EEG-Based Perceived Tactile Location Prediction

Deng Wang, Yadong Liu, Dewen Hu, and Gunnar Blohm

***Abstract*—Previous studies have attempted to investigate the peripheral neural mechanisms implicated in tactile perception, but the neurophysiological data in humans involved in tactile spatial location perception to help the brain orient the body and interact with its surroundings are not well understood. In this paper, we use single-trial electroencephalogram (EEG) measurements to explore the perception of tactile stimuli located on participants' right forearm, which were approximately equally spaced centered on the body midline, 2 leftward and 2 rightward of midline. An EEG-based signal analysis approach to predict the location of the tactile stimuli is proposed. Offline classification suggests that tactile location can be detected from EEG signals in single trial (four-class classifier for location discriminate can achieve up to 96.76%) with a short response time (600 milliseconds after stimulus presentation). From a human-machine-interaction (HMI) point of view, this could be used to design a real-time reactive control machine for patients, e.g., suffering from hypoesthesia.**

***Index Terms*—Electroencephalogram (EEG), prediction, spatial location perception, tactile.**

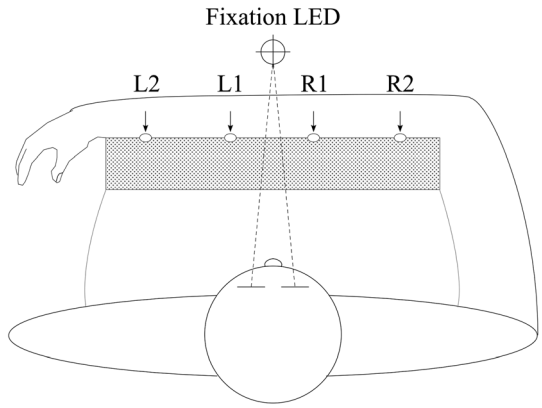

Fig. 1. Experimental setup. Participants were instructed to lie on the bed while a custom-made tactile device was placed below their right forearms between wrist and elbow. A fixation LED was positioned 5 cm above the center of the stimuli.

I. Introduction

TACTILE perception for human is an important sensory modality that helps us to interact with the world. It can be regarded as the interpretation of information provided by skin sensations about the body. The information may be related to evaluation of object shape [1], [2], surface texture including temperature, roughness, hardness, moistness, stickiness [3]–[5], or even participants' feelings [6]. Also it may be related to judgment of spatial information, for example, orientation [7]. Furthermore, tactile information is important in object manipulation tasks [8]. To our knowledge, not many studies have investigated perceived tactile location discrimination. In [9], participants were instructed to verbally report the perceived position in millimeters of touches presented between the elbow and the wrist. With eye fixations at different eccentricities, they showed that there is a systematic shift in the perceived location of a tactile stimulus on their left or right forearms. Researchers have reported both eye position-related errors [9] and head position-related errors [10], and Pritchett and Harris [11] investigated how they affect the perceived location of touch to the forearm; the direction of both head and eyes caused a shift in the tactile localization. Work by Spitoni *et al.* [12] compared the judgment of perceived stimulus distance with perceived intensity of contact sensation, while two simultaneous tactile stimuli were applied on the right forearm and right thigh, respectively; this paper showed that the cognitive processes underlying the perceived stimulus distance and intensity tasks were supported by partially different brain networks using fMRI [12].

Here, we investigate whether we can use EEG decoding algorithms to infer the location of perceived tactile stimuli on the right forearm in real-time. In [13], de Lafuente and Romo found that the pressure of a tactile stimulus on the skin can be read out from firing of neurons in primary somatosensory cortex (S1). However, the recordings were obtained via an array of invasive microelectrodes. As one of noninvasive neurophysiological measures to decode human brain activity, electroencephalography (EEG) is more convenient, inexpensive and harmless [14]. Furthermore, since first EEG recordings from the human scalp by Hans Berger in 1924 [15], the patterns of electrical activity produced on an EEG and the related event-related potentials (ERPs) have being extensively used in neuroscience, cognitive science, cognitive psychology, brain-computer interface (BCI), etc. This kind of technique has many advantages over some of other brain image techniques to study brain activity. The main advantage of noninvasive EEG lies in its very high temporal resolution.

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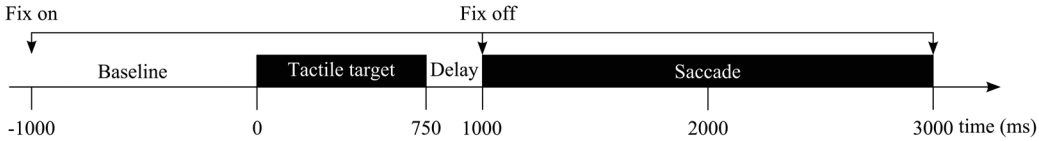

Fig. 2. Experimental task and stimulus sequence. During each trial, participants fixated the LED above the stimulus box in a dark environment. After a baseline period of 1000 ms, the tactile target was presented randomly at one of four locations for 750 ms (except for the catch trials). After a short 250 ms delay, the LED disappeared, signaling the subject to make an eye movement to the remembered target location. Reappearance of the LED signaled the start of a new trial.

In this paper, we use single-trial EEG measurements as a tool to explore human brain processing in a tactile stimulus location discrimination task. More specifically, four solenoid actuated tactile stimuli (two left of body midline - denoted as L2 and L1; and two right - denoted as R1 and R2) equally spaced (5 cm apart) were located on the participants' right forearms against their skin. To predict the location of the perceived tactile stimuli, a simple approach of feature extraction combined with SVM classification is proposed. Experimental results are encouraging: within only 600 ms after stimulus onset, we can correctly infer which stimulus was perceived.

The remainder of the paper is organized as follows: Section II describes our EEG-based tactile data collection experiment, followed by the proposed EEG data analysis method. Results are presented in Section III. Section IV concludes this paper with several recommendations for future directions.

II. Perceived Tactile Data Collection

A. Participants

Ten healthy volunteers (five females, one left-handed, aged between 21 and 35 years, mean age 26.9 ± 5.2SD) were recruited from the population of staff and students of the Centre for Neuroscience Studies at Queen's University. All of them had normal or corrected-to-normal vision, gave informed written consent, and were free from neurological or psychiatric impairments. The experiment was approved by the Research Ethics Board at Queen's University.

B. Experiment Setup

The participants were initially instructed to lie down on their back in an MRI magnet with a high-density 256-channel MRI-compatible HydroCel Geodesic Sensor Net application. The stimulus box was located on the right forearm. Their torso and head were tilted. The stimulus box contained four solenoid tactile stimulators (L2, L1, R1, and R2) and a fixation LED. The solenoids were encased in the box with pins facing upwards, and they were equally spaced (5 cm apart) centered on the body midline, whereas the cue LED was positioned 5 cm above the center of the stimulus box. Through a mirror, participants could look at the LED (Fig. 1). Eye tracking was not used since timing and accuracy of the delayed eye movements were not critical to the experiment and the restrictive MRI environment did not allow us to obtain an independent measure of eye movements.

C. Experimental Procedure

As shown in Fig. 2, each experimental trial started with the onset of the LED. The first 1000 ms was a baseline period, during which participants were instructed to fixate the central LED. A vibration was then administered through solenoid activation at one of the four locations on the right forearm for 750 ms, followed by a memory delay of 250 ms. Subsequently, the LED was extinguished which indicated participants to move their eyes to the memorized target location and fixate it until the LED turned on again, i.e. the next experimental trial started. Each experimental trial lasted 4000 ms and was presented on average about 40 times (L2: 41, L1: 41, R1: 38, and R2: 40). We also added 40 trials with null stimulus events (catch trials) where no tactile stimulation was presented; catch trials were presented in a pseudorandom order to make them as unpredictable as possible. A session thus involved a total of 200 trials. Before the actual data recording, a short set of training trials was given to familiarize participants with the LED and task. Imaging was performed using a Siemens 3T scanner but we did not analyze fMRI data in the present study. Continuous EEG were simultaneously recorded at a sampling rate of 250 Hz using a 256-channel Geodesic Sensor Net (Electrical Geodesics, Inc.), referenced online the vertex. All data were converted to MATLAB format and offline preprocessed using the Statistical Parametric Mapping software package, version 12[1] (Wellcome Department of Cognitive Neurology, London, UK) and custom MATLAB scripts.

D. Data Analysis

The continuous EEG recordings were first band-pass (Butterworth, order 4) filtered with a cutoff frequency of 4 and 40 Hz, then, segmented off-line into trials ranging from -100 to 800 ms relative to stimulus onset. To investigate the influence of the EEG oscillatory power on tactile discrimination, time-frequency representations were computed across all channels and participants using a Morlet wavelet transform approach (cycle equals 5 for the wavelets). EEG data were then band-pass filtered according to the main difference in frequency range for the following analysis. To investigate how much poststimulus time would yield the best classification accuracy, eight time intervals [0 $\sim$ 100 ms], [100 $\sim$ 200 ms], [200 $\sim$ 300 ms], 300 $\sim$ 400 ms], [400 $\sim$ 500 ms], [500 $\sim$ 600 ms], [600 $\sim$ 700 ms], and [700 $\sim$ 800 ms] relative to stimulus onset were compared, while the time window from -100 to 0 ms was as reference window. To investigate the optimal EEG channel set, the selected time interval was then used. We select the channel set by performing the following steps: (a) compute the wavelet packet Entropy differences between the selected time interval and the reference interval according to (3) for the set of candidate channels (the size of this set increased from 15 to all 158 EEG channels); (b) sort the set of

[1]SPM12: available at http://www.fil.ion.ucl.ac.uk/spm/software/spm12

candidate channels into a list in descending order according to Entropy difference value according to (2); (c) compute the classification accuracies for the selected channel set at each size according to (1) and chose the optimal channel set which presents the highest classification accuracy obtained by using a training-test ratio of 50%-50% test. For each trial, eye blinks and movements related to artifacts were automatically detected by the SPM12 threshold method (threshold was ± 200 μV during $[-100 \sim 800$ ms] time interval) and flagged trials were excluded from the following analysis.

For each individual trial: $x^k \in \mathbb{R}^{C\times T\times N}$, where $k = \{L2, L1, R1, R2\}$ denotes the target location, C, T, and N denote the number of channels, number of sampled time-points, and number of trials, respectively. A feature vector F^k was calculated and represented by

$$F^k = \text{select\_}ch(1 \cdots c) \tag{1}$$

where c stands for the number of selected EEG channels, and

$$\text{select\_ch} = \text{sort}(E_{\overline{x(c,:)^k}}, \text{'descending order'}) \tag{2}$$

$$E_{\overline{x(c,:)^k}} = E_{\overline{x(c,t_{\text{active}})^k}} - E_{\overline{x(c,t_{\text{reference}})^k}} \tag{3}$$

where

$$t_{\text{active}} = \{t_0 \cdots t_{100} | t_{100} \cdots t_{200} | t_{200} \cdots t_{300} | t_{300} \cdots t_{400} | t_{400} \cdots t_{500} | t_{500} \cdots t_{600} | t_{600} \cdots t_{700} | t_{700} \cdots t_{800}\}$$

$$t_{\text{reference}} = t_{-100} \cdots t_0,$$

$c = [1 \cdots C]$, and E stands for the Shannon entropy which was calculated using the different time intervals

$$E_{\overline{x(c,t)^k}} = \overline{x(c,:)^k} \log_2 \overline{x(c,:)^k} \tag{4}$$

where $\overline{x(c,:)^k} = mean(x(c,:,n)^k, 3)$ is the average across all trials for target location k.

A linear support vector machine (SVM [16]) was then used for determining the target location within the time window for each individual participant. The LIBSVM toolbox [17] was employed as the classifier. We used a linear kernel function with default values for the other parameters. To validate the actual performance for the online test, training-test were used, i.e., the first part of all trials (first session) was used as the training set, and the remaining trials (second session) were assigned to the test data set.

III. Results

No eye tracking was used in this experiment because the restrictive MRI environment did not allow us to obtain an independent measure of eye movements. However, prior to recording data, a short set of training trials was given to familiarize participants with the experimental task. The behavioral results, i.e., the saccadic eye-movements averaged from all 10 participants recorded at EOG channels for four positions are shown in Fig. 7 which shows participants basically did not make eye movements during the fixation time period but made eye movements during the response time period. It should also be pointed out that in this paper the classification accuracy did not depend on participants' eye response. We only used the first part of the fixation time period for predicting the perceptual position even if there are trials with a wrong response. What's more, we believe that not using an eye tracker is actually an advantage for future applications.

TABLE I
Summary of the Number of Nonartifact Trials for Each Participant

Participant	# Total trials	# Non-artifacts	Rate (%)
1	160	142	88.75
2	160	150	93.75
3	160	151	94.38
4	160	158	98.75
5	160	132	82.50
6	160	157	98.10
7	160	154	96.25
8	160	138	86.25
9	160	160	100.0
10	160	151	94.38
Mean			**93.31**

The number of nonartifact trials is summarized in Table I. These non-artifact trials are trials without eye blinks and movements, i.e., the amplitudes of EEG are between ± 200 μv for the $[-100 \sim 800$ ms] time interval relative to stimulus onset. It can be seen that most participants followed the instructions correctly in most trials: average correct rate: 93.31%, standard deviation (SD): 5.74%, except for participant 5. The simple threshold method yields low rejection rate, which indicates that the method is well suited even within a high noise scenario. We discarded those bad trials in the following EEG-based classification analysis.

In order to examine the frequency band related to tactile location discrimination, a time-frequency representation of EEG data was computed from $[|\text{L2} - \text{L1}| + |\text{L2} - R1| + |\text{L2} - \text{R2}| + |\text{L1} - \text{R1}| + |\text{L1} - \text{R2}| + |\text{R1} - \text{R2}|]/6$ by filtering the resulting signal using the Morlet wavelet transform using all EEG channels and participants. For example, $|\text{L2} - \text{L1}|$ means that we computed the time-frequency difference between tactile location L2 and L1. Fig. 3 shows the result of this analysis and reveals an increase in beta-band (25-32 Hz) synchronization starting 550 ms and ending 600 ms after stimulation onset. One-sample t-tests showed that the differences of high beta ($25 \sim 32$ Hz), alpha ($10 \sim 15$ Hz) and lower beta ($16 \sim 20$ Hz) bands in Fig. 3 are all significant ($\text{T}_{25\sim32\text{ Hz}} = 10.6539$, $\text{p} < 0.05$; $\text{T}_{10\sim15\text{ Hz}} = 13.6073$, $\text{p} < 0.05$; $\text{T}_{15\sim20\text{ Hz}} = 12.6775$, $\text{p} < 0.05$). We only selected the high beta-band ($25 \sim 32$ Hz) in the subsequent analyses for all participants because it presented the highest discriminative accuracy (89.73 ± 1.57) compared to what was achieved ($87.19 \pm 1.65\%$) for the $[350 \sim 450$ ms] time interval of the $10 \sim 20$ Hz band. Moreover, it is well known that power and phase in different frequency bands are correlated with different regions on tactile detection. Especially, beta band oscillations reflect changes in an active status of sensorimotor functions and it has been demonstrated that power in high beta band (20 to 40 Hz) have substantial influence on

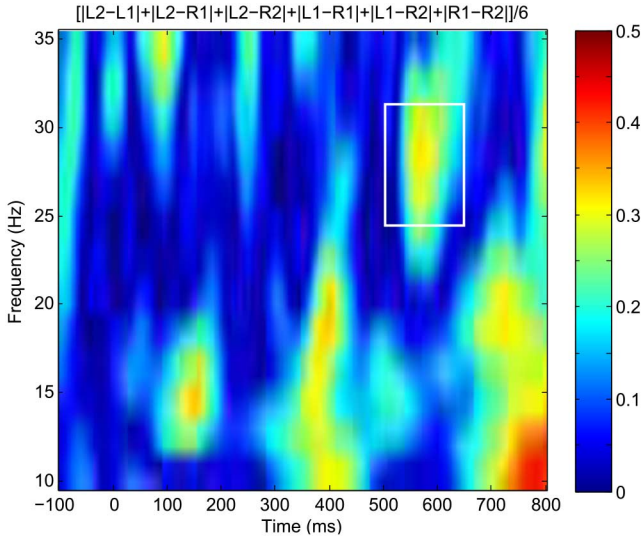

Fig. 3. Time-frequency representation of EEG data $[|\mathrm{L2}-\mathrm{L1}|+|\mathrm{L2}-\mathrm{R1}|+|\mathrm{L2}-\mathrm{R2}|+|\mathrm{L1}-\mathrm{R1}|+|\mathrm{L1}-\mathrm{R2}|+|\mathrm{R1}-\mathrm{R2}|]/6$ across all channels and participants.

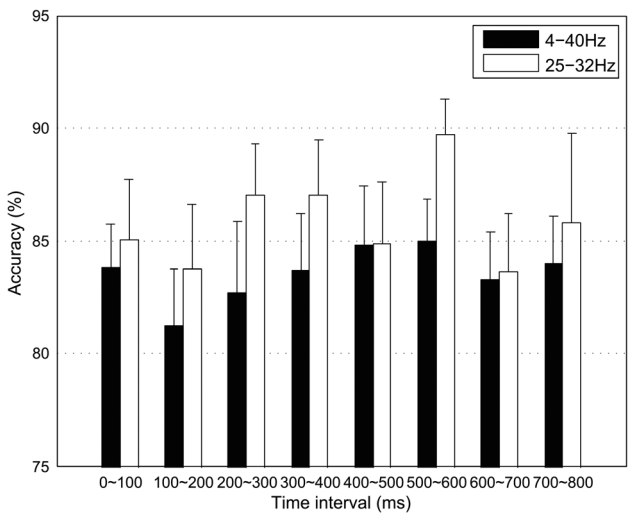

Fig. 4. Comparison of single-trial EEG (25-32 Hz) versus (4-40 Hz)-based classification accuracy with respect to eight different time intervals across all EEG channels and participants.

the perception of tactile stimuli [18]. Therefore, in the following analysis, the EEG trials were band-pass filtered between 25 and 32 Hz. Note that all results reported here and below were averaged over all trials and all participants.

Next, we investigated how the decoding accuracy depended on the different time intervals (windows $[0 \sim 100$ ms], $[100 \sim 200$ ms], $[200 \sim 300$ ms], $[300 \sim 400$ ms], $[400 \sim 500$ ms], $[500 \sim 600$ ms], $[600 \sim 700$ ms], and $[700 \sim 800$ ms], see Fig. 4). The best accuracy of mean $\pm$ standard error of mean (SEM): $89.73 \pm 1.57\%$ was achieved for the $[500 \sim 600$ ms] time interval using training-test ratio of 50%-50% test and all 158 EEG channels after the 25-32 Hz band-pass filtered.

For the channel reduction, the $[500 \sim 600$ ms] time interval was used when comparing accuracies at different sizes of the channel set. Fig. 5 shows that the classification accuracy in training-test ratio of 50%-50% tests for all participants as

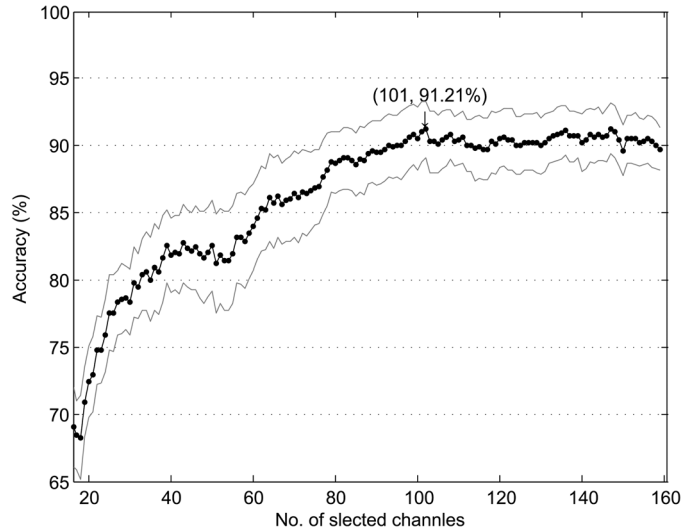

Fig. 5. Comparison of single-trial-based classification accuracy with respect to the number of selected channels using $[500 \sim 600$ ms] time interval. The size of channel set increased from 15 to all 158 EEG channels. The thick line indicates the median and the thin lines are standard error of mean.

a function of the number of selected channels (from 15 to 158 variables). As can be seen from Fig. 5, there is a general increasing trend in classification accuracy as the number of selected channel grows until the number is equal to 101. In contrast, the accuracy remains stable when more than 101 channels are selected. According to the frequency and order of the selected channels, a weight vector was calculated. More specifically, each selected channel in the variable *selected_ch* [see (2)] was first assigned an initial value $[0 \sim 1]$. The higher the rank, the larger is the value. The weight value of each channel is the average across all stimulus localizations and participants. Using the weight vector, we plotted the channel distributions that contribute to the discrimination of tactile localization (L2, L1, R1, and R2) for three different sizes of the channel set ($\mathrm{n} = 256$, 158 and 101, see Fig. 6). Results suggest that the frontal and parietal cortices are most involved in the discrimination of tactile localization. Following these results, in the rest of the paper, we chose to use 101 channels.

Furthermore, the effect of the size of training/test set on measured decoding performance was investigated (see Table II). For comparison, we divided all nonartifact-contaminated epochs to form groups of 10%–90% training set–test set up to 90%–10% training set–test set data ensembles. Based on Table II, a training-test ratio of 90%–10% clearly yields the best classification accuracy ratio, i.e., 96.76%.

To avoid the results to be overtraining in a training-test ratio of 90%–10%, we used 10-fold cross-validation tests, i.e., 90% of all trials at random in each class were used for the training set, and the remaining trials were used for validation to determine performance. This was repeated 10 times for different partitions of the training set. To get more robust results, the above process was repeated 10 times and the results are shown in Table III.

Finally, Fig. 7 shows the EOG traces across all trials for each stimulus location (L2, L1, R1, and R2). Overall, for each stimulus location, the subject keeps stable fixation during the first 1 s baseline period. Subsequently, saccade brings eye's fixation to

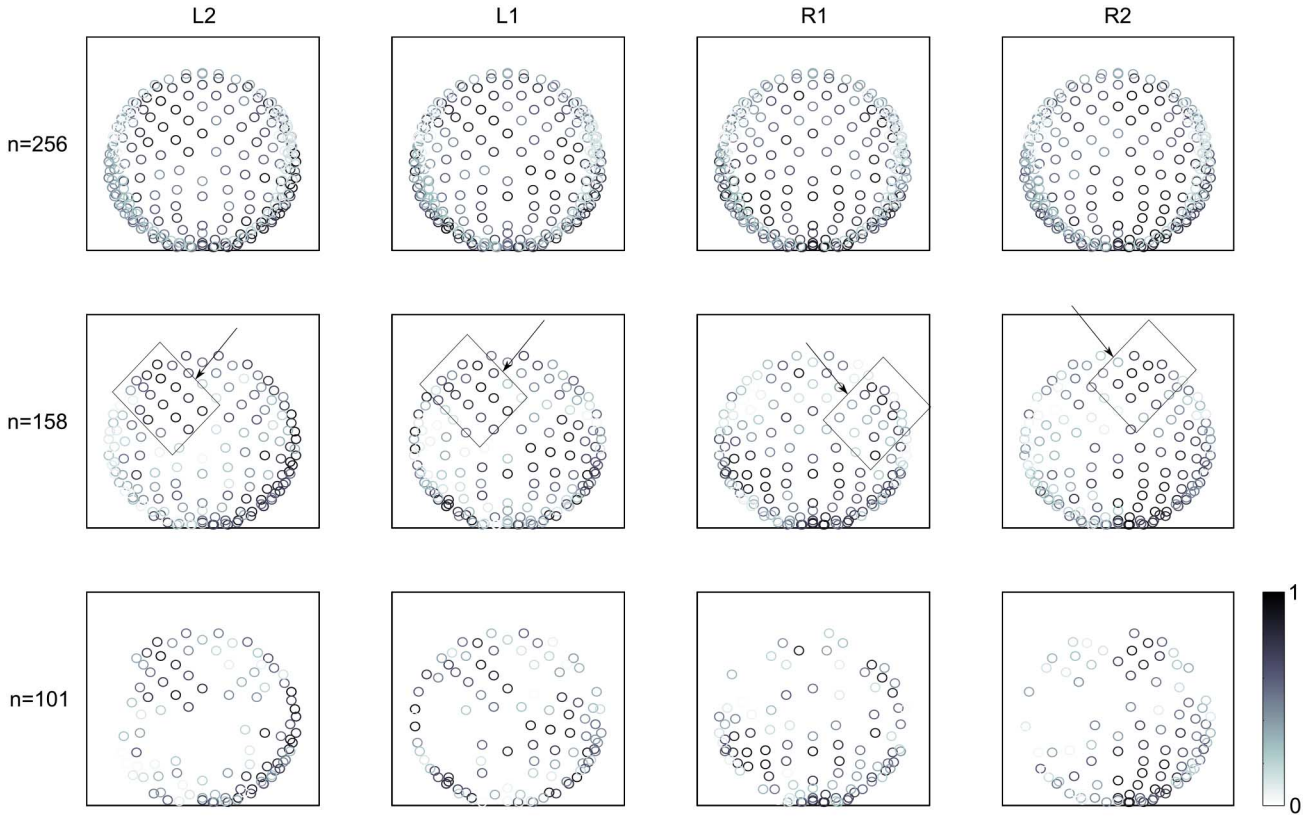

Fig. 6. Comparison of channel distribution which contribute to the discrimination of tactile localization (L2, L1, R1, and R2) for three different sizes of the channels set (256, 158 and 101). The scale of black color stands for the weight value of the selected channel. Darker indicates more ability to the discrimination of tactile localization. Regions of interest in sensor space are indicated by arrows and squares.

TABLE II
TRAINING (THE FIRST PART OF ALL TRIALS) - TEST (THE REMAINING PART): COMPARISON OF SINGLE-TRIAL-BASED CLASSIFICATION ACCURACIES (%) FOR EACH PARTICIPANT AND DIFFERENT TEST SUBSETS USING [500 $\sim$ 600 ms] TIME INTERVAL AND THE SELECTED 101 CHANNELS

Participant	Training-test partition								
	10-90%	20-80%	30-70%	40-60%	50-50%	60-40%	70-30%	80-20%	90-10%
1	76.15	95.92	93.02	93.33	96.77	98.04	97.50	100.00	100.00
2	44.20	75.41	82.41	86.02	91.14	88.89	92.00	100.00	100.00
3	67.59	84.50	92.98	95.92	96.34	98.53	98.08	97.30	100.00
4	63.95	64.89	83.48	82.00	79.76	81.16	81.48	89.47	95.45
5	33.66	60.00	64.56	82.35	82.46	83.33	84.21	88.46	93.75
6	56.79	56.16	73.44	87.50	95.74	97.44	96.77	95.45	100.00
7	67.41	78.33	85.85	91.21	93.42	95.24	93.88	100.00	100.00
8	39.50	72.64	71.28	77.78	94.12	94.64	97.67	96.77	100.00
9	45.00	86.79	89.36	95.06	98.55	94.55	95.45	93.33	88.89
10	39.53	78.26	80.39	77.01	83.78	91.67	95.65	96.88	89.47
Mean	**53.38**	**75.29**	**81.68**	**86.82**	**91.21**	**92.35**	**93.27**	**95.77**	**96.76**
(SEM)	**(4.68)**	**(3.91)**	**(3.00)**	**(2.20)**	**(2.13)**	**(1.93)**	**(1.84)**	**(1.32)**	**(1.45)**

the remembered target location. From Fig. 7, we noticed that the EOG traces from different participants various a lots although the average traces could be distinguished. From the view of the behavioral aspects of eye-movement, we conclude that it is not wise to make a target tactile stimulus detection based on these EOG data, especially for a single trial. In this paper, we focused on EEG differences in the neural response using only a short time window from stimulus onset.

IV. CONCLUSION AND FUTURE WORK

In this paper, we attempted to explore human neural processing for tactile stimulus location discrimination based on

TABLE III
10-FOLD CROSS-VALIDATION TEST: COMPARISON OF SINGLE-TRIAL-BASED CLASSIFICATION ACCURACIES (%) FOR EACH PARTICIPANT USING THE [500 ∼ 600 ms] TIME INTERVAL AND THE SELECTED 101 CHANNELS

Participant	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Accuracy	99.80	93.50	96.38	90.74	87.26	89.30	95.17	94.00	95.45	90.94
(SEM)	(0.12)	(0.27)	(0.23)	(0.33)	(0.68)	(0.45)	(0.27)	(0.32)	(0.39)	(0.38)

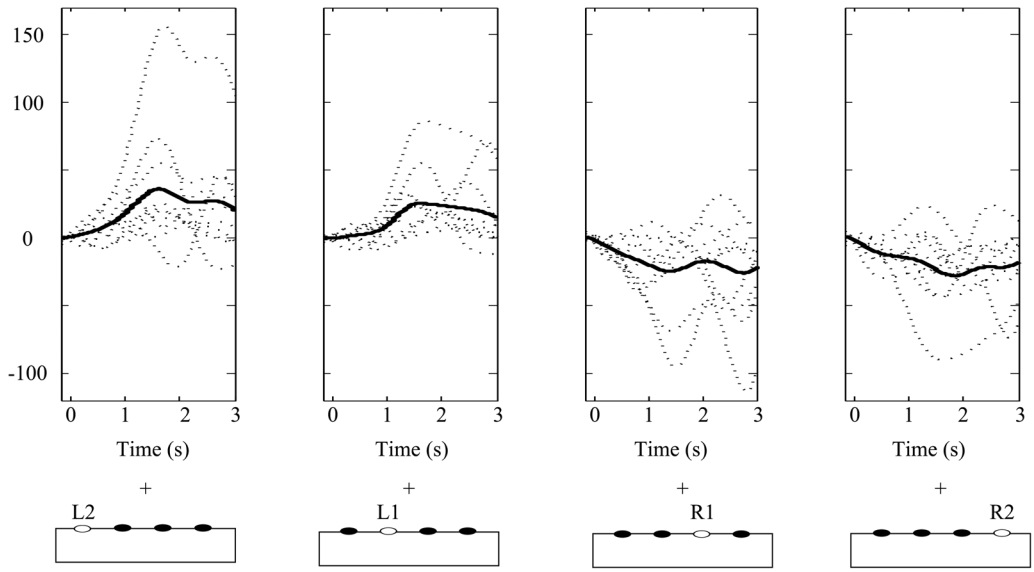

Fig. 7. EOG traces for four different trial type. Dotted lines represent EOG traces for all participants, and bold lines represent the mean traces across all participants. The corresponding stimulus location (white circle) onto the stimulus box and the central fixation cross (cue LED) 5 cm above the box are presented in the lower panels.

high temporal resolution EEG recordings. Our results shown that using a short period EEG recording, it is sufficient to predict stimulus location from forearm stimulation.

It is well known that people with hypoesthesia-impaired tactile sensibility have difficulties to generate actions to interact with environments. From a human-machine-interaction (HMI) point of view, this study could lead to practical rehabilitation or assisting devices for patients with schizophrenia or certain movement disorders to detect the perceived tactile stimulus and its location using real-time EEG recordings. We hope that the future studies along the aforementioned research directions could be used to better understand human mechanisms of tactile perception and develop actual applications especially for patients whose voluntary actions are not a product of choice.

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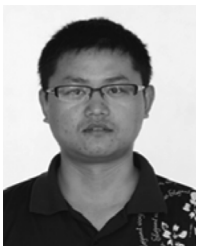

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