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Real-Time Estimation of Tongue Movement based on Suprahyoid Muscle Activity

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Abstract— **In this study, we introduce a real-time method for tongue movement estimation based on the analysis of the surface electromyography (EMG) signals from the suprahyoid muscles, which usual function is to open the mouth and to control the position of the hyoid, the base of the tongue. Nine surface electrodes were affixed to the underside of the jaw and their signals were processed via multi-channel EMG system. The features of the EMG signals were extracted by using a root mean square (RMS) method. The dimension of the variables was reduced additionally from 108 to 10 by applying the Principal Component Analysis (PCA). The feature quantities of the reduced dimension set were associated with the tongue movements by using an artificial neural network. Results showed that the proposed method allows precise estimation of the tongue movements. For the test data set, the identification rate was greater than 97 % and the response time was less than 0.7 s. The proposed method could be implemented to facilitate novel approaches for alternative communication and control of assistive technology for supporting the independent living of people with severe quadriplegia.**

I. Introduction

The motor function of the tongue often remains intact even in the cases of severe movement paralysis. Therefore, tongue movements offer a great potential for the design of novel highly-efficient human-machine interfaces for alternative communication and control. Numerous approaches for deriving control signals from intentional tongue motions have been proposed: detection of tongue position via measurement of the magnetic fields of a permanent magnet attached to the tongue [1,2]; detection of lingual proximity by light-emitting diodes and photodiodes placed on an artificial palate plate [3,4]; measurement of the force applied by the tongue to a force sensor array mounted on an artificial palate plate [5,6]; and direct tongue manipulation of a joystick or switch inserted into the oral cavity [7]. However, such methods require insertion of a measuring instrument into the oral cavity which entails certain risks and discomfort to the patient such as increased psychological stress, oral health problems, obstruction of speaking and drinking, suffocation by accidental ingestion, electric shock, battery fluid leakage, etc.

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Surface electromyography (EMG) signals are used widely for pattern recognition of human motions [8-12]. The same approach can be applied to the estimation of tongue movements without inserting a measuring instrument into the oral cavity. Tongue motions result from the contractions of the lingual muscles. However, the detection of the EMG activities of the lingual muscles requires the installation of surface electrodes or needle electrodes within the oral cavity which may cause serious difficulties for the practical application of such approach. That is why we have focused on the surface EMG signals measured at the underside of the jaw. Such electromyogram contains signal components that are related to the activity of the suprahyoid muscles whose function is to open the mouth and to control the position of the hyoid (the base of the tongue) when the tongue moves. In our previous studies, we have reported on the results from a feasibility study on the estimation of the tongue movement from the EMG signals at the underside of the jaw without using the EMG signals of the lingual muscles [13, 14].

In this paper, we propose a novel method for real-time estimation of tongue movement based on principal component analysis (PCA) and artificial neural networks and evaluate the effectiveness of the proposed method in terms of precision and speed.

II. Real-time estimation of tongue movement

A. Mechanism of tongue movement

Tongue movements are produced by the coordinated actions of the lingual muscles that include the intrinsic muscles of the tongue (superior longitudinal muscle of tongue, inferior longitudinal muscle of tongue, transverse muscle of the tongue, vertical muscle of tongue) which control the tongue shape and the direction of tongue tip, and extrinsic muscles of the tongue (genioglossus muscle, styloglossus muscle, hyoglossus muscle, palatoglossus muscle) which control the tongue position in anterior direction and move the tongue downward and backward (Fig. 1) [15]. The detection of the EMG activities of the lingual muscles requires the installation of surface electrodes or needle electrodes within the oral cavity. That is why we decided to focus on the EMG signals of the suprahyoid muscles (digastric muscle, stylohyoid muscle, mylohyoid muscle, and geniohyoid muscle) which are observable at the underside of the jaw. The primary function of the suprahyoid muscles is to open the mouth or to initiate the swallowing movements. However, some of these muscles also support the hyoid (the base of the tongue) during the tongue movement and the EMG signals measured at the underside of the jaw change when the tongue position changes. That fact can be used for estimation of tongue movements from the EMG signals. The mylohyoid

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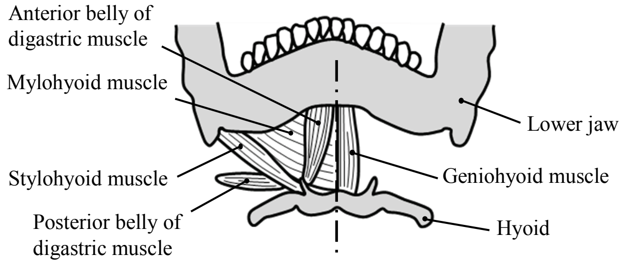
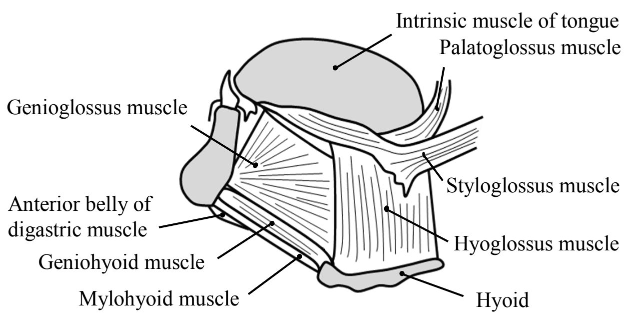


(a) Frontal plane



(b) Sagittal plane

Figure 1. Lingual muscles and hyoid muscles.

muscle supports the hyoid when the tongue moves in a lateral direction. The geniohyoid muscle supports the hyoid when the tongue moves in anterior direction, and the hyoid is supported by the stylohyoid muscle when the tongue is crimped to the palate. The coordinated voluntary tongue movements cause contractions of the suprahyoid muscles that can be detected in the surface EMG and can be utilized as control commands for assistive devices.

B. Estimation algorithm

The EMG signal processing is explained below (see also Fig. 2).

1. EMG signals of the suprahyoid muscles were measured at nine points at the underside of the jaw by monopolar induction.
2. The EMG potential from neighboring muscles (crosstalk) was analyzed by calculation of the potential differences between every two electrodes for all combinations of the electrode signals (${}_9C_2 = 36$ signals).
3. To extract the feature quantities, the root mean square (RMS) of all 36 signals were calculated as per eq. (1). The smoothening numbers n were set sequentially to 100, 300 and 500.

$$RMS_n = \sqrt{\frac{1}{n}\sum_{i=1}^{n} EMG_i^{\,2}} \tag{1}$$

4. This way, we composed a feature quantity $Y(t) = [RMS_{100}, RMS_{300}, RMS_{500}]^t$. $Y(t)$ is 108-dimensional quantity (36 channels × 3 values for n).
5. The 108-dimensional feature quantity $Y(t)$ was reduced to a new, 10-dimensional quantity $Z(t)$ by using PCA.

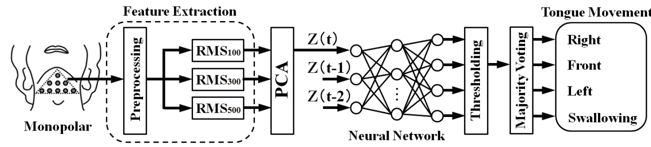


Figure 2. Tongue movement estimation algorithm.

(a) Frontal plane (b) Sagittal plane

Figure 3. Electrodes for EMG measurement.

6. The input signals to the neural network were determined from the last three sequential samples $F(t) = [Z(t), Z(t\text{-}1), Z(t\text{-}2)]^t$. This way, the feature vectors took into consideration not only the current sample but also the previous two samples.
7. The signals for teaching the neural network on the identifying tongue movements were generated by summation of RMS signals from all 32-channels and threshold processing.
8. The tongue movements were linked with the feature vector $F(t)$ by adjustment of the connection weights of the neurons in the network via using a backpropagation learning algorithm.
9. The output signals (estimation) from the neural network were binarized by threshold processing.
10. Finally, the tongue movement was determined by applying the majority rule among k recent estimations.

III. Experiment and Analysis

A. Experimental condition

The subjects of this experiment were five adult men with normal tongue function (21.8 ± 0.8 years old, 169.0 ± 4.8 cm, 63.0 ± 7.0 kg, mean ± SD). We analyzed the surface EMG from nine surface electrodes installed at 20 mm intervals on the underside of the jaw. The indifferent electrode was attached to the ear lobe (Fig. 3). We used disposable electrodes (SMP-300; Mets Inc.) that were connected via EMG leads (BR-331S; Nihon Kohden Corp.) to a bio-amplifier (NB6101HS; Nabtesco Corp.) the which gain of which was set to 1,950. The bio-amplifier's cut-off frequencies of the high-pass filter and the low-pass filter were set to 2.3 Hz and 320 Hz respectively.

EMG signals were measured for three voluntary tongue movements. Participants were asked to push with the tongue sequentially on the right, on the left, and on the front side of the mouth cavity. Apart from the voluntary tongue movements, the participants were also required to perform one action of saliva swallowing. These four measurements constituted one set of operation. Each subject was asked to perform eight sets of tasks. Each action needed to be completed in one second. Subjects were asked to rest for one second before they start the next action. The EMG signals of the suprahyoid muscles were digitalized at sampling frequency of 2,000 Hz through an analog-to-digital converter (AIO-163202FX-USB; Contec Co. Ltd.).

B. Condition of learning and estimation

Four of these eight sets of data were used for the learning processes of the neural networks. The remaining four sets were used for estimation of the tongue movements. The neural network was constructed by using Matlab (Neural Network Toolbox; The MathWorks Inc.). The number of inner layers was 15. The frequency of learning was 5,000 times. The estimation precision was tested for the frame shift period d of 0.5, 2.5, 5.0, 10, and 25 ms. The numbers of votes for majority rule of k were 1, 5, 10, 20, and 50.

In addition, we explored how $Y(t)$ influences the accuracy of the tongue movement estimation algorithm. For that purpose, we studied the estimation accuracy of the proposed algorithm for four values of $Y(t)$, namely:

$Y(t)=RMS_{100}$

$Y(t)=RMS_{300}$

$Y(t)=RMS_{500}$

$Y(t)=[RMS_{100}, RMS_{300}, RMS_{500}]^t$.

The results are shown in Table 1.

C. Index of evaluation

We used the following two indices to evaluate the precision and the speed of estimation of the developed algorithm, as follows.

i) Rate of correct identification of movement (Rate of correct identification R_{CI})

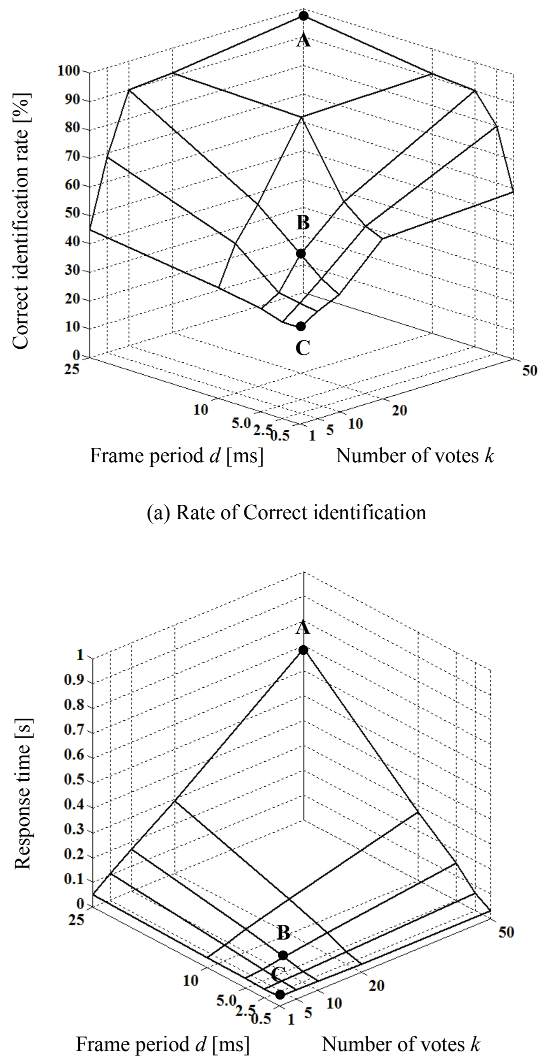
$$R_{\mathrm{CI}} = \frac{Number\ of\ correct\ identifications}{Total\ number\ of\ identifications} \times 100[\%] \qquad (2)$$

ii) Time from the start of the movement until the identification (Response time t_r)

IV. Results and discussion

The average rates of correct identification and response times for all five subjects are shown in Fig. 4(a) and 4(b) respectively. Figure 5 presents the results of the estimation by the proposed algorithm for conditions A, B and C in Fig. 4. The increased frame shift period d and the increased number of votes for the majority rule of k indicate that the rate of correct identification has been improved. As shown in the same figure, the initial rates of correct identification of 33.8% in (C) (d = 0.5, k = 1.5), were improved to 97.5% in (A) (d = 25, k = 50). However, the response time has increased from 0.04 s to 0.69 s, suggesting a tradeoff relation.

The effect of the frame shift period d was discussed previously by Kelvin et al. [16]. Our experiments also confirmed that estimation accuracy can be improved by choosing a long shift period. Although an increased number of votes for rule of majority k prolongs the response time from the start of movement to the completion of the estimation, it stabilizes the output signal and improves the estimation accuracy (Fig. 4).



(a) Rate of Correct identification

(b) Response time

Figure 4. Estimation results of tongue movement (A: d = 25 ms, k = 50; B: d = 1.0 ms, k = 20; C: d = 0.5 ms, k = 10).

Table 1 presents a relation between feature quantity $Y(t)$ and accuracy of estimation (frame shift period d is 25 ms, and the numbers of votes for majority rule of k is 50). Results also show that the accuracy of estimation for RMS_{500} is higher than the accuracy of the procedure when $Y(t) = RMS_{100}$ or $Y(t) = RMS_{300}$ was used which suggests the trend that the greater the number of samplings leads to a higher the accuracy of estimation. In addition, the estimation by all three *RMS*s $Y(t) = [RMS_{100}, RMS_{300}, RMS_{500}]^t$ provided the best accuracy of estimation, with identification rate 98.8 ± 2.8 % and response time of 0.67 ± 0.09 s.

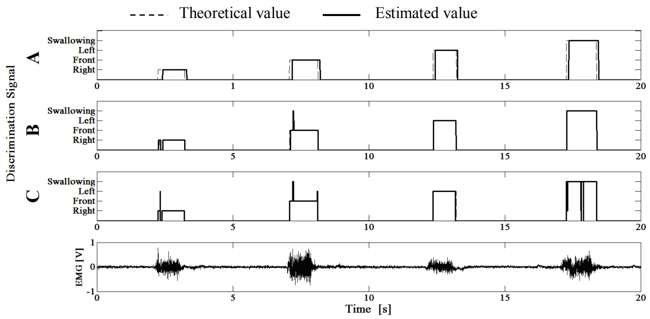


Figure 5. Effects of frame period d and number of votes k on estimation precision (A: $d = 25$ ms, $k = 50$; B: $d = 1.0$ ms, $k = 20$; C: $d = 0.5$ ms, $k = 10$).

Table 1 Effects of feature value on estimation precision.

$Y(t)$	Correct identification rate [%]	Response time [s]
RMS_{100}	93.8 ± 4.4	0.75 ± 0.10
RMS_{300}	93.8 ± 6.3	0.70 ± 0.10
RMS_{500}	96.3 ± 3.4	0.67 ± 0.12
All	98.8 ± 2.8	0.67 ± 0.09

RMS processing has the same effect as a low pass filter, where the degree of smoothening was determined by the number of samples n. By defining a large number of signal components as feature quantities of the EMG signals, we can attain high accuracy of estimation of the tongue motions.

Results showed that the initially obtained 108-dimensional feature quantity contained signal components that do not contribute to the accuracy of estimation but unnecessarily increase the amount of calculations. Therefore, to reduce the number of the feature quantity and to ignore the components that do not contribute to the estimation accuracy, we applied PCA to the input signal of the neural network. Although the average response time for estimation of the tongue movements is greater than the response time of some other human motions (which is approximately 0.2 s), the accuracy and the speed of recognition of the tongue movements are sufficient for most cases of control of assistive devices by people with severe disabilities. In our future work, we intend to examine the response time and the accuracy of user's commands derived by the procedure presented herein in tasks for tongue control of assistive devices.

V. Conclusion

We have proposed a novel method for estimation of the voluntary movements of tongue in real-time from surface EMG signals of suprahyoid muscles observed at the underside of the jaw that minimizes the signal artifacts due to saliva swallowing. Then we conducted a test to confirm that the proposed method allows precise estimation of the tongue motions. Test results showed identification rate greater than 97 %, and response time of less than 0.7 s. It is expected that the proposed method could be used for the design of novel algorithms that can be applied to the operation of electric wheelchairs and computers for supporting the independent living of persons with movement disabilities and elderly people in the future.

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