

# Detection of Motor Imagery of Swallow With Model Adaptation: Swallow or Tongue?

H. Yang<sup>1</sup>, C. Guan<sup>1</sup>, K. K. Ang<sup>1</sup>, C. Wang<sup>1</sup>

<sup>1</sup>*Institute for Infocomm Research, Agency for Science, Technology and Research (A\*STAR), Singapore 138632.*

Correspondence: H. Yang, Institute for Infocomm Research, A\*STAR, Singapore 138632. E-mail: hjyang@i2r.a-star.edu.sg

**Abstract.** Conventional methods to treat dysphagia patients require assistance from speech therapists, which may incur high cost for intensive training. We investigate the use of motor imagery of swallow for dysphagia stroke rehabilitation to answer this question: can a simple yet related motor imagery of tongue protrusion model be used to detect motor imagery of swallow? To achieve successful detection, the non-stationarity of EEG signals across sessions and modalities is addressed with model adaptation by measuring feature consistency between training and evaluation data. Current results on 6 healthy subjects yield average accuracies of 72.12% and 71.81% using swallow model and tongue model based on features of dual-tree complex wavelet transform (DTCWT-FT). This demonstrates the feasibility of using the motor imagery of tongue model to detect motor imagery of swallow for dysphagia stroke rehabilitation purposes.

**Keywords:** Motor imagery of swallow, motor imagery of tongue protrusion, model adaptation, dual-tree complex wavelet transform

## 1. Introduction

Brain computer interface have shown potentials in stroke rehabilitation [Daly and Wolpaw, 2008; Gallas et al., 2010], as evidenced by the similar pathways activated by motor imagery and executed movements. Oropharyngeal dysphagia frequently occurs in stroke patients which increases mortality due to pulmonary complications [Gallas et al., 2010]. Conventional methods for treating swallowing disorders are changing food and positions, performing tongue strength training and pharyngeal and effortful swallow maneuvers [Burkhead et al., 2007], and thermal and neuro-muscular stimulation [Kiger et al., 2006]. Both voluntary saliva swallowing and tongue elevation activate the left lateral pericentral and anterior parietal cortex, and anterior cingulate cortex and adjacent supplement motor area [Martin et al., 2003]. These shared activation regions suggest the possibility of using motor imagery of tongue protrusion (MI-Ton) model to detect motor imagery of swallow (MI-SW). In this abstract, we propose a novel method to test the hypothesis that a simple yet related MI-Ton model can be used to detect the complex MI-SW.

## 2. Materials and Methods

10 healthy subjects with ages of  $34.90 \pm 8.13$  (mean  $\pm$  SD) years participated in the experiments by giving a written informed consent. The experiments consisted of three sessions. Each session consists of 80 trials of MI-SW (1st and 2nd sessions) or MI-Ton (3rd session) and 80 trials of idle. Subjects are advised to imagine swallowing a cup of water/juice, or fruit, or food in MI-SW; and imagine protruding his/her tongue as far as possible for MI-Ton. A preparation “+” is shown for 2 s following the acoustic tone. The cue in the form of a virtual character performing swallowing or tongue protrusion, or a filled circle is displayed for 3 s. The subject then performs the action for 12 s after cue disappears and the rest time of 6 s follows at the end of the trial. The EEG and EMG measurements are obtained with 34 channels Neuamps EEG acquisition hardware (30 channels for EEG and 4 for EMG recordings), which are bandpass filtered between 0.5 Hz and 100 Hz. DTCWT-FT features are employed which consist of power, phase, coarse representation and statistical features such as mean, variance, skewness and kurtosis of wavelet coefficients [Yang et al., 2012]. In model adaptation, we assume that a small amount of evaluation data can be used to select the suitable model generated during the  $n$ -times and  $r$ -folds cross-validation. The features for training data in  $(n, r)$ <sup>th</sup> model and evaluation data are firstly clustered, the cluster with minimum impurity for training data is selected by

$$\hat{i} = \arg \min_i \frac{\min(N_{tr}^0(i), N_{tr}^1(i))}{\max(N_{tr}^0(i), N_{tr}^1(i))} \quad (1)$$

where  $N_{tr}^k(i)$  denotes the number of features of class “ $k$ ” in cluster  $i$ . The  $(\hat{n}, \hat{r})$ <sup>th</sup> model with the maximum number of consistent features (i.e., whose label is consistent with the dominant cluster label) between training ( $N_{tr}^c(\hat{i}, n, r)$ ) and

evaluation data ( $N_{te}^c(\hat{i}, n, r)$ ) in cluster ( $\hat{i}$ ) is selected by

$$(\hat{n}, \hat{r}) = \arg \max_{(n,r)} (N_{tr}^c(\hat{i}, n, r) + N_{te}^c(\hat{i}, n, r)) \quad (2)$$

### 3. Results

The session-to-session classification accuracies for 6 selected subjects whose cross-validation accuracy is above 60% are shown in Table 1. The best accuracy is reported by searching 8 non-overlapping time segments, SVM with linear kernel is used as the classifier. It can be seen that average accuracies of 68.75 % and 69.74 % are achieved using

Table 1: Session-to-session classification accuracies (%) for motor imagery of swallow with/without model adaptation

Subject/Session.	No adaptation		With adaptation/no. of trials	
	MI-SW <sup>1</sup>	MI-Ton <sup>2</sup>	MI-SW/30 <sup>3</sup>	MI-Ton/40 <sup>4</sup>
lj/01	71.25	72.50	76.15	77.50
lj/02	75.63	80.63	74.62	84.17
hj/01	75.63	68.13	75.38	69.17
hj/02	78.13	67.50	83.85	76.67
cr/01	77.50	80.63	83.08	85.00
cr/02	81.25	96.25	84.62	95.83
wy/01	69.38	66.25	74.62	64.17
wy/02	68.75	65.00	70.00	67.50
cc/01	56.25	59.38	56.92	59.17
cc/02	60.00	63.13	63.85	63.33
mt/01	55.63	57.50	62.31	60.00
mt/02	55.63	60.00	60.00	59.17
$A_{as}$	68.75	69.74	72.12	71.81
t-test	1 vs. 2	3 vs. 4	1 vs. 3	2 vs. 4
P value	0.62 (xx)	0.87 (xx)	0.0008 (**)	0.044 (**)

$A_{as}$ : Average Accuracy. xx: insignificant; \*\*: significant

MI-SW model and MI-Ton model, respectively. The accuracies are further improved with the use of model adaptation, which are: 72.12 % and 71.81 % for MI-SW model and MI-Ton model, respectively. The improvements are significant for subjects ‘lj’, ‘hj’ and ‘cr’ using MI-Ton model, and subjects ‘hj’, ‘cr’, ‘wy’ and ‘mt’ using MI-SW model.

### 4. Discussion

Our results on healthy subjects reveal that comparable performance can be achieved by using the motor imagery of tongue model to detect motor imagery of swallow with and without model adaptation. The use of a small amount of evaluation data to select suitable model to classify the test data has significantly improved the classification accuracy, e. g., from 68.75 % to 72.12 %, and from 69.74 % to 71.81 % for swallow model and tongue model, respectively. Statistical paired *t*-tests at 5 % significance level shows no significant difference in classification accuracies obtained using swallow model and tongue model, both for using model adaptation and not using model adaptation.

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