p < 0.001$, [last half] $t(9) = 4.43$, $p < 0.001$, Fig. 8).

Next, we evaluated the robustness of these results by cross-validating the predictions between the first and second halves of the data. One half of the data were used for the calculation of weighting coefficients using the dynamic mode Eq. (3), and then angle predictions were computed from the other half of the data. This analysis is important as a test of the feasibility of this approach for controlling the auditory tele-existence robot “TeleHead” in real-time.

The Pearson’s product-moment correlation coefficients between the actual and predicted angles were relatively high ([first half]: $r = 0.55 \pm 0.17$, [last half]: $r = 0.58 \pm 0.14$). We investigated whether there were any differences between the correlation coefficients calculated from the two test data sets. Paired t-test could not find a significant difference between them ($t(9) = 1.46$, $p = 0.91$). There was also no significant difference between the AICs calculated from the two test data sets (paired t-test: $t(9) = 1.39$, $p = 0.90$).

This dynamic model has sufficient ability to predict the time series of head-rotation angles, and has the potential to control the robot in real time.

D. Generalization ability of the dynamic model

For predicting various kinds of head-rotation movements from neck EMG signals, generalization ability is one of the important elements. In order to evaluate this ability, the dynamic model was applied to the EMG data obtained from unknown tasks to the model itself. The first half of the data, “rotating movements,” were used for the calculation of weighting coefficients using the dynamic model Eq. (3), and then angle predictions were computed from the data, “quick and slow movements.”

Figure 9 shows examples of trial data from a single subject. When using the static model, estimated angle data have a tendency to mistakenly predict larger angles than the actual ones (Fig. 9(a), dashed line). In contrast, the dynamic model could suppress the effect of dynamics (over/undershoot), and correctly compensated for the magnitudes of head-rotation angles (Fig. 9(a), gray line). This tendency was observed in the different rotation-speed tasks (slow movements, Fig. 9(b)).

The AIC of the dynamic model was significantly smaller than that of the static model ([quick movement] paired t-test: $t(9) = 4.22$, $p < 0.01$, [slow movement] $t(9) = 4.18$, $p < 0.01$, Fig. 8). That indicated that the dynamic model was more efficient for head-rotation movements compared to the static one.

The correlation coefficients between the actual and predicted angles were also high ([quick movement] $r = 0.72 \pm 0.25$ [slow movement] $r = 0.79 \pm 0.23$).

These results indicate that the dynamic model has a high generalization ability of estimation from neck EMG signals.

IV. Discussion

We have built a model that estimates continuous human head movement from neck EMG signals. Our proposed model, which considered not only static but also dynamic effects, effectively suppressed the over/undershoot, and predicted head-rotation movements well. This result indicates that the proposed model has the potential to reconstruct the observed data from neck EMG signals properly.

A. Implementation of human-robot interface

We implemented this proposed method to construct an interface with an acoustical telepresence robot (TeleHead) [1-3]. We confirmed that the proposed method enables us to control the robot effectively. Although there was some over/undershoot on estimated head-rotation angle by the dynamic model, the TeleHead worked without problem. Furthermore, the estimated angle preceded actual head movement just as EMG signals precede actual muscle movement, which almost perfectly compensates for mechanical and control delays of the head following movement of the TeleHead.

B. Computational cost

The only time-consuming part of the proposed method is calculating the weighting coefficients of each sensor. After doing so, the calculation of the prediction is almost instantaneous. The proposed model is superior not only in terms of prediction abilities but also computational performances, making it very easy to implement in the actual human-robot interface.

C. Comparison among other estimation methods

The proposed dynamic model is the first step to control the TeleHead by using neck EMG signals. To evaluate the advantage of the proposed model, it is necessary to compare with other EMG-based motion decoding methods, such as linear state space models, support vector machines, etc. It is an issue in the future.

D. Preprocessing

The magnitudes of raw EMG signals will change drastically for a number of reasons, such as the state of the electrodes, the distance between the electrodes, the configuration of muscles, skin condition, etc. Raw EMG signals normalized by maximum voluntary contraction (MVC) have a physically meaningful value, and the use of it would be expected to make our results in Fig.6 clearer.

E. Improvement of estimation in front

The errors between actual and predicted angles of Fig. 7 were large in relatively small head-rotation angles. Because muscle activation levels are less in front, that would cause the less precise estimation. To solve this problem, Moon et al. suggested that the image observation was used [15]. This hybrid estimation method might improve the precision of angles in front.

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