Evaluation of somatosensory cortical differences between flutter and vibration tactile stimuli

Sang Woo Han, Yoon Gi Chung, Hyung-Sik Kim, Soon-Cheol Chung, Jang-Yeon Park, and Sung-Phil Kim

Abstract— In parallel with advances in haptic-based mobile computing systems, understanding of the neural processing of vibrotactile information becomes of great importance. In the human nervous system, two types of vibrotactile information, flutter and vibration, are delivered from mechanoreceptors to the somatosensory cortex through segregated neural afferents. To investigate how the somatosensory cortex differentiates flutter and vibration, we analyzed the cortical responses to vibrotactile stimuli with a wide range of frequencies. Specifically, we examined whether cortical activity changed most around 50 Hz, which is known as a boundary between flutter and vibration. We explored various measures to evaluate separability of cortical activity across frequency and found that the hypothesis margin method resulted in the greatest separability between flutter and vibration. This result suggests that flutter and vibration information may be processed by different neural processes in the somatosensory cortex.

I. INTRODUCTION

Our nervous system can sense, interpret and control environments using information acquired from external mechanical stimuli. A number of neurophysiologic and psychophysical studies have attempted to understand how the nervous system processes information of mechanical stimuli. Until recently a majority of studies have been focused on the neural mechanisms in response to pain. However, recent drives of information technology into smart mobile computing systems underline the importance of processing vibrotactile information generated from haptic devices. Accordingly, it becomes more demanding to understand how our brain deals with vibrotactile information.

The human nervous system can sense various mechanical stimuli as the mechanoreceptors and their sensory afferents vary according to the stimulus type. In particular, two mechanoreceptors detect different vibrotactile stimuli. Meissner corpuscles detect a relatively low-frequency stimulation of cutaneous flutter (5-50 Hz) and Pacinian corpuscles detect high-frequency rapid stimulation of cutaneous vibration (50-400 Hz) [1-3]. The mechanoreceptive afferent from each of these mechanoreceptors projects onto the primary somatosensory cortex (S1) and secondary somatosensory cortex (S2) through independent sensory channels [4-5]. The previous neuroimaging studies have shown that flutter induced increases in contralateral S1 and bilateral S2 activities whereas vibration induced increases in bilateral S2 activity [6-7].

It has been known that separation between flutter and vibration occurs around the vibrotactile frequency of 50 Hz, supported by physiological evidence from spectral differences between Meissner and Pacinian corpuscles as well as the separate afferent pathways departing from these two mechanoreceptors [6-8]. With respect to the brain activity, the difference in the topology of activation patterns over S1 and S2 between flutter and vibration suggests that the somatosensory cortex may play a key role in handling vibrotactile sensory inputs from multiple sensory channels. Yet, it is unclear whether it is possible to discriminate the somatosensory cortical activity for flutter and vibration.

Hence, in this study, we aim to distinguish somatosensory cortical activity between flutter and vibration. Specifically, we explore a variety of separability measures and investigate which measures provide correct separation between flutter and vibration. Many neuroimaging studies showed different activation patterns over S1 and S2 in response to flutter and vibration, but here we focused on the discrimination of the applied stimuli between flutter and vibration reversely from the cortical activation patterns. To this end, we performed an fMRI study in humans by providing vibrotactile stimulation with a range of frequency from 20 to 200 Hz. Then, we examined the blood oxygenation level dependent (BOLD) signals in S1 and S2 in response to various frequencies. We applied different separability measures including the hypothesis margin, Ward's method, Fisher discriminant, and Bhattacharyya distance described in the Methods section, which have been widely used in pattern recognition problems [10-12], to these somatosensory cortical BOLD data. We evaluated which measure produced the most discrimination between flutter and vibration.

^{*} This research was supported by the Pioneer Research Center Program through the National Research Foundation of Korea funded by the Ministry of Science, ICT & Future Planning (2011-0027921).

S. W. Han and Y. G. Chung are with Department of Brain and Cognitive Engineering, Korea University, Seoul, Republic of Korea (e-mail: realhsw@korea.ac.kr, uskeywest@korea.ac.kr).

H. S. Kim, S. C. Chung and J. Y. Park are with the School of Biomedical Engineering, College of Biomedical and Health Science, KonKuk University, Chungju, Republic of Korea (e-mail:hyungshikkim@gmail.com, scchung@kku.ac.kr, jyparu@kku.ac.kr).

S. P. Kim is with Research and Business Foundation, Korea University, Anam-5ga, Seongbuk-gu, Seoul, Republic of Korea, 136-713 (corresponding author : +82-10-2232-0520; fax: +82-2-926-2168; e-mail: spkim@korea.ac.kr).

II. METHODS

A. Experimental procedures

Ten healthy subjects (9 male, 1 female, ages of 25.60±4.22, right-handed) participated in this study They were given the information about the study and gave informed consent. This study was approved by Korea University Institutional Review Board (KU-IRB-11-46-A-1).

Vibrotactile stimuli from 20 to 200 Hz with an increment of 20 Hz were applied to the tip of the right index finger using an MR compatible stimulation device developed in our group [9]. The vibration stimulation was delivered through a 10×10 mm² pad attached on the fingertip. The stimulation strength was maintained to be 330 mV for all the frequency values. The fingertip was stimulated for 30 seconds followed by a 30 seconds resting period. Each stimulus with a particular frequency was provided sixteen times.

B. Data acquisition

A 3T MRI system (Magnetom TrioTim, Siemens Medical Systems, Germany) with a standard 32-channel head coil scanned anatomical images (T₁-weighted 3D MPRAGE, TR = 1,900 ms, TE = 2.48 ms, flip angle = 9°, FOV = 200 mm, voxel size = $0.8 \times 0.8 \times 1.0$ mm³) and functional images (T₂^{*}-weighted gradient echo-planar imaging, TR = 3,000 ms, TE = 30 ms, flip angle = 90°, FOV = 192 mm, slice thickness = 2 mm, voxel size = $2 \times 2 \times 2 \text{ mm}^3$). Functional images were preprocessed using SPM8 (Wellcome Department of Imaging Neuroscience, UCL, UK). The preprocessing procedure was conducted, including slice-timing correction, normalization, and smoothing with a 4-mm full-width-half-maximum (FWHM) isotropic Gaussian kernel.

C. Data analysis

As our study focused on how the somatosensory cortical activity differentiated flutter and vibration, we first selected all the relevant cortical regions. Specifically, we determined regions of interest (ROIs) as S1 (postcentral gyrus, Brodmann areas (BA) 3 and 1), posterior parietal cortex (PPC; BA 5 and 7), and S2 (the upper bank of the lateral sulcus (LS), BA 40) using the WFU PickAtlas 3.0 (http://fmri.wfubmc.edu/software/PickAtlas).

To investigate an overall relationship between the percentage change of the BOLD signals and the stimulation frequency, we calculated the average percentage change of the BOLD signals in each ROI for each subject. The average percentage change was defined as the mean of the percentage changes of the BOLD signal intensity from resting to stimulation in those voxels that showed a significant linear relationship between the BOLD signal and frequency (p<0.05).

D. Separability index

We used several separability measures, which have been used for many pattern recognition applications, to assess how far two BOLD signal groups separated from each other. We used the average percentage change data from six ROIs, including contralateral and ipsilateral S1, PPC and S2, composing a set of feature vectors for separability index calculation. We divided the average percentage change data into two groups by assuming boundary frequency at f and calculated the separability index between groups for each f. We assigned one class label (*e.g.* -1) to the feature vectors corresponding to the frequencies lower than f and the other class label (*e.g.* 1) to the remaining data. We computed four different separability measures with these class-labeled data for each f. We varied f from 50 to 170 Hz, assuming that each group should contain at least two different frequency values. The frequency with the maximum separability index was selected as the boundary frequency. The four different separability indices used in this study were briefly illustrated below.

1. Hypothesis margin

A margin defined in many learning algorithms generally measures a classification confidence when making decision [10]. The hypothesis margin evaluates the margin using the nearest hitting point and the nearest missing point. As an illustration, suppose that each sample in a given dataset, P, is assigned to one of two classes. For a data sample x, the hypothesis margin, $\theta_p(x)$, is calculated as,

$$\theta_{p}(x) = \frac{1}{2} \left(\left\| x - nearmiss(x) \right\| - \left\| x - nearhit(x) \right\| \right)$$
(1)

where *nearhit*(x) and *nearmiss*(x) indicate the nearest point to x in P with the same and the different class labels, respectively.

The hypothesis margin provides a distance measure on the hypothesis class. The margin of a hypothesis with regard to an instance is a distance between the hypothesis and the closest hypothesis that assigns an alternative label to the given instance.

2. Ward's method

Ward's method has been widely used as a basic separability measure in cluster analysis. This method measures a distance between two clusters, C_a and C_b , by calculating a difference between the sum of squares of scatterness within each cluster and the sum of squares of scatterness by merging the two clusters into one, C_{ab}

$$\Delta(A,B) = \sum_{i \in A \cup B} \left\| \vec{x}_{1} - \vec{m}_{A \cup B} \right\|^{2} - \sum_{i \in A} \left\| \vec{x}_{1} - \vec{m}_{A} \right\|^{2} - \sum_{i \in B} \left\| \vec{x}_{1} - \vec{m}_{B} \right\|^{2}$$
$$= \frac{n_{A}n_{B}}{n_{A} + n_{B}} \left\| \vec{m}_{A} - \vec{m}_{B} \right\|^{2}$$
(2)

where m_j is the center of cluster *j*, and n_j is the number of points in it. $\Delta(A,B)$ is called a merging cost of combining the cluster *A* and *B*.

3. Fisher's Discriminant Ratio

The Fisher discriminant ratio (FDR) is a ratio of between-class scatterness to within-class scatterness. The between-class scatter matrix S_B and within-class scatter matrix S_w are given as,

$$S_{\mathcal{B}} = \sum_{k=1}^{c} (\mu_{k} - \mu)(\mu_{k} - \mu)^{\prime}$$
(3)
$$S_{\mathcal{W}} = \sum_{k=1}^{c} \sum_{k \in C_{j}} (\mu_{k} - \mu)(\mu_{k} - \mu)^{\intercal}$$
(4)

where μ is the grand mean and μ_i is the mean of class C_i .

It is easy to see that for equiprobable classes $|S_W|$ is proportional to $\sigma_1^2 + \sigma_2^2$ and $|S_B|$ is proportional to $(\mu_1 - \mu_2)^2$. Combining S_B and S_W , the FDR is given by [11]



Figure 1. The average percentage change of the BOLD signals versus vibrotactile frequency in each ROI, including S1 (BA3 and 1, top), PPC (BA5 and 7, mid), and S2 (BA 40, bottom).



Figure 2. Separability index for the boundary frequency. Four different separability indices were measured from the cortical activation data for each possible frequency boundary from 50 to 170 Hz. The separability index was normalized off the maximum value.

4. Bhattacharyya distance

Bhattacharyya distance is based on a distance between two probability distributions [12]. It has been used as a class separability measure for feature selection and related to the upper and lower bounds of the Bayes error probability [13]. For two probabilistic random clusters, Bhattacharyya distance is defined as:

$$D_{\text{pust}} = \frac{1}{8} \left(M_{\text{s}} - M_{\text{s}} \right) \left[\frac{\sum_{i} + \sum_{s}}{2^{s}} \right]^{-1} \left(M_{\text{s}} - M_{\text{s}} \right) + \frac{1}{2} \ln \frac{\left| \sum_{i} + \sum_{s} \right|}{\sqrt{\left| \sum_{i} \right| \left| \sum_{s} \right|}}$$
(6)

where M_i is the mean vector of class *i* and \sum_i is the covariance matrix of class *i*.

III. RESULTS

We first investigated how the average percentage change signals varied with vibrotactile frequency. We examined the average percentage change from each of three ROIs. Fig.1 shows that the average percentage change appeared to decrease as the stimulation frequency increased from 20 to 200 Hz. We observe that the average percentage change decreased more with frequency in S1 and PPC than S2.

Next, we investigated the boundary frequency between flutter and vibration using four different separability index methods. The separability index results of each vibrotactile frequency using each method are shown in Fig. 2. We found that the hypothesis margin and the Bhattacharraya distance yielded the largest separability at 50 Hz (between 40 and 60 Hz), which is known to differentiate flutter and vibration. In particular, the hypothesis margin showed the most distinguishable separability peak at 50 Hz compared to other frequencies. Bhattacharraya distance showed another high separability at 170 Hz. Both Ward's method and FDR showed the highest separability at 110 Hz.

IV. CONCLUSIONS

In this study, we investigated how somatosensory cortical activation patterns differ in response to two different types of vibrotacile stimuli such as flutter and vibration. We compared various separability indices to measure distances between BOLD signal clusters. We found that the hypothesis margin method led to the greatest separability between flutter and vibration at the frequency of 50 Hz.

Our results demonstrated that distinction between flutter and vibration could be observed in the somatosensory cortical activity alone. These results suggest that the frequency of 50 Hz might be a critical point for the human nervous system in processing vibrotactile information. However, we also observed that some separability measures failed to detect the 50 Hz boundary frequency. We will further investigate what caused these separability measures unable to discriminate flutter and vibration in the somatosensory cortical activity. It might help us understand essential elements in the cortical activity patterns to discriminate flutter and vibration.

References

- Delmas, P., Hao, J., Rodat-Despoix, L., "Molecular mechanisms of mechanotransduction in mammalian sensory neurons." Nat. Rev. Neurosci. 12, 139-53, Feb 2011.
- [2] Lumpkin, E.A., Caterina, M.J., "Mechanisms of sensory transduction in the skin." Nature 445, 858-65, Feb 2007.
- [3] McGlone, F., Reilly, D., "The cutaneous sensory system." Neurosci Biobehav. Rev. 34, 148-59, Aug 2009.
- [4] Bolanowski SJ Jr, Gescheider GA, Verrillo RT, and Checkosky CM. "Four channels mediate the mechanical aspects of touch." J. Acoust. Soc. Am. 84: 1680-1694, Nov 1988.
- [5] Labs SM, Gescheider GA, Fay, RR, and Lyons CH. "Psychophysical tuning curves in vibrotaction." Sens. Processes. 2: 231-247, Sep 1978.
- [6] Francis, S.T., Kelly, E.F., Bowtell, R., Dunseath, W.J., Folger, S.E., McGlone, F., "fMRI of the responses to vibratory stimulation of digit tips." NeuroImage. 11, 188-202, Mar 2000.
- [7] Harrington, G.S., Hunter Downs, J., "fMRI mapping of the somatosensory cortex with vibratory stimuli. Is there a dependency on stimulus frequency?" Brain Res. 897, 188-92, Apr 2001.
- [8] Golaszewski, S.M., Zschiegner, F., Siedentopf, C.M., Unterrainer, J., Sweeney, R.A., Eisner, W., Lechner-Steinleitner, S., Mottaghy, F.M., Felber, S., "A new pneumatic vibrator for functional magnetic resonance imaging of the human sensorimotor cortex." Neuroscience Lett. 324, 125-128, May 2002.
- [9] Kim, H.S., Choi, M.H., Chung, Y.G., Kim, S.P., Jun, J.H., Park, J.Y., Yi, J.H., Park, J.R., Lim, D.W., Chung, S.C., "Development of a simple MR-compatible vibrotactile stimulator using a planar-coil-type actuator." Behav. Res. Methods. Oct 2012.
- [10] Gilad-Bachrach, R., Navot, A., Tishby, N., "Margin based feature selection - theory and algorithms." Proceedings of the twenty-first International Conference on Machine learning, Banff, Alberta, Canada, pp. 43-50, 2004.
- [11] Theodoridis, S., Koutroumbas, K., "Introduction to Pattern Recognition: A Matlab Approach." 4th ed., Academic Press, 2010.
- [12] Kailath, T., "The divergence and Bhattacharyya distance measures in signal selection.", IEEE Trans. on Communication Technology, 15, pp. 52-60, February 1967.
- [13] Choi, E.S, Lee, C.H, 2003. "Feature extraction based on the Bhattacharrya distance." Pattern Recogn. 36, 1703-1709, Nov 2002.