Classification of somatosensory cortex activities using fNIRS

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ABSTRACT

The ability of the somatosensory cortex in differentiating various tactile sensations is very important for a person to perceive the surrounding environment. In this study, we utilize a lab-made multi-channel functional near-infrared spectroscopy (fNIRS) to discriminate the hemodynamic responses (HRs) of four different tactile stimulations (handshake, ball grasp, poking, and cold temperature) applied to the right hand of eight healthy male subjects. The activated brain areas per stimulation are identified with the t-values between the measured data and the desired hemodynamic response function. Linear discriminant analysis is utilized to classify the acquired data into four classes based on three features (mean, peak value, and skewness) of the associated oxy-hemoglobin (HbO) signals. The HRs evoked by the handshake and poking stimulations showed higher peak values in HbO than the ball grasp and cold temperature stimulations. For comparison purposes, additional two-class classifications of poking vs. temperature and handshake vs. ball grasp were performed. The attained classification accuracies were higher than the corresponding chance levels. Our results indicate that fNIRS can be used as an objective measure discriminating different tactile stimulations from the somatosensory cortex of human brain.

1. Introduction

The aim of the present study is to decode the hemodynamic responses (HRs) evoked by multiple pain and touch stimuli in the somatosensory cortex using functional near-infrared spectroscopy (fNIRS). Researchers have examined different neurophysiological signals to understand the working of the somatosensory cortex for different pain and touch stimulations [1]. Among those signals are event-related potentials (ERPs), which are acquired by electroencephalography (EEG) from the scalp [2,3]. Recently the authors have examined the relationship between empathy and social touch as reflected in attenuation of EEG oscillations in the mu band [3]. EEG, with its high temporal resolution, detects brain signals very quickly but the main disadvantage is its poor spatial resolution [4,5]. The other technique widely used to detect brain areas that are activated in the course of tactile stimulation is functional magnetic resonance imaging (fMRI). fMRI, with its high spatial resolution relative to that of EEG [6–9], can easily localize changes in the regional cerebral blood flow (rCBF). A comprehensive review of fMRI has found the current technique to be limited due to the high cost of its scanners, bulky size, and high sensitivity to motion artifacts [10].

Researchers therefore have begun to explore another brain-imaging technique, fNIRS, which measures brain activity through hemodynamic responses associated with neuron behavior [11–14]. fNIRS is a portable, noninvasive, inexpensive method of monitoring cerebral hemodynamic activity at moderate depths (surface cortices), which makes it suitable for the study of various stimulations in remote and challenging environments [15–18]. fNIRS can detect changes in both oxy-hemoglobin (HbO) and deoxy-hemoglobin (HbR), which are strong absorbers of near-infrared light (650–1000 nm). In this spectrum of light, bones, skin and tissue are mostly transparent [19]. fNIRS provides a better temporal/spatial resolution tradeoff as compared with EEG and fMRI. In the recent past, researchers have used fNIRS in a variety of fields such as neuroscience [20,21], sports medicine [22], behavioral studies [23–26], clinical medicine [27], and brain-computer interface (BCI) [28–31].

To date, only limited research has been undertaken to decode different stimulations using fNIRS [32–37]. In all of these studies, the authors have identified only different brain regions or changes in HRs related to different noxious or innocuous stimulations. The authors, meanwhile, have applied only specific types of noxious stimulation including thermal [32,33], painful pressure [35], electrical stimulation [36], and dental pain [34,37], and have compared the corresponding HR to innocuous stimulation. There is as yet no study that has used classification methods to distinguish between even noxious and innocuous stimulation.

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In the present study, we decoded different pain and touch stimulations (poking, cold temperature, handshake and ball grasp) using fNIRS. Linear discriminant analysis (LDA) was used to distinguish between the four HRs based on the mean, peak value and skewness of HbO. Pre-processing techniques of noise removal and statistical analysis were used to enhance classification accuracy. The results obtained in this study demonstrate that fNIRS-determined features can be used to distinguish and classify the HRs of the four different tactile stimulations.

2. Materials and methods

2.1. Subjects

Eight healthy male subjects (average age: 30.75 ± 2.81 years) participated in the experiment. All of the subjects had normal sensation in their right hand and no history of any neurological disorder. All of them were informed about the nature of the experiment as well as its purpose, before providing written informed consent. During each experiment, the subject was asked to sit down on a comfortable chair, to relax, close his eyes, and avoid any major body movement. Their right hand was placed palm-up on a table in a comfortable position. The complete experimental procedure was conducted in accordance with the Declaration of Helsinki.

2.2. Sensory stimuli

Four different sensory experiments were performed with the subjects. Two were passive stimuli (poking and cold temperature) and two were active stimuli (handshake and ball grasp). In the application of passive stimuli, the subject does not have to move any of his body to produce the sensation, whereas in the application of active stimuli the subject has to move his hand and fingers to feel the sensation. Each experiment consisted of 10 trials. Each trial included a task duration of 10 s followed by a resting-time duration of 30 s. Before the start of each experiment, 60 s baseline data were collected in the resting state. Each experiment was 460 s in total (60 ± (10 + 30) × 10). For each experiment, prompts for the start and end of the task period were shown to the investigator using a Microsoft power point presentation with predefined time intervals.

Fig. 1 shows the experimental paradigm for a task, in which four tasks (poking, temperature, hands shake, and ball grasp) are serially performed. For the poking experiment, the subject’s right-hand middle finger was poked by a nail during the task period with a frequency of 1.5–2.0 Hz. Before the start of the experiment, every subject was poked twice in order to determine the level of pain they could feel. Care was taken to poke the same finger with the same frequency and pressure.

For the temperature sensation experiment, a computer-controlled thermode (3 × 3 cm) was used (Q-Sense, Medoc Advanced Medical Systems, Israel). The thermode was placed on the right-hand index and middle fingers of the subject. The temperature was set to 20 °C. The thermode was set at the correct temperature for the experiment, applied to the fingers of the subject upon the start of the task period, and removed at the end of each task period. Care was taken to apply the thermode to the same site with the same pressure.

For the handshake experiment, the investigator placed his right hand on the subject’s right hand during each task period. Because the subject was sitting with closed eyes, two different sounds were used to signify the start and end of the task period so as to indicate the time to close and open his hand, respectively.

For the ball grasping experiment, the investigator placed a billiard ball in the right hand of the subject in such a way that it was not touching the palm, the subject grasping the ball using only his thumb and fingers. Two different sounds were played to signify the start and end of the task period to indicate the time to close and open his fingers, respectively.

2.3. fNIRS signal acquisition

For this study, we upgraded our own developed multi-wavelength fNIRS system to 32 channels [38,39]. A special cap, made of nylon, was designed so that it can be worn on the subject’s head tightly and the light emitting diodes (LEDs) and photodiodes can be attached to the subject’s scalp through the holes. While attaching the emitters (LEDs) and detectors (photodiodes) on the subject’s head, hair was moved to the sides so that the optodes could be attached properly to the subject’s scalp. This system consists of eight tri-wavelength LEDs (L735/805/850-40B32, Epitex Inc., Japan) and fifteen photodiodes (S1223-01, Si Photodiode, Hamamatsu Photonics, Japan). Each LED can emit light at three wavelengths: 735 nm, 805 nm, and 850 nm. The LED has a total radiant power of 9 mW at each wavelength. We used LEDs rather than lasers as the light sources because LEDs are inexpensive, easy to use and there is no need for fiber cables (LEDs being directly attachable to the human body). Each photodiode, used in our system, can detect light at wavelengths ranging from 320 nm to 1100 nm, with an active area of 3.6 mm x 3.6 mm. A uniform intensity of LEDs and the gain of the photodiodes were controlled by the drive circuitry. The head cap was designed in such a way as to enable later accommodation of sensors from an EEG system as well.

Fig. 2(a) shows the placement of the LEDs and photodiodes over the left somatosensory cortex of the subject. The red circles indicate the detectors and blue squares indicate the LEDs. The numbers written in between the LEDs and photodiodes indicate the channel numbers. Accordingly, following the International 10–20 system, channel 18 was positioned at the Cz location. It should be noted that the complete somatosensory cortex area was covered by this configuration in the left hemisphere. Fig. 2(b) shows the picture of a subject wearing the cap. Each LED was turned on and off sequentially, and the light diffused through the cortical region was detected at the nearest detectors. A total of 64 light-intensity signals (8 LEDs × 2 wavelengths × 4 neighboring detectors) were acquired at a sampling rate of 5.3 Hz. Finally, during the experiment, all the lights in the room were switched off to minimize signal contamination from the ambient light sources.

2.4. Data processing

The signals from the fNIRS system were imported and further analyzed and classified offline using MATLAB™ 7.9.0 (MathWorks, USA). The data were stored in a host-computer text file in the form of digitized raw-intensity values. From those values, the changes in optical density ΔA, could be calculated at each discrete time k as follows.

\[ \Delta A(k, \lambda) = -\ln \left( \frac{I_{\text{out}}(\lambda)}{I_{\text{in}}(\lambda)} \right) = l \cdot D(\lambda) \cdot \Delta \mu(\lambda, k), \]

(1)

where \( \lambda \) is the wavelength of light, \( I_{\text{in}} \) is the intensity of incident light, \( I_{\text{out}} \) is the intensity of detected light, \( l \) is the distance between the sensors, and \( D(\lambda) \) is the light absorption coefficient of the tissue at wavelength \( \lambda \).
emitter and the detector, $D$ is the differential pathlength factor (DPF), and $\Delta \mu_a$ is the change of the absorption coefficient of the tissue. The changes of oxy-hemoglobin ($\Delta c_{\text{HbO}}$) and deoxy-hemoglobin ($\Delta c_{\text{HbR}}$) were measured using the modified Beer-Lambert law \[40,41\]

$$
\begin{equation}
\begin{bmatrix}
\Delta c_{\text{HbO}}(k) \\
\Delta c_{\text{HbR}}(k)
\end{bmatrix}
= 
\begin{bmatrix}
1 & 1 \\
1 & 1
\end{bmatrix}
\begin{bmatrix}
D(\lambda_1)\alpha_{\text{HbO}}(\lambda_1) \\
D(\lambda_2)\alpha_{\text{HbO}}(\lambda_1)
\end{bmatrix}^{-1}
\begin{bmatrix}
\Delta A_{\lambda_1}(k, \lambda_1) \\
\Delta A_{\lambda_2}(k, \lambda_2)
\end{bmatrix}
\end{equation}
$$

with $\lambda_1 = 735$ nm, $\lambda_2 = 850$ nm, $D(\lambda_1) = 6.3125$, and $D(\lambda_2) = 5.235$ \[42\], according to the values for the wavelength-dependent absorption coefficients $\alpha_{\text{HbO}}$, $\alpha_{\text{HbR}}$ taken from the UCL Department of Medical Physics and Bioengineering website \[43\]. Since HbO signals are more direct to the given stimuli than HbR signals (i.e., the signal-to-noise ratio of HbO is higher than that of HbR) \[44\], the mean, peak value, and skewness values only of the HbO concentration changes were used in the subsequent analysis.

fNIRS, in detecting the hemodynamic response, picks up the physiological noises of respiration, pulse and low-frequency Mayer waves. To remove these noises and to minimize signal variations, fNIRS data need to be pre-processed. Since each of our trials included a 10 s task period followed by a 30 s rest period, the frequency in each trial was approximately 0.025 Hz (i.e., 1/40). First, we applied a second-order low-pass filter with a cutoff frequency of 0.15 Hz to remove the physiological noises of respiration (about 0.3 Hz) and cardiac activity (about 1 Hz). Second, the detrending technique was used to remove the trend of the signal (e.g., a low-frequency drift) from the time-series data \[45\]. For this purpose, we utilized Matlab’s \texttt{detrend} function, which
removes the best fit straight-line (i.e., $x = at + b$) from the given data $x(t)$. In the final step of pre-processing, due to the wide variation in the filtered data, the rescaling method was applied [46].

2.5. Brain activation map

In this study, we adopted the $t$-value comparison between the measured data and the desired hemodynamic response function (dhrf) to select the active trials for further analysis [47]. The dhrf, which is the expected HR for a given stimulus, was computed by convolving the stimulus pattern (i.e. 10 s task and 30 s rest) with the canonical HR function. In this study, we used the canonical HR function with the following parameters: dispersion of response: 1 s, dispersion of undershoot: 16 s, ratio of peak to undershoot: 6, length of kernel: 21 s (see [41] for further information on the canonical HR function).

The $t$-value is the ratio of the weighting coefficient to the modeled HR (in the process of fitting the measured HR to the dhrf), and its standard error. In a $t$-test, we normally try to find the evidence of a significant difference between the measured HR and the dhrf. The $t$-value measures the size of the difference relative to the variation in our sample data. A positive high $t$-value indicates that the measured signal is highly correlated with the dhrf, whereas a near to zero or a negative $t$-value indicates that the measured HR is significantly different from the dhrf. For each trial, the $t$-value was computed for all 32 channels, and then the averaged $t$-value for each channel was computed by taking the mean of all 10 trials. To calculate the $t$-value, we used the robustfit function available in Matlab\textsuperscript{™}. The robustfit function, $[b, stat] = \text{robustfit}(dhrf, t1, S(:,i))$, uses robust regression to fit the measured HR of a specific trial $t1, S$ of specific channel $i$ as a function of dhrf, and returns the vector $b$ of coefficient estimates and a $stat$ structure with the statistical data including the $t$-value, $p$-value, standard error, etc. The channels whose $t$-value was greater than the critical $t$-value ($t_{crit}$) was selected for further analysis. In this study, the value of $t_{crit}$ used was 1.652. This value is computed from the degree of freedom (the no. of data points in one trial) and the statistical significance level. In this study, the total number of data points in one trial was 213, and the significance level was set to 0.05 for one tailed test [47].

All $t$-values were normalized within the range of 0–1 using the following equation

$$a' = \frac{a - \min(a)}{\max(a) - \min(a)},$$

where $a$ denotes the original $t$-value, $a'$ the normalized $t$-value, and $\min(a)$ and $\max(a)$ the minimum and maximum $t$-values in the respective trial. All $t$-values were normalized to keep equal standard for all plots.

2.6. Feature selection and classification

The active channels for each stimulation were averaged together to make a mean signal, and then the trials were separated from the mean signal. In this study, the signal mean (SM), peak value (SP) and skewness (SK) of HbO were used as the classification features. The SM value was computed by averaging the data points within a 0.5–15 s window to represent the asymmetry of a signal in terms of the probability distribution around its mean relative to a normal distribution and, thus, differentiate the shapes of HbO signals.

In this study, LDA, due to its simplicity and execution speed, was used for the offline classification of four different stimuli. LDA is a linear classifier that discriminates between different classes of data based on hyper-planes [19]. The separating hyper-plane is designed in such a way as to minimize the interclass variance and maximize the distance between the class means. For classification purposes, we used

Fig. 3. Activation map (handshake).
40 signals (10 trials × 4 experiments) for each subject. The classification accuracies were calculated using 10 runs of 10-fold cross-validation; that is, the data were randomly distributed into 10 sets (i.e., 40/4 = 10), trained on 9 datasets and tested on 1. This process was repeated 10 times and after which the mean accuracy was obtained.

3. Results

Figs. 3–6 plot the t-values for each trial and each experiment for all eight subjects. These plots were made to check the consistency of the active channels in each experiment across all ten trials. The numbers

![Activation map (ball grasp)](image)

![Activation map (poking)](image)
shown in the figure represent the channel numbers in the covered brain region, and the color in each pixel represents the signal intensity. Fig. 7 plots the t-values calculated by comparing the averaged HR for each activity with the dhrf. The averaging was done over all ten trials and all eight subjects. Because the data used were averaged over all eight subjects, the plot demonstrates the overall activation trends. Fig. 8 is the representation of data presented in Fig. 7 in a bar graph format. Fig. 9 compares the average HbO signals and its standard deviation for all four stimulations applied to the subjects. The averaging was performed over all 10 trials and eight subjects for all of the stimulations. The shaded areas around the mean signals represent the standard errors. Fig. 10 represents Subjects 2’s three-dimensional (3D) plot for the SK, SM, and SP values of HbO (x-, y-, and z-axes, respectively). The graph displays the data for all 40 features (10 trials of each experiment), which are marked by crosses (∗ in red color) for handshake,
circles (o in blue color) for ball grasp, steric (* in black color) for poking, and plus (+ in magenta color) for temperature. It can be seen that the feature values were scaled between 0 and 1 using Eq. (3).

Cross-subject analysis was performed to determine the consistency of the classification accuracies across the subjects. Table 1 provides the classification accuracies with their standard deviations for individual subjects across all four stimulations. The average classification accuracy was 50.31 ± 2.81%. After investigating the classification accuracies for the four stimulations, we also investigated the classification accuracies within the active and passive stimuli. Table 1 additionally provides the classification accuracies for both of these investigations. The average classification accuracy for poking vs. cold-temperature stimuli was 78.12 ± 2.87% and, for handshake vs. ball-grasp stimuli, it was 75.94 ± 2.04%.

4. Discussion

In this study, the authors used the fNIRS technique to decode the responses of four different tactile stimulations from the left somatosensory cortex of the brain. fNIRS, because of its noninvasiveness, low cost, and ease of operation, is widely used in brain imaging studies. Previous studies have reported that, along with the high activation of primary somatosensory cortex, different brain areas including the prefrontal cortices, anterior insular cortex and thalamus were also activated during tactile stimulation as applied to subjects [1]. In this study, four different tactile stimulations (handshake, ball grasp, poking and cold temperature) were investigated.

To compare the different brain activities, first the spatial and temporal information of the fNIRS signals were analyzed. The activation
and the dhrf for a specific generated by computing the correlation level between the measured HR channels within the area under observation. The activation map was eight subjects) for the individual stimulations. Fig. 9 shows clear and Fig. 9 is the averaged HbO response (averaged over all 10 trials and all Fig. 9) was examined to determine the intensity of the brain activity. along with the activation map, the temporal magnitude of HR (shown in information about the signal strength in a given location. Therefore, brain regions are activated. The activation map can only provide in-

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erent stimulations indicate that for different stimulations different brain regions are activated. The activation map can only provide information about the active location in the brain; it cannot reveal any information about the signal strength in a given location. Therefore, along with the activation map, the temporal magnitude of HR (shown in Fig. 9) was examined to determine the intensity of the brain activity. Fig. 9 is the averaged HbO response (averaged over all 10 trials and all eight subjects) for the individual stimulations. Fig. 9 shows clear and significant differences between the HbO signals corresponding to the four stimulations. It serves to demonstrate, thereby, that the responses for each stimulation can be separated from the others based on the respective relevant HRs from the somatosensory cortex.

The classification was performed using LDA to distinguish HbO signals as fNIRS data features. Fig. 10 shows a 3D scatter plot for the four different classes (hand shake, grasp, poking, and temperature) after classification of the fNIRS data based on the selected features (mean, skewness and peak value) for Subject 2. The separability of the HRs arising during the four stimulations is clear. The average classification accuracy achieved in this study was 50.31 ± 2.81%. Regarding the HR-based classification using fNIRS, the previous study by Power et al. has performed a 3-class classification (mental singing, mental arithmetic, and rest) and achieved an average classification accuracy of 56.2% [51]. Hong and Santosoa [47] have obtained an average classification accuracy of 46% while classifying four different sounds in the auditory cortex of brain. In another study by Naseer and Hong [13], the authors have reported an average four-class classification accuracy of 73.3% for the prefrontal and motor cortex signals. But in [13] the authors have used two different brain regions and distinctive tasks to acquire four different brain signals whereas in this study, we used only the left somatosensory cortex to acquire four different brain signals and the average classification accuracy of 50.31%. In a four-class classification, the chance level is 25% (i.e., 100/4), and our obtained classification accuracies for all subjects were higher than the chance level; even the lowest accuracy from Sub. 1 was 37.25 ± 4.72%. In the two-class classification cases, average classification accuracies of 78.12 ± 2.87% and 75.94 ± 2.04% were obtained for the passive tasks (poking vs. cold temperature) and active tasks (handshake vs. ball grasp), respectively. It is noted that the classification accuracies varied among the subjects and even among the different tasks. These variations can be attributed to both individual-subject differences and trial-to-trial variations in the signals caused by background activity or as-yet-unknown sources [48,49].

In this study, the experiments were performed only with male subjects aged 27–36, though differences in the HRs of females and older individuals relative to those of young males have already been reported [52-54]. One additional factor that should be noted is that all of our subjects were healthy subjects, whereas HRs can differ for patients with locked-in syndrome (LIS), amyotrophic lateral sclerosis (ALS) or any other neurological disease [55]. One final factor is that, in this experimental paradigm, the experiments were performed separately to increase the number of trials per experiment. If the same stimulations were provided in a random order during the same session [47,56], the

maps shown in Figs. 3–6 illustrate the spatial distribution of activation among the 32 channels. The plots were shown to illustrate the consistency of activation area in each trial for the specific experiment. The data shown in these figures show that, for a specific task, the activated brain region is consistent within most of the trials for individual subjects. Small inconsistencies were found in some of the trials but these can be attributed as the trial-to-trial variation present in the fNIRS signals [48,49]. Figs. 3–6 also demonstrate the variations, in activated brain region, present within the subjects for the same task. The subjectwise variations in the somatosensory cortex activities could be seen in the previous fNIRS literature as well [50].

Fig. 7 illustrates the spatial distribution of activation among the 32 channels within the area under observation. The activation map was generated by computing the correlation level between the measured HR and the dhrf for a specific stimulus. The activation map can only provide information about the active location in the brain; it cannot reveal any information about the signal strength in a given location. Therefore, along with the activation map, the temporal magnitude of HR (shown in Fig. 9) was examined to determine the intensity of the brain activity. Fig. 9 is the averaged HbO response (averaged over all 10 trials and all eight subjects) for the individual stimulations. Fig. 9 shows clear and significant differences between the HbO signals corresponding to the four stimulations. It serves to demonstrate, thereby, that the responses

Table 1
Four- and two-class classification accuracies for all eight subjects.

<table>
<thead>
<tr>
<th>Subject No.</th>
<th>Four-class classification accuracies [%]</th>
<th>Poking vs. cold temperature classification accuracies [%]</th>
<th>Handshake vs. ball grasp classification accuracies [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>37.25 ± 4.72</td>
<td>64.5 ± 4.38</td>
<td>68 ± 2.58</td>
</tr>
<tr>
<td>2</td>
<td>55.25 ± 2.65</td>
<td>76.5 ± 1.6</td>
<td>72 ± 2.58</td>
</tr>
<tr>
<td>3</td>
<td>54.25 ± 1.69</td>
<td>61.5 ± 5.48</td>
<td>85 ± 1.2</td>
</tr>
<tr>
<td>4</td>
<td>51 ± 2.43</td>
<td>74.5 ± 2.83</td>
<td>71.5 ± 3.37</td>
</tr>
<tr>
<td>5</td>
<td>46 ± 3.16</td>
<td>90 ± 1.14</td>
<td>70.5 ± 1.6</td>
</tr>
<tr>
<td>6</td>
<td>53.25 ± 2.06</td>
<td>91.5 ± 2.41</td>
<td>80 ± 2.11</td>
</tr>
<tr>
<td>7</td>
<td>54.25 ± 3.07</td>
<td>80 ± 1.74</td>
<td>75 ± 1.27</td>
</tr>
<tr>
<td>8</td>
<td>51.25 ± 2.7</td>
<td>83.5 ± 3.37</td>
<td>85.5 ± 1.58</td>
</tr>
<tr>
<td>Average</td>
<td>50.31 ± 2.81</td>
<td>78.12 ± 2.87</td>
<td>75.94 ± 2.04</td>
</tr>
</tbody>
</table>

Fig. 10. 3D scatter plot of the mean, peak, and skewness values of the HbO of 40 trials (Sub. 2).
HRs and classification accuracies would have differed and the paradigm would be more suitable for BCI purposes.

5. Conclusions

This study investigated the feasibility of functional near-infrared spectroscopy (fNIRS) for classification of hemodynamic responses evoked by four different tactile stimulations (handshake, ball grasp, poking and cold temperature). The data were collected from the left somatosensory cortex of the brain utilizing our own developed multi-channel fNIRS system. The active channels for individual stimulations were mapped by t-value comparison between the measured signal and the desired hemodynamic response function. The classification of the four different stimulations was performed using linear discriminant analysis as a classifier. The higher classification accuracies obtained in this study show that the hemodynamic responses for the different tactile stimulations are distinguishable. The overall results of this study indicate that fNIRS offers a great potential for application to the decoding of different tactile stimulations in the somatosensory cortex.

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