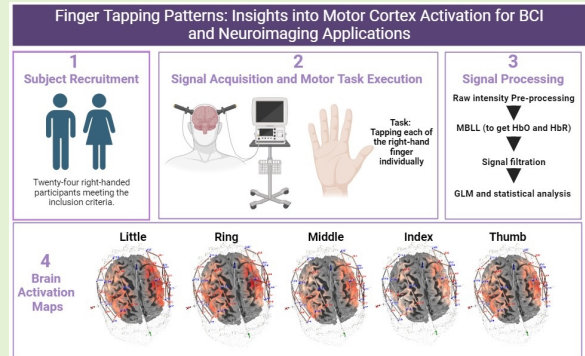


Unraveling the Motor Cortex for Individual Finger Tapping Movements: An fNIRS Study

Haroon Khan^{+a}, M. N. Afzal Khan^{+b}, Usman Tariq^b, Hasan Al-Nashash^{*b}, and Peyman Mirtaheri^{*a}

Abstract—Finger tapping is one of the most reliable and widely utilized tasks for evoking activity in the motor cortex area of the brain, both for the brain-computer interface (BCI) and for evaluating the progress of certain brain diseases. Keeping in view the importance of dominance of the right hand, the goal of this study is to understand the response of each finger tapping alongside proposing a suitable finger tapping task both for BCI and medical imaging. With this in mind, we recruited twenty-four healthy subjects. Functional near-infrared spectroscopy (fNIRS) was used for brain imaging while the subjects performed a series of finger-tapping tasks utilizing each of the five fingers individually. From average hemodynamic results, the middle finger tapping task showed a maximum amount of activation in the motor cortex, whereas the index finger tapping task had the minimum activation compared to the other four fingers. The little finger and ring finger tapping tasks gave the most significant and widespread activation, respectively when compared through brain activation maps. The activation was clustered on a single region for the little finger and ring finger tapping tasks, whereas a wider area showed a very strong activation for the thumb-tapping task, whereas a wider area showed a very strong activation for the little finger and ring finger tapping tasks. Conclusively, this study is a step towards standardizing finger tapping and its related motor area activations, demonstrating that little finger tapping can best suit the purpose of a finger tapping task for BCI and medical imaging applications.

Index Terms—Brain-computer interface (BCI), Functional near-infrared spectroscopy (fNIRS), Cortical activation, Individual finger tapping



The activation was clustered on a single region for the little finger and ring finger tapping tasks, whereas a wider area showed a very strong activation for the thumb-tapping task, whereas a wider area showed a very strong activation for the little finger and ring finger tapping tasks.

I. INTRODUCTION

Over the past few decades, using brain signals to achieve various goals has gained popularity among researchers. Brain-computer interface (BCI) systems and brain imaging for medical purposes (e.g., progression of a disease/disorder) are among the hot discussion topics. A BCI technique serves as a conduit between peripheral equipment and the brain. BCI system receives instructions from the brain to control specific external actions [1]. Brain-machine interface or mind-machine interface are two of the standard terms that are also used instead of BCI. Research has been concentrated in this area for over twenty years, allowing for the creation of multiple prototype systems. Both patients and healthy study participants utilize BCI [2]. Among different tasks used for neuronal activation, finger tapping is one of the most widely utilized tasks in BCI applications. Finger tapping is also commonly

used for assessing motor performance, muscle control, and motor ability in the upper extremities due to its reliability and reproducibility [3]. The investigation of finger-tapping skills has been utilized to assess the stages of Parkinson's Disease [4], [5]. Likewise, finger-tapping tasks can provide insights into various neuromuscular issues such as cerebral palsy and stroke [6], [7]. Moreover, it has been utilized to investigate the neural systems and maintenance of timing behavior and to measure changes in hemodynamic responses when participants engage in tapping tasks with varying difficulties [8]. Therefore, it is necessary to investigate activation from different finger-tapping (i.e., thumb, index, middle, ring, and little fingers) to trigger particular neural processes. Aiming to this goal, we suggest the finger with the best activation among the five fingers for the functional near-infrared spectroscopy (fNIRS)-based studies, which can better serve the purpose of BCI systems and neuroimaging.

The asterisk indicates the corresponding authors and the plus sign indicates authors with equal contribution

H. Khan and P. Mirtaheri are with the Department of Mechanical, Electronics, and Chemical Engineering, Oslo Metropolitan University, Pilestredet 46, 0167 Oslo, Norway (email: haroonkh@oslomet.no; peymanm@oslomet.no).

M. N. A. Khan, U. Tariq, and H. Al-Nashash are with the Department of Electrical Engineering, American University of Sharjah Sharjah, United Arab Emirates (e-mail: khamn@aus.edu; utariq@aus.edu; hnashash@aus.edu).

Several methods exist for acquiring brain signals. These include, magnetoencephalography (MEG) [9], [10], functional magnetic resonance imaging (fMRI) [11], [12], fNIRS [13], [14], and electroencephalography (EEG) [15], [16]. fNIRS is a non-invasive imaging method that measures the localized blood flow within the brain by utilizing near-infrared light with a wavelength between 650 and 1000 nm [17]. Using fNIRS, we aim to measure two

blood chromophores that absorb radiation and change significantly in the aforementioned spectrum, i.e., oxy-hemoglobin (ΔHbO) and deoxyhemoglobin (ΔHbR) [18]. The hemodynamic response (HR), also known as the local concentrations of $\Delta HbO/\Delta HbR$, changes during activity in the brain and reflects the rise in the local oxygen levels [19].

The significant applications of fNIRS include brain development at early stage [20], discernment and perception [21], psychological symptoms [22], stroke, and neurological damage [23], medical and network imaging [24], and BCI applications [25], [26]. These applications emphasize the tremendous potential for fNIRS as a suitable neuroscience instrument. In contrast to fMRI, EEG, and positron emission tomography methods, fNIRS offers flexibility, minimum effort to setup time, and less sensitivity to motion artifacts [27]. fNIRS also offers acceptable spatial and temporal resolutions. Some of the core areas of research in fNIRS are spatial and temporal resolution enhancements. They include contemporary methods like an initial dip. Initial dip detection can reduce the time needed to generate BCI instructions [28], [29].

Over the past few years, fNIRS research has focused on using various stimulating protocols. These studies used almost all cerebral cortices to collect the HR data. Numerous studies have tested the prefrontal cortex using activities like mental math, mental enumeration, and puzzle-solving. Studies based on the sensory cortex have included heat stimulation [30], electrical stimulation [31], painful stimuli [32], and poking. The motor cortex is frequently stimulated by finger tapping task [33], [34]. Among the various stimulation types as discussed previously, finger tapping is one of the most utilized tasks for evoking brain activity. Over the last decade, hundreds of studies in fNIRS-based brain imaging have been conducted using this task. The utilization of finger tapping as a way to evoke brain activity ranges from BCI to medical imaging. With the help of studies that have utilized finger tapping, researchers can investigate the mental timing system without the complexities associated with intricate motor execution or feedback mechanisms [35]. Therefore, investigating the correlation between the brain and finger-tapping tasks can enhance our understanding of neuromuscular impairments, thus contributing to a better understanding of this field.

In the authors' pilot study [34], we investigated the maximum classification accuracy obtained by classifying five different finger-tapping tasks. We used signal-mean, peak, minimum, skewness, kurtosis, variance, median, and peak-to-peak values as features for classification. The extracted features were then classified using classical classification methods like artificial neural networks and quadratic discriminant analysis. Among all the classification techniques used in the study, extreme gradient boosting-based classification outperformed all others with an average accuracy of 0.77.

In addition to our previous work, this study pursues finding the most appropriate task from the motor cortex

(specifically finger tapping) to yield the maximum detected activation. While doing so, this study compares the activation results by tapping the five fingers of the right hand individually and compares the resulting activation. Keeping in view several different parameters, the aim is to propose an appropriate finger that can yield a desirable amount of activation among five and can be used for evoking brain activity.

II. MATERIAL AND METHODS

A. Ethical Consideration

The Norwegian Centre for Research Data AS (NSD) approved the data collection and protection protocols before the experiments. Experiments were conducted following the latest declaration of Helsinki [36]. Participants' data is protected under the NSD rule (reference no. 647457). Anonymity is ensured during the data processing process. Before participating in the experiment, each participant signed an approved written consent form by NSD. In addition, ethical approval was granted by regional committees for medical and health research ethics (REK) Norway (reference no. 322236).

B. Participants' Recruitment, Training, and Interaction

Twenty-four right-handed participants (including males and females; range: 24 – 34 years) participated in the experiment. The male participants had an average age of 30.44 ± 3.03 years. In contrast, the average age of female participants was 29.17 ± 3.06 years. The needed number of subjects was calculated statistically using the online power calculator at <http://biomath.info/power/prt.htm>, after setting the values of the statistical level of significance (α) and the statistical power ($1-\beta$) to 5% and 80%, respectively. A total of sixty-six sessions were recorded, ranging from one to five sessions per participant depending on their participant's comfort with participating in multiple sessions. Handedness is defined as "the individual's preference to use one hand predominately for uni-manual tasks and/or the ability to perform these tasks more efficiently with one hand [37]". Right-handedness was defined as the ability to write with the right hand. In this study, right-handedness was preferred since approximately 90% of the world's population is right-handed [38], with the left brain hemisphere being the dominant one. All participants had normal or corrected-to-normal vision. The participants reported no history of neurological, visual, or motor impairment. Extensive instructions were given to the participant before the actual experiment regarding the experimental protocol, the duration of the experiment, and the number of trials. To ensure results, participants were asked to remain calm and avoid movements (head or body movements) that might affect their results. The participant sat in a comfortable chair, and any discomfort during the experiments resulted in the termination of the experiments. A dark room with the least amount of external sounds was preferred for the study to avoid external noise as much as possible.

C. fNIRS Instrumentation and Data Acquisition

The experiments were performed with a continuous-wave optical tomographic NIRScout machine. NIRScout collects data using dual wavelengths ($\lambda_1 = 760 \text{ nm}$, $\lambda_2 = 850 \text{ nm}$) and sampling frequency of 3.9063 Hz . Sixteen emitters and detectors were used in the experiment positioned over the motor cortex area of the brain. NIRStar 15.2 software was used for signal acquisition. The NIRxcap shower cap was used to reduce external light further.

D. Brain Montage

A head circumference measurement was performed before the experiments began to ensure that the appropriate NIRxcap size was selected. The C_z is marked as the mid-point between the nasion to anion through a preauricular point(left and right). The optodes were then positioned over the motor cortex using the 10 – 10 international positioning system. We used optode holders to keep the distance between the optodes at 3 cm. In total, 16 emitters and detectors were used to collect data. The predefined montage in NIRStar 15.2 for motor₁₆ \times 16 was applied. The optodes configuration used in the study is shown in Fig. 1 [34].

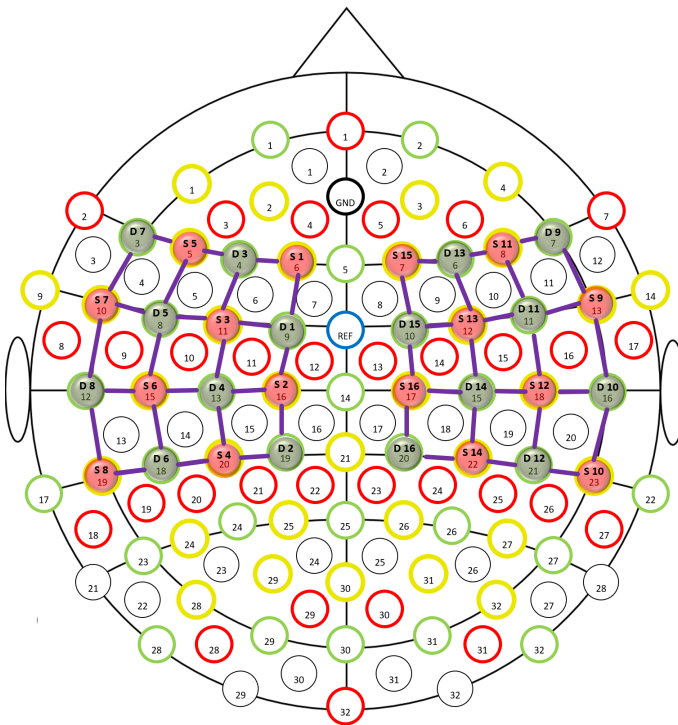


Fig. 1. Positioning of emitters and detectors over the motor cortex according to the 10-10 international positioning system

E. Experimental Design

The experimental design was in the block design format composed of blocks of rest and task, as shown in Fig. 2. The initial and final rest of 30 sec is given for the

data to come to baseline. The duration of each finger-tapping task was set to 10 sec to ensure an adequate hemodynamic response. A single experiment consisted of 3 sessions; each session had of five blocks of rest and a task (each finger tapping starting from thumb to little finger). In one complete experiment, there were three sessions totaling 350 sec of experimental length. The instruction for finger tapping was presented on a computer monitor using NIRStim 4.0.

F. Signal Pre-processing

The software Satori v1.4 (Brain Innovation, Germany) and MATLAB® 2021a (The MathWorks Inc., USA) were used to pre-process acquired fNIRS signals. The processing includes removing corrupted data, spikes introduced as noise, and data truncation. The data truncation was done to get the data from the start of the first trial to the end of the last trial. Gain and coefficient of variation were utilized for rejecting the channels with insufficient quality ('bad') data. For the current experiment, the gain was set at three, and the coefficient of variation was set to 7.5 %. The higher the value of the coefficient of variation, the higher will be the noise. Finally, the modified Beer-Lambert's Law was used to convert the optical densities to the concentration changes, i.e., ΔHbO and ΔHbR . Fig. 3 shows the overall signal pre-processing pipeline.

G. Data Fliteration and Statistical Analysis

The acquired signals were filtered to eliminate the contamination due to heart-beat, respiration, and induced frequency due to paradigm. The trial length in the experiment was 20 sec. Therefore, the frequency due to the paradigm will be 0.15 Hz . Hence, the acquired signals were filtered using a band-pass filter of bandwidth 0.01 to 0.5 Hz [39].

H. General Linear Model (GLM)

In an ideal world, the hemodynamic response occurring in response to tapping any of the five fingers should be the same, but it's not the case in the real-world scenario. The response that is considered to be ideal is known as the desired hemodynamic response. So, in order to extract the closest or comparable results to the desired hemodynamic response function, the generalized linear model (GLM) was used in this study. Applying the General Linear Model (GLM) in fNIRS research involves the integration of experimental design knowledge and signal morphology based on a priori knowledge [40] to model the hemodynamic response. This approach allows for an unbiased linear estimation of the hemodynamic response to a series of stimuli by accounting for physiological nuisance signals. In the field of fNIRS, the GLM serves as a widely accepted statistical method for quantifying changes in ΔHbO and ΔHbR . The t -value, p -value (≤ 0.05 statistically significant), and oxygenated hemoglobin were used for the purpose of statistical testing. A t -test (Eq.

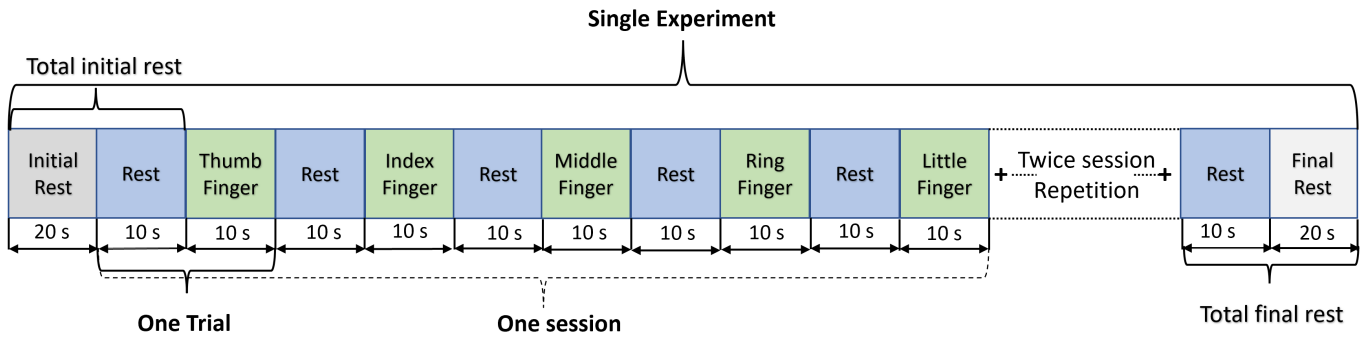
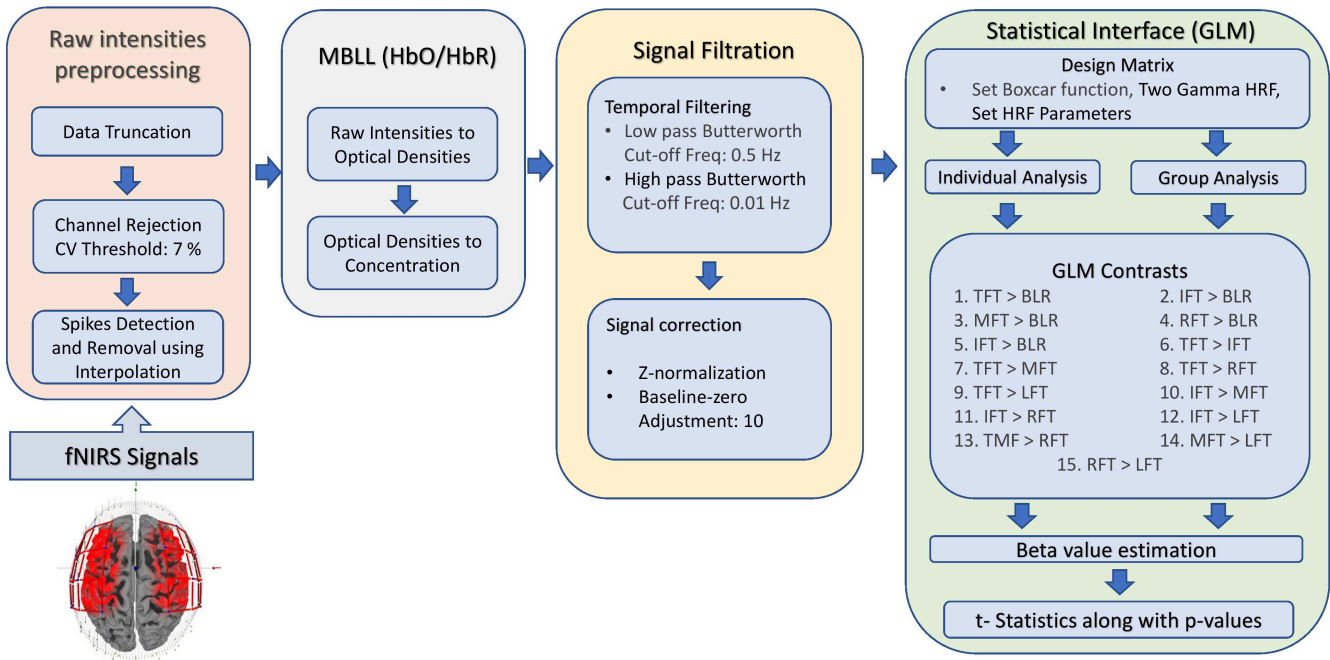


Fig. 2. Experimental Paradigm: The experimental paradigm consists of three sessions; each session contains trails of each finger tapping; a single trial consists of 10 sec of rest followed by 10 sec of tapping task.



MBLL: Modified Beer-Lambert law, TDDR: Temporal Derivative Distribution Repair, GLM: General Linear Model, BLR: Baseline Rest, TFT: Thumb Finger Tapping; IFT: Index Finger Tapping; MFT: Middle Finger Tapping; RFT: Ring Finger Tapping; LFT: Little Finger Tapping

Fig. 3. Signal processing pipeline

1) is used to test the regression coefficient β and residual error e . The t -values are calculated by using the following formula [41]–[43]:

$$t = \frac{c^T \beta}{\sqrt{e^2 c^T (X^T X)^{-1} c}} \quad (1)$$

where $X \in R^{N \times M}$ represents the design matrix (M denotes the number of time points, and N represents the β dimension), $\beta \in R^{M \times L}$ (where L is the number of channels) is the corresponding response signal strength for $\Delta HbO/\Delta HbR$ at the respective L channel. The error term is represented by e . The GLM fitting procedure finds the set of β values that explains the data with a perfect fit.

III. RESULTS

A. Event-Related Average Responses

Using GLM, the extracted ΔHbO , ΔHbR , and ΔHbT responses averaged for all the finger tapping tasks are shown in Fig. 4. The resulting activation in the motor cortex can be clearly seen for all the finger-tapping tasks. For individual subjects, the variance in data was relatively high, but for the averaged results, a significant amount of activation could be seen in all five cases. An exciting thing that can be noticed in the case of ΔHbO (red) is that each finger's response is significantly different.

For the case of the thumb, ring, and little fingers, the response keeps increasing during the stimulation duration. However, it is not the case for the index and the middle fingers. In the case of the index and middle fingers, the

response attained a saturation point even though the subjects were still performing the task. For the index finger, the ΔHbO response achieved a Plato midway between the task duration and did not increase from there. Whereas, for the middle finger, a peak was achieved, and the response started declining right after that peak time. The average maximum activation value was achieved for the middle finger, whereas the least activation was achieved for the case of index finger tapping. This finding is of particular interest because, for motor tasks, index finger tapping is one of the most commonly used tasks; however, the results of ΔHbO activation show that the response due to tapping other fingers is far more significant than the index finger.

B. Comparison of the Temporal Characteristics

Two of the most important attributes (temporal characteristics) that are used to define the shape of the hemodynamic response in literature are peak value and time to peak. These two features were selected as they well describe the characteristics of a time-domain signal. However, other time-domain features like slope, mean, etc. can be investigated as well. These temporal characteristics of signals are among the widely used features for classification as well. In the case of the current study, the visual inspection of Fig. 4 shows a significant difference in the aforementioned attributes for all five finger-tapping tasks. Comparing the achieved ΔHbO responses, the highest peak achieved among all five finger tapping tasks was through middle finger tapping. Alongside that, the middle finger tapping showed the fastest time to peak. Moreover, there was a significant difference between the average hemodynamic responses achieved for each finger-tapping task. This is another exciting trend that can aid future studies in the field of fNIRS-based studies utilizing finger-tapping tasks. The time to peak and peak values for ΔHbO of each finger are summarized in Fig. 5 and Fig.6, respectively.

C. Comparison of Brain Area Activation

To investigate the activation resulting in response to the tapping of each finger, activation maps were made. The average activation maps achieved for each finger are shown in Fig. 7. As all the subjects were right-handed, the left motor cortex showed dominant activation compared to the right motor cortex for all five finger-tapping tasks. From Fig. 7, it can be noticed that the least amount of activation achieved was for the index finger tapping task. Whereas the ring finger and little finger gave significantly detectable activation in the left motor cortex with a wide activation area. One way to explain this phenomenon is the strategy behind the activation of different muscle groups in the hand to move individual fingers. Muscles that control the fingers and thumb reside within the hand (intrinsic) and the forearm (extrinsic). Three of the extrinsic finger muscles have a compartment and tendon for each of the four fingers [44]. Based on the measurements of

EMG activities and isometric force with the fingertip, the intrinsic muscles of the index finger behaved as a single unit whose region of activation overlapped that of the extrinsic flexor and extensor muscles [45]. On the other side of the coin, we could also look at sensory feedback in a finger tapping task; the side of the thumb is mostly touching the surface while tapping, and not the full finger area. If the sensory receptors are supposed to send information to control the forces and muscle activations, then the sensory information from the thumb would be limited. When sensory feedback is limited or inhabited, a rougher control based on previous experiences (involving the cerebrum) will occur [46], [47]. Thus, it makes it more probable that the index finger or the thumb has less significant brain activations due to the group of muscles that are activated.

D. Statistical Comparison Over Each Channel

In order to find the locations where each finger was giving a strong response, statistical analysis was performed on individual channels as well. A graphical demonstration of activation for each finger over each channel is given in Fig. 8. Interestingly, the little finger outperformed the activation of all other fingers on all channels. Channels 1 to 24 were positioned over the left motor cortex, whereas channels 25 to 48 were on the right motor cortex. As all the subjects were right-handed, the region of interest is the left motor cortex. In this particular scenario, a channel was considered active if the t -value was above 0.8. The most channels that showed activity (higher t -value) were for the little finger. A total of 14 channels were active for averaged activity in response to little finger tapping. This was followed by activity on six channels for the ring finger, four channels for the middle finger, two for the index, and five for the thumb finger. All the active channels mentioned above represent a particular active brain area while the task is being performed. The common activation area was near the frontal eye field, pre-motor, and supplementary motor cortex in the case of the thumb, ring-, and little finger. In the case of the little finger, the supramarginal gyrus part of Wernicke's area, pars triangularis Broca's area, and middle temporal gyrus also showed activity. Whereas for the middle finger, the activity was only restricted to the pre-motor and supplementary motor cortex.

IV. DISCUSSION

In this study, we have investigated the spatial variability of hemodynamic responses (ΔHbO , ΔHbR , and ΔHbT) in the primary motor cortex area in response to five different tasks (i.e., tapping of thumb, index finger, middle finger, ring finger, and little finger). The aim of the study is to propose the finger that best suits the purpose of motor-related activation in response to finger-tapping tasks. Alongside this, the study aims to localize the area activated as a result of the tapping of each finger. To the best of the authors' knowledge, this is the first study in

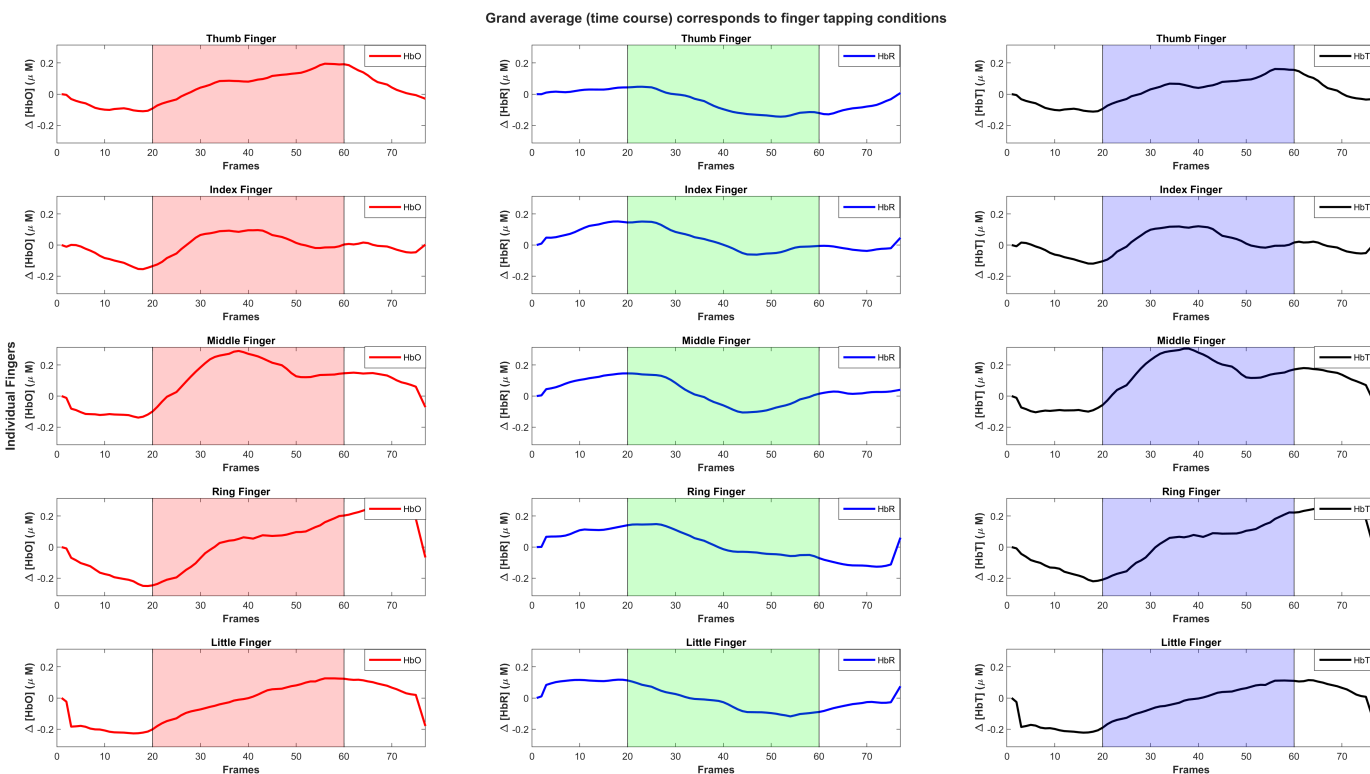


Fig. 4. Average ΔHbO , ΔHbR and ΔHbT response for individual fingers across all the channels and subjects

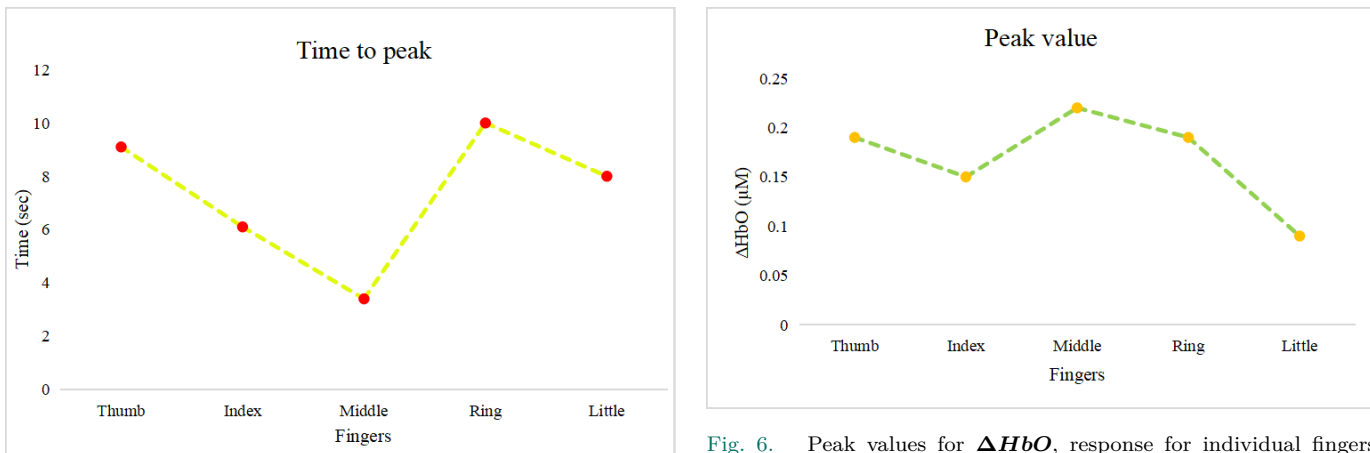


Fig. 5. Time to peak for ΔHbO , response for individual fingers averaged across all the channels and subjects

Fig. 6. Peak values for ΔHbO , response for individual fingers averaged across all the channels and subjects

the field of fNIRS that aims to localize the brain area responsible for each finger tapping and to propose the most appropriate finger-tapping task for motor-related activities, especially for the fNIRS-based studies. As a finding of the study, the most effective finger-tapping task that activated the most amount of brain area is suggested. In previous studies, researchers have utilized different finger-tapping tasks for the purpose of classification. The most commonly used tasks among recent studies are thumb, index, and little finger tapping [18], [48]. Similarly, in the authors' previous work, we tried to classify the five fingers tapping task to achieve maximum

accuracy by varying temporal features and classification techniques [34]. Moreover, this study aims to compare the hemodynamic responses occurring in response to tapping different fingers. Summarized below are the findings of the current study.

The changes in ΔHbO were significantly different for each of the five fingers. The averaged ΔHbO kept rising until the stimulation's end for the thumb, ring finger, and little finger. However, for the case of the index finger and the middle finger, the data reached a plateau and didn't increase any further, even though the subjects were still performing the task. However, the ΔHbO response started decreasing as soon as the stimulation ended in the case of all five fingers. While comparing the responses of ΔHbR ,

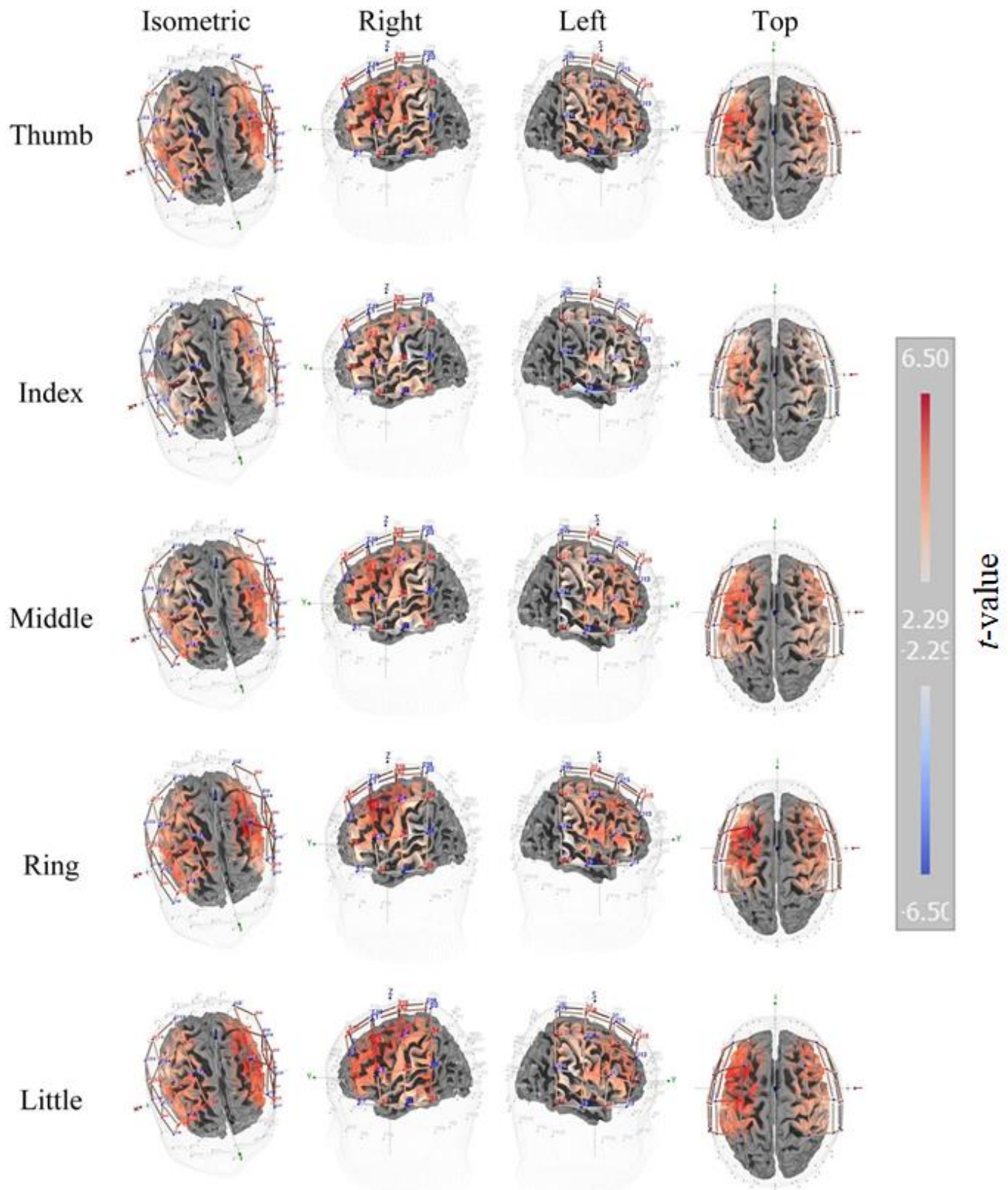


Fig. 7. Average amount of activation for individual fingers averaged across all the channels and subjects. The columns represent different viewing angles (from left to right; isometric, left, right, and top views, respectively). The rows correspond to activity against each finger tapping task (From top to bottom: thumb, index finger, middle finger, ring finger, and little finger, respectively). The positive y (in green) represents the posterior side of the brain, while the negative y corresponds to the anterior side.

no significant difference was noted in the hemodynamic response signal. A significant difference was observed while

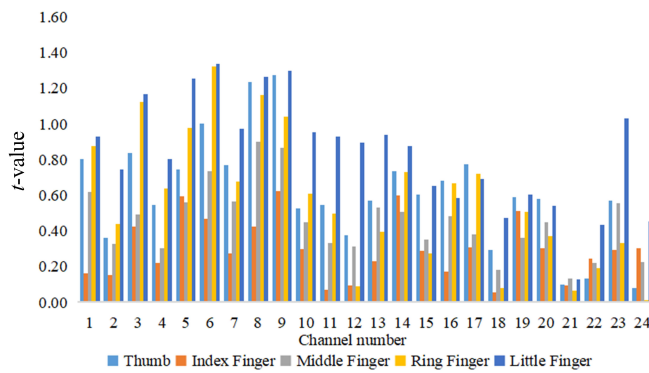


Fig. 8. Activation achieved over all channels against tapping task of each finger.

comparing the activation maps for each of the five fingers. Interestingly, the least amount of activation was observed in the index finger tapping task, which is among the most commonly used tasks for motor area activation in the BCI studies. Little finger tapping yielded the most amount of activation. The area of activation was spread all over the motor cortex area. The little finger was followed by the ring finger, thumb, middle finger, and index finger. For all participants, the left motor cortex was more active than the right motor cortex area.

Different avenues were discovered while comparing the specific channels that were activated in response to the stimulation. It was noticed that the little finger-tapping task-evoked the strongest activity in the most amount of channels. The channels covered the brain area that ranged from the frontal eye field, pre-motor, and supplementary motor cortex to the supramarginal gyrus part of Wernicke's area, pars triangularis Broca's area, and middle temporal gyrus. On the other hand, the activity for the middle finger tapping was confined to the pre-motor and supplementary motor cortex. This finding indicates that if the goal is to detect the activity without compromising on repeatability, the little finger-tapping task will best suit the purpose. Whereas if the goal is the detection of the activity at a very precise brain location, middle finger tapping is the task to be preferred.

Summarizing the study's limitations, the study participants were not prohibited from any caffeine intake before the experiment. The presence of caffeine element might have affected the results of the study. The surrounding noise (both sounds and light) was tried to be kept as low as possible; however, there might be some contamination in the signal due to these factors. Moreover, the results might be influenced by the boredom of the subjects as they had to sit in a dark room for a long interval of time with almost no movement. Finally, using dense optode configuration in future studies will aid in more precise brain area identification.

The index finger tapping task is the most widely utilized task for motor area activation. To the best of the author's knowledge, no study in the field of fNIRS has addressed the activation issue related to finger tapping (i.e., which

finger gives the most activation). One of the reasons for the utilization of index finger tapping is that it is easy to move this finger and execute a task. As it is easy to move, the amount of activation associated with this finger is also much less as compared to other fingers (e.g., middle-, ring-, and little finger). On the contrary, the movement of the little finger and ring finger comparatively activates more muscle groups and requires more attention, resulting in stronger activation throughout the motor cortex area of the brain. Therefore, it leaves an open question for future studies to investigate whether this type of response is due to the effort that is involved in the execution of the task or not. Also, whether replacing the index-finger tapping task with the little finger tapping task can improve the results or not. Furthermore, in future studies, left-handed persons can be recruited to validate whether a similar effect is noted in their case. These types of studies will significantly aid the field of Biomedical Imaging.

V. CONCLUSION

This study is a step towards standardizing the most appropriate finger-tapping task for utilization in functional near-infrared spectroscopy (fNIRS)-based medical imaging as well as the brain-computer interface (BCI) applications. The current work compares the changes in the hemoglobin levels as well as the activation in the motor area that resulted in response to the tapping task of all five fingers of a hand. The results of the study showed that among all of the fingers, the middle finger tapping task showed the highest peak value when it comes to the hemodynamic response. Not only that, but the time to peak is also the shortest for middle finger tapping. As regards the brain area activation, the activation in response to the middle finger tapping task was strong and confined to a relatively narrow area, whereas for the case of the little finger tapping task, the whole motor area showed widespread strong activation. Therefore, using little finger tapping as a task for future fNIRS-based studies focusing on motor area activation can lead to better and reproducible results.

CONFLICT OF INTEREST

The authors declare no conflicts of interest.

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