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ESCUELA TÉCNICA SUPERIOR DE INGENIEROS
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Portraying Human Motor Imagery: A MEG Study

Parth Chholak

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Summary:

The understanding of the neurophysiological mechanisms responsible for performing motor imagery (MI) is essential for the development of Brain-Computer Interfaces (BCI) and neurorehabilitation. Our magnetoencephalographic (MEG) experiments with eight voluntary participants confirm the existence of two types of motor imagery: kinesthetic imagery (KI) and visual imagery (VI). These two types of motor imagery are distinguished by the activation or inhibition of different brain areas in Mu (Alpha and Beta) frequency regions. In particular, event-related synchronization analysis shows that VI activates Mu waves in the Occipital and Precuneus region, whereas KI inhibits Mu activity in motor-associated structures and the inferior parietal lobule. A model for neural communication and motor inhibition is proposed, claiming Mu wave as a carrier for MI content. Validation of this model using coherence of brain signals and machine learning is presented along with the identification of a unique 45 Hz signal that is being utilized to carry MI content inside the brain.

Keywords: Brain computer interface, Neurorehabilitation, Mental processes, Motor imagery, Motor command inhibition, Phase-amplitude coupling, Artificial neural network, Event related desynchronization, MEG

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Background

Context

With the passing evolution, from a single-cell amoeba to the humongous and diverse variety of flora and fauna that we see around today, a key life supporting phenomenon has been ubiquitous, that is the ability of a living organism to move. This ability is crucial for survival, be it an animal hunting for its prey or a sunflower following the sun across the sky to maximize photosynthesis, although the extents and intricacies of these movements are heterogeneous.

A ballet dancer balancing the full bodyweight on toes while performing a pirouette or a singer possessing a vocal range of as much as 5-octaves are just a few examples of humans making their mark in this endeavor to create the most incredible and exquisite body movements. And this study is aimed at understanding, remedying and possibly improve this human ability.

Previous research shows how real movements and imagination of those movements share a common neural circuitry and this has led to the possibility of using imagination as a means for rehabilitation of amputees, stroke patients and other humans that have lost the ability to move. Thus, our focus will be on the imagination of movements as well as the bridge towards reproducing real movements from motor imagery.

Document structure

In what follows, this section is first a brief review of the state-of-the-art literature on the subject and the popular methods being applied for the experiments and analysis. We then highlight the areas where we find a gap and delineate how this study would like to contribute in filling that gap. Once the objectives are clearly set, the detailed description of our methodology is provided highlighting the implementation of wavelet analysis procedures and algorithms for machine learning that we utilize here. The results from both these kinds of analysis are then provided which is followed by the discussion of the obtained results and our attempts at explaining them by providing a hypothesis on neural communication.

State of the art

Motor imagery: A review

For the purpose of this work, we use the definition of motor imagery (MI) as *the dynamic simulation of the brain that manifests as a result of the rehearsal of a given motor act in the working memory without any overt movement of the corresponding muscles*. This MI can be classified into two categories, namely, visual (VI) and kinesthetic imagination (KI) (Guillot, et al. 2012).

Hanakawa (T. Hanakawa 2016) pointed out how various mental processes are dealt with in the literature using the same name as Motor imagery and provided a 4-factor characterization to avoid confusion and conflict of ideas. The four factors are as follows:

- 1) **Motor control:** This step differentiates between the studies based on the specificity of the information provided during the experiment, calling the ones with complete descriptions representing preparation stage whereas the ones with less specific information representing planning stage.

- 2) **Explicit/Implicit imagery:** This step focuses on identifying whether the imagery was intentional (Explicit) or generated unintentionally through sensory-triggered motor related process, e.g., observation of movement.
- 3) **Sensory modality:** This step distinguishes the studies on the basis of the sensory system being used to imagine the movement. The sensory mechanisms can be visual, somatosensory (kinesthetic), auditory (e.g. sound of climbing stairs) or any possible combination of these three.
- 4) **Agency:** This step separates the studies based on the whether the imagination was performed by first-person or third-person.

We would like to give an example to better explain the difference between planning and preparation stages. In the experiment with the imaginary movement of the right/left finger after hearing a beep, the stage corresponding to the time before announcing which hand's finger has to be moved is called *planning stage*, while the stage after specifying the hand and before hearing the beep is called *preparation stage*.

This 4-factor characterization helps to differentiate and uniquely identify the different kinds of MI studies. The difference in the corresponding neural activities is then to be expected. However, different neural processes can share a partially common neural circuit as was observed in the studies carried out by (Hanakawa, Dimyan and Hallett, Motor planning, imagery, and execution in the distributed motor network: a time-course study with functional MRI. 2008), where they showed that there exists a substantial overlap between the explicit and implicit motor imagery. Similarly, it has been shown that MI shares neural substrates with the real movements (RM) from numerous transcranial magnetic studies (TMS) [(Izumi, et al. 1995); (Kasai, et al. 1997); (Liang, et al. 2007); (Mizuguchi, et al. 2013); (Stinear and Byblow 2003)]. Furthermore, (Solodkin, et al. 2004) showed that KI rather than VI is closer to the RM based on the extensive overlap of the corresponding neural networks. Curiously, MI was also shown to activate the neural circuits corresponding to memory and emotions (Kosslyn, Ganis and Thompson 2001).

The diverse literature and studies have led to the identification of various brain regions that can take part in MI. Let us review the most popular ones. First, we'll start with the primary motor cortex (M1) and the associated controversy.

Primary motor cortex

The huge amount of discrepancy of results associated with M1 can be explained to a certain extent by its definition. Many researchers previously followed the nomenclature of Talairach and Tournoux's atlas, whereas some referred to it as the posterior region of the precentral gyrus, which in reality encompasses both premotor cortex (PMC) and M1 and some others used the "precentral knob" which is only a subset of M1 representing hand movements (T. Hanakawa 2016). On top of it, the presence of methodological differences in the experiments and the difficulty to monitor the compliance with the MI instructions (Sharma, Pomeroy and Baron 2006) only made things worse. It is not surprising then that there exists a controversy on the involvement of M1 during MI, with studies both in favor [Dechent et al., 2004 (Dechent, Merboldt and Frahm 2004); Lotze et al., 1999b (Lotze, et al. 1999); Porro et al., 2000 (Porro, et al. 2000); Solodkin et al., 2004 (Solodkin, et al. 2004); Guillot et al., 2008 (Guillot and Collet, Construction of the motor imagery integrative model in sport: a review and theoretical investigation of motor imagery use. 2008); Sharma et al., 2008] and against [Gerardin et al., 2000; Hanakawa et al., 2008] its involvement. Keeping the controversy aside, the studies still

seem to suggest that M1 is indeed activated during MI, but much weaker in comparison to the RM [Guillot et al., 2012]. And, Kasess et al. [2008] reported contribution from supplementary motor area (SMA) to inhibit M1 during MI.

Prefrontal Cortex

Prefrontal areas like ventrolateral prefrontal cortex (PFC) and anterior cingulate cortex are also found to be involved in inhibition of movements (Krams, et al. 1998). A transcranial magnetic stimulation (TMS) study by Duque et al. (Duque, et al. 2012) validates that indeed PFC is involved in inhibition, more specifically in choosing between the responses. The role of premotor cortex (PMC) is also shown to be inhibitory in nature and responsible for timing the neuronal impulses [(Duque, et al. 2012); (Kroeger, et al. 2010)].

Figure 1 - Ventrolateral Prefrontal Cortex marked by Brodmann areas 44, 45 and 47. (W. Contributors 2018)

Subcortical areas

Cerebellum and Basal ganglia also participate in suppression of movements (T. Hanakawa 2016). Parkinson's disease, known to affect basal ganglia, causes patients to have slower speed of MI (Dominey, et al. 1995) and this shows that basal ganglia only mediates the signal and not affect the MI content (T. Hanakawa 2016).

Parietal cortex

Posterior parietal cortex has been shown to be active during MI in various neuroimaging studies [(Ehrsson, Geyer and Naito 2003); (Gerardin, et al. 2000); (Hanakawa, Immisch, et al. 2003), (Hanakawa, Dimyan and Hallett, Motor planning, imagery, and execution in the distributed motor network: a time-course study with functional MRI. 2008); (Iseki, et al. 2008); (Naito, Kochiyama, et al. 2002)]. When the patients with lesions in this area are asked to predict beforehand the time necessary to perform movement tasks, they typically underestimate/overestimate (Sirigu, Duhamel, et al. 1996). This strongly contrasts with

patients having precentral motor cortical dysfunction that exhibit impaired movement, but retain the ability to estimate motor performance times (Sirigu, Cohen, et al. 1995). This result suggests that there is a separate mechanism for choreographing the movement and to mentally simulate the movement for estimating the movement time and that this temporal analysis mechanism is localized near the parietal cortex. It's intriguing to note that bilateral parietal lesions can cause a person to accidentally execute movements when asked to imagine them and be completely unaware about it (Schwoebel, Boronat and Branch Coslett 2002). This result hints towards the possibility that the mental simulation of MI is inhibited by a mechanism also localized near the parietal lobe (in one of the two hemispheres or both) that fails in order to give way to actual execution of movements during MI. Sensory modalities related to movement also can stimulate the brain activity, such as vibratory stimuli to induce illusion of kinesthesia activates the primary somatosensory areas and the M1 region [(Naito, Roland and Ehrsson, I feel my hand moving: a new role of the primary motor cortex in somatic perception of limb movement. 2002), (Naito, Matsumoto, et al. 2011)] or the sound of footsteps inducing activity in the posterior superior temporal sulcus (Bidet-Caulet, et al. 2005). The temporoparietal junction has been linked with own-body imagery and self-location [(Blanke, et al. 2005); (Ionta, et al. 2011)]. It is no surprise then that KI activates motor associated areas and the inferior parietal lobe, whereas VI activates visual-related areas (Occipital lobe) and the superior parietal lobe (Precuneus) [(Guillot, Collet and Nguyen, et al. 2009)]. Interestingly, a recent TMS study also shows inferior parietal lobe exerting inhibitory control on M1 region during MI [(Lebon, et al. 2012)].

Figure 2 - Superior temporal sulcus and other relevant areas. (Contributors 2015)

Supplementary motor area

Experiments by (Park, et al. 2015) identified SMA to be the best predictive region to distinguish between hand rotation and grasping movements which seems to suggest that the role of SMA is to augment the content of the signals rather than mediating the signal. It was reported that EMG activity during MI experiments, corresponding to the failures of inhibitory control, was observed in both agnostic as well as antagonistic muscles as a function of the weight to be lifted in the imagination (Bakker, Boschker and Chung 1996) and the type of muscle

contraction (Guillot, Lebon, et al. 2007) and this seems to suggest that the content of imagination affects the inhibitory mechanism. Ideas for inhibitory mechanisms that can take this into account and explain the rest of the results are required.

The underlying structure seems to be dissociable and hierarchical for the neural representations of observed, imagined and imitated actions (Macuga and Frey 2012). Therefore, the differential analysis of each brain region mentioned above can be used to understand their contribution to the functioning of this structure.

Lastly, we would like to point out that event-related synchronization (ERS (Takeuchi, et al. 2015) and event-related desynchronization (ERD) [(Kasahara, et al. 2015); (Wolpaw and McFarland 2004)] in EEG have recently become a part of many ways to understand MI.

Functional MRI (fMRI)

fMRI is a powerful visualization tool for cerebral cortical activation. It is based on the basic assumption that regional increase in brain activity is coupled with regional cerebral blood flow having higher oxyhemoglobin (diamagnetic) content as compared to deoxyhemoglobin (paramagnetic) content. The spatial resolution offered is about 1 mm, while the temporal resolution is as poor as 1 second.

Positron emission tomography (PET)

PET is a nuclear medicine functional imaging technique based on detecting gamma ray pairs that are emitted by positrons in diametrically opposite directions. The concentration of positron in a region corresponds to the regional glucose uptake or the tissue metabolic activity. The images obtained by PET are three-dimensional with spatial resolution of about 1 cm and temporal resolution of approximately 1 minute.

Electroencephalography (EEG)

EEG is an electrophysiological monitoring method which allows measuring the surface currents on the scalp of a person resulting from the ionic currents inside the brain to communicate between the neurons. Typically, an EEG study uses 30-100 electrodes all across the scalp surface and thus lacks the high spatial resolution as fMRI, but possesses better temporal resolution of 0.1-0.01 seconds. EEG studies are prone to movement and electrical artifacts and hence longer recordings are difficult to perform. Another shortcoming of EEG is that only the 2D scalp surface can be measured and the 3D brain volume remains hidden to EEG.

Magnetoencephalography (MEG)

MEG uses a similar approach as EEG, but instead of measuring the electrical activity from the scalp surface, it measures the magnetic field perpendicular to the scalp surface. This limits the MEG to only observe the internal electrical activity that is tangential to the scalp surface. However, it is important to note that MEG offers a much better spatial resolution of 5-10 mm and high temporal resolution of 0.001 seconds. The MEG recordings allow significant reduction in artifacts as well, but are very expensive. The machine price is about 2-3 million euros, and each one-hour register costs about 600 euros.

Figure 3 - Spatial and temporal resolution comparison of popular neuroscience medical imaging techniques.
(Kameyama, Murakami and Jinzaki 2016)

Transcranial magnetic stimulation (TMS)

TMS is a method to locally stimulate the brain electrically by inducing EMI current through a changing magnetic field on a coil that is placed near the head of a person.

Motivation and Objectives

Motivation of the project

The path to understand the underlying neural structure and mechanisms that guide MI was highlighted in the previous section. However, somewhere in this labyrinth of research with sometimes different things being called the same and vice versa, the true answer is lost. This project is aimed at understanding each study distinctly and then conducting new experiments using MEG that have not been done before, to validate the previous work and to hypothesize new neural mechanisms for MI.

Objectives

- Read and review scientific literature on imaginary movement studies that have been carried out in the past.
- Create MATLAB programs, utilizing Cogent, to conduct MEG experiments with audio/visual stimuli.
- Conduct MEG recordings for imaginary movement experiments.
- Perform wavelet and other analyses on the MEG data using Brainstorm and MATLAB.
- Utilize artificial neural networks (ANN) to further investigate and validate.
- Discuss the results and explain them using the knowledge of existing literature.
- Prepare papers, posters and presentations.

Materials and Methods

Experiment

The Vectorview MEG system (Elekta AB, Stockholm, Sweden) with 306 channels (102 magnetometers and 204 planar gradiometers) was used to acquire neurophysiological data. This system was placed inside a magnetically shielded room (Vacuum Schmelze GmbH, Hanau, Germany) at the Laboratory of Cognitive and Computational Neuroscience, Center for Biomedical Technology, Technical University of Madrid, Spain. Fastrak digitizers (Polhemus, Colchester, Vermont) were used to obtain the three-dimensional head shape. Three fiducial points (nasion, left and right preauricular) and more than 300 points on the scalp were acquired for each subject. Vertical electrooculogram (EOG) was placed to capture blinks and other undesirable eye movements. The sampling frequency was 1000 Hz and an online anti-alias bandpass filter between 0.1 and 330 Hz was utilized.

The experimental study consisted of eight right-handed untrained subjects, both male (6 persons) and female (2 persons) between the ages of 20 and 31 with normal or corrected-to-normal visual acuity. All of them provided a written informed consent before the commencement of the experiment. The experimental studies performed were in accordance with the Declaration of Helsinki.

The subjects were sat in a comfortable reclining chair with their legs straight and arms resting on an armrest in front of them. The subjects were asked to take their shoes off before the experiment. The subjects were informed visually on the screen in front of them about which limb they must move after the next beep. The subjects were required to imagine moving their arms and legs after being presented with the audible beeps as the cue.

Each beep followed the subjects imagining to move their limbs and this counted as one trial. The number of trials varied between the subjects from 16-28 per limb. The beeps were presented with time gaps varying from 6-8 seconds, randomly distributed.

Figure 4 - Experiment design. The arrows indicate the beginning of each of four series.

The whole experiment was divided into 4 series with one-fourth of the total number of trials in each series. Each series consisted of equal number of trials for all 4 limbs. There was a 20-second gap after finishing all trials of a limb in a particular series. There was a resting 60-second interval between each limb.

Pre-processing

Artifacts in MEG recordings due to eye-movement, heartbeat, breathing or blinking were removed using the temporal signal-space separation method by Taulu and Hari (Taulu and Hari 2009).

Marking events in MEG data

The MATLAB code was used to produce all audio/visual stimuli in this study to log the time of the beginning and ending of each movement imagination (event) in a text file. This text file was

then used to mark the times corresponding to the beginning of each imagination when viewing the MEG file (in .fif format) in the Brainstorm interface.

Importing epochs using events

Once the events were marked corresponding to the beginning of each limb movement imagination, we extracted epochs of 5-second duration at the beginning of these event timings.

Similarly, the time corresponding to the resting state with closed eyes was also marked with subsequent 20-second trials for the background activity of each subject.

Wavelet analysis

For each limb, we used Morlet wavelets (with 1-Hz central frequency and 3-second FWHM) to evaluate the time-frequency spectrogram for all extracted epochs of that limb and then averaged the spectrograms for the limb. Then, the spectrogram was also averaged over the desired frequency range, for example, mu band (8-30 Hz).

The same process was repeated over the background resting state using the same parameters. To evaluate ERS/ERD, we took a difference of the spectrogram for the trials and the averaged-over-time spectrogram of the background and then further normalized it by dividing this difference by the average of this averaged-over-time spectrogram of the background. This normalized difference was positive for ERS and negative for ERD.

Coherence

To check if there was any communication between different areas of brain, we calculated the cross-coherence in the time series obtained from the electrodes in the respective regions and took an average across all the epochs for that subject.

Artificial neural network (ANN)

We first used ANN to differentiate between left arm and right arm data by training ANN using 75% of the MEG trials and testing it with the resting 25% trials.

The network comprised of an input layer corresponding to the total number of MEG channels training/testing the network. This was followed by 3 hidden layers comprising of 30, 15 and 5 neurons, respectively. There was a single neuron in the output layer. The transfer function employed in the ANN was a hyperbolic tangent sigmoid. The input data was limited to come only from the 1.5-3.5 second time interval for each 5-second epoch. The input data also passed through a low-pass filter of order 70 with a cutoff frequency changing according to each study. The training algorithm used was scaled conjugate gradient due to its high efficiency for pattern recognition problems. The training stopped as soon as any one of the following conditions was met:

- The error function for the output neuron evaluated was less than $1e-5$.
- Batch training with all input data ran for at least 5000 times.

The parameters chosen above are not universal or even the best for this particular application. They have been found using hit-and-trial method and chosen to provide better results than that obtained in the previous EEG studies.

Mixing the input data improved the efficiency of the machine learning algorithm. We used regular mixing.

Regular mixing: We mixed all inputs and the corresponding targets for the entire 2-second time interval (randomly varied in the 1.5-3.5 second interval). Then, we trained the ANN for 2 seconds.

Although training the network for 2 seconds was more difficult than for 1 second, the latter shorter training time led to losing a lot of information. Therefore, we try other two strategies which may give more information for shorter training time:

- 1) Training the network for 500 batch trainings alternately with samples from the first and second seconds. This means that first we trained the network using samples from 1.5-2.5 seconds for 500 batch trainings. Then, we trained ANN using samples from 2.5-3.5 seconds for 500 batch trainings. This constituted a single iteration. We did 500 such iterations.
- 2) Training the network for 500 epochs alternately with odd and even samples from the entire 2 seconds.

The ANN analysis was then repeated to segregate between left and right legs and then between both arms and both legs collectively for all subjects.

Changing the parameters, like input channels and cut off frequency or the training method, we obtained interesting insights into the working of the brain during MI.

Results

We start with presenting the results of the wavelet analysis for all 8 subjects, averaged across the trials for each of the 4 kinds of limb movements. The results of the wavelet analysis shown in Fig. 5 represent the normalized difference in wavelet energy during the trials and the resting state of the same subject. The details of evaluating this difference are described in the section Methods and Methodology.

Wavelet energy varying with time

The variation of wavelet energy with time for the delta, alpha and beta bands was evaluated by integrating the wavelet energy (after the subtraction and normalization with the background) across the respective frequencies over all the MEG channels. For the purpose of this study, we call 1-5 Hz as delta, 8-12 Hz as alpha and 10-30 Hz as beta waves, respectively.

The following figure shows the frequency band energy for one of the subjects, Sub-1.

Figure 5 - Time series of frequency-band wavelet energy for each limb.

It is interesting to notice that the trend in the band energies for all three bands is similar. This suggests all the frequencies were working in cohesion during the entire MI period. However, across all subjects, there was no common distinction in the band energy between each of the four limbs, namely left hand (LH), right hand (RH), left leg (LL) and right leg (RL). Therefore, we evaluated the band energies averaged over all 4 limbs.

Figure 6 - Time series of frequency-band wavelet energy averaged across limbs.

The same trend for all energy bands is of course evident here also. Since the temporal variation of the band energy is not providing any other useful information, we average the wavelet energy over the entire 5 second trials for the rest of studies related to the wavelet and coherence analysis.

Average activity in Mu band

Figure 7 - The difference in wavelet energy for the frequency range of 8-30 Hz (Mu-waves), most often associated with motor activity. (Yin, Liu and Ding 2017)

It can be seen that the mu activity is localized near the occipital and superior parietal lobes in the 3rd and 4th column. On the contrary, the mu activity for the two left panels in the first row and the leftmost panel in the second row is positioned around the inferior parietal lobe and the motor-related areas. This distinction follows the same rule as mentioned earlier for classifying between VI and KI, respectively. Hence, Sub-1, 2 and 5 can be categorized with a KI-dominant MI whereas, Sub-3, 4, 7 and 8 tend to imagine in a VI-dominant fashion. Sub-6 does not fit into any of these 2 categories and is to be treated exceptionally for the rest of this study as well.

Red colour indicates event-related synchronization (ERS) of mu wave as compared to the background resting state, while blue colour shows event-related desynchronization (ERD).

As discussed in the state-of-the-art review, there is a possibility that a mediatory inhibition mechanism exists in the vicinity of the inferior parietal lobe, especially in the case of KI. Observing ERD then in the case of KI in that very region leads us to think that this inhibitory mechanism utilizes ERD. We propose that mu waves are acting as carrier waves for the MI related information encoded by the brain in gamma band (30-150Hz). Further discussion on this topic is presented in the Discussions and Conclusions section.

Other brain areas that are known to be associated with MI are Cerebellum, Basal ganglia and ventral PFC. Since, MEG can only view the activity on the top cortical surface, subcortical regions like Cerebellum and Basal ganglia can't be distinctly analyzed. We then looked for the frequency range where we could find ventral PFC activity.

Average activity in Delta band

Figure 8 - Average delta-band wavelet energy for each subject.

It is observed that only the KI-dominant group seems to have a distinctly excitatory behavior in the ventrolateral PFC region, whereas the VI-dominant group tends to show distributed excitation/inhibition across the surface of the brain.

Quantifying the event-related potentials

To quantify the ERS/ERD, we calculated average of the difference of wavelet energy during the trials and resting state respectively, over all the channels. The difference was then normalized by dividing with the average wavelet energy of the resting state, as before. To get a more distinct trend, we further divided this normalized difference with the inter-subject minimum of this normalized difference. The subsequent graph for mu activity is given below.

Figure 9 - Average mu-band wavelet energy across every channel for each subject.

The following graph shows the normalized difference of energies in the delta band. It's interesting to see that subjects with KI (Sub-1, 2 and 5) have the strongest ERD for both mu and delta bands. Subjects with VI have insignificant ERD/ERS. Sub-6 being exceptional shows strong ERS.

Figure 10 - Average delta-band wavelet energy across every channel for each subject.

The insignificance of ERPs in the delta band for VI, as illustrated Average activity in delta band, is also validated in the quantified ERP graph.

To further investigate our hypothesis, claiming mu waves as a carrier wave and the movement specific information being carried in the gamma band, we decided to calculate the coherence of brain signals across the different channels as a way to evaluate the communication between those channels.

Coherence

Figure 11 - The coherence over the frequency of 10 Hz (μ) between the time series emerging from an electrode in the inferior parietal lobe in the left/right hemisphere and the rest of the brain. The first two rows correspond to the results when an electrode in left hemisphere is chosen, while the last two rows correspond to the electrode being chosen in the right hemisphere. Red colour corresponds to positive coherence and blue colour to negative coherence.

The lack of coherence for KI group reflects poor connectivity of brain regions and the reverse is true for the VI group. Fortunately, the results hold well even if we choose a symmetric point in the right hemisphere.

After testing the carrier wave frequency band, we then went onto looking for a common frequency band in the gamma frequency range. It is not surprising that each brain is different and has different activities going on in the gamma band as well. But to our surprise, the only frequency exhibiting a common behavior among the subjects of both the KI and VI group respectively was found to be 45 Hz.

We observe better connectivity for VI and suppressed connectivity for KI when we evaluate the coherence for this 45 Hz frequency (Gamma-1).

Figure 12 - Coherence at 45 Hz between one electrode from the inferior parietal lobe (left hemisphere) and the rest of the brain.

The results hold good even when we choose a point in the other brain hemisphere.

Figure 13 - Coherence at 45 Hz between one electrode from the inferior parietal lobe (right hemisphere) and the rest of the brain.

We believe that the carried information for MI is encoded at this frequency and the incoherence observed at this frequency for KI supports our hypothesis.

Machine learning

Machine learning is a strong and widely used approach to develop brain-computer interfaces (BCIs). The advantage and reason for using machine learning here is that it offers a completely different and independent way to verify the analysis done using wavelet analysis.

The following studies are carried out to compare the accuracy of machine learning in differentiating between left and right hands with respect to the chosen parameters for one of the subjects with KI, Sub-5.

Effect of cut-off frequency on ANN performance

After evaluating the most informative 72 channels using principal component analysis (PCA), this study is performed to compare the effect of cut-off frequency on the accuracy of ANN, where Y is the cut off frequency and X is the number of input channels. The mixing used here was regular mixing, as described in the Methods and Methodologies section. The statistics obtained for 10 separate ANN trainings are as follows.

X = 72; Y = **30 Hz** | Regular mixing

	% Mean accuracy
Mean	75
Min	83.33
Max	77.5

X = 72; Y = **10 Hz** | Regular mixing

	% Mean accuracy
Mean	65.83
Min	58.33
Max	75

X = 72; Y = **4 Hz** | Regular mixing

	% Mean accuracy
Mean	36.67
Min	25
Max	50

Among the three tested cut-off frequencies, 30 Hz shows the best results. The other two, namely 4 and 10 Hz, lack the presence of μ -waves and cover only delta or delta and theta ranges respectively.

Effect of the choice of input channels on ANN performance

The next study was carried out to compare the effect of the choice of input channels. The choice of 15 channels is based on choosing the channels that correspond to the ones that were found to be the most significant in the figure for event-related potentials (marked red in the figure below), while the chosen 102 channels are all magnetometers that carry all non-redundant MEG information, as opposed to gradiometers.

Figure 14 - Selection of magnetometer MEG channels corresponding to the most significant brain regions that are affected by ERS/ERD for Bull.

The obtained results are presented below.

X = 72; Y = 30 Hz | Regular mixing

	% Mean accuracy
Mean	75
Min	83.33
Max	77.5

X = 15; Y = 30 Hz | Regular mixing

	% Mean accuracy
Mean	28.33
Min	8.33
Max	41.67

X = 102; Y = 30 Hz | Regular mixing

	% Mean accuracy
Mean	63.33
Min	41.67
Max	75

The best results were obtained using the 72 most informative channels (PCA).

The failure of 15 input channels can be attributed to simply the lack of complete information being processed in the brain to distinguish between the left/right hands. Although it is interesting to note that 12 out of these 15 channels were also a part of the best performing 72 channels. Furthermore, $12/15 = 0.8 > 0.706 = 72/102$, suggests that it is no coincident that these channels are common with the best 72 channels.

Both the above results further support our hypothesis that indeed the carrier frequency and brain activity in these brain regions represent the most relevant information for MI.

ANN performance variation with cut-off frequency

The effect of cut-off frequency then was further explored and the ANN accuracy was plotted against the cut-off frequencies varying from 5-60 Hz for all the subjects.

Figure 15 - Mean ANN accuracy (%) versus cut-off frequency (Hz).

It is interesting to note, first, that the classification accuracy between the left and right hands is in general higher for KI as compared to VI and second, inclusion of mu frequency leads to better performance for KI as opposed to VI. Lastly, the inclusion of the 45 Hz frequency band always improves the classification accuracy, except for the exceptional case of Sub-6.

Effect of mixing strategy on ANN performance

The next study was then organized to study the effects of different kinds of mixing, as discussed in the Methods and Methodologies section, on the machine learning accuracy.

X = 72; Y = 30 Hz | **Regular mixing**

	% Mean accuracy
Mean	75
Min	83.33
Max	77.5

X = 72; Y = 30 Hz | **Sequentially picking from the first and second seconds**

	% Mean accuracy
Mean	50.83
Min	41.67
Max	58.33

X = 72; Y = 30 Hz | **Sequentially training from the odd and even sample sets**

	% Mean accuracy
Mean	50

Min	33.33
Max	75

The results indicate that regular mixing is the most efficient mixing technique among the three tested mixing strategies. However, changing the number of times batch training is performed and the number of iterations in each batch training may improve the results from the two alternate strategies. Also, regular mixing after choosing the odd and even samples in the second alternative strategy may also improve performance.

Differentiating between left and right legs

After evaluating the ANN performance to differentiate between left and right hands, we applied the same methods to train ANN to differentiate between left and right legs and chose the same parameters.

Subject	30 Hz	45 Hz
1	34.17%	35%
2	24.17%	45%
3	41.25%	46.25%
4	36.67%	36.67%
5	43.33%	38.33%
6	56.67%	56.67%
7	74.17%	70%
8	72.5%	60.83%

The results are counterintuitive at the first glance, showing better performance for the VI group in general as compared to the KI group. Changing the cut-off frequency from 30-45 Hz improves/deteriorates the ANN performance with no apparent scheme, as opposed to the results for differentiating between hands.

Differentiating between hands and legs

All the previous ANN studies were performed using a fraction of the complete dataset for each subject, i.e., either the data for legs was used or the data for hands. But the wavelet and coherence analysis was performed on the entire dataset including each limb. It only seems fair to test the chosen ANN training parameters on the entire dataset then, for example to differentiate between hands and legs. We show the results for choosing the input channels for the same subject as we chose before for this analysis, Sub-5.

	102 channels	15 channels
Mean	64.17%	68.33%
Min	50%	58.33%
Max	75%	83.33%

The results clearly show better performance of ANN for the choice of 15 channels identified using ERS/ERD as compared to using all the magnetometer channels.

Discussion and Conclusions

To summarize, we categorized the subjects into two groups, one with dominant KI and another with VI. Our results are in agreement with previous EEG studies of motor imagery and real movement in untrained subjects (Maksimenko, et al. 2018). Similar to our results (*Figure 16 - Average wavelet energy between 1-30 Hz. Validation of previous EEG results.*), for VI subjects, the brain activity in the wide region of 1-30 Hz represented ERS in the occipital and superior parietal lobes, whereas the activity during real movements showed ERD in the inferior parietal lobe similar to our observations for KI subjects.

Figure 16 - Average wavelet energy between 1-30 Hz. Validation of previous EEG results.

The concurrence of the involvement of the inferior parietal lobe, known to exhibit inhibitory control during KI-dominated MI, and ERD in the same brain region hints towards the possibility of ERD as a mechanism to perform inhibitory control.

Mu as a carrier wave

Lisman and Jensen (Lisman and Jensen 2013) hypothesized that a theta-gamma neural code exists for neural communication, which was then evidenced in experiments. Their model suggests that theta waves are carriers of neural processing, manifesting in the form of gamma waves, between different regions of the brain for sequential processing. We would like to extend the same strategy to mu waves instead of theta waves for MI.

During ERS, the synchronization of cells with mu activity helps to carry the information without any hurdles. Observing ERS in the visual area for VI is then to be expected. Whereas, during ERD, the carrier signal is distorted and so the transmission of gamma signal is inhibited.

Validation from coherence studies

The next analysis was performed using cross-coherence for the frequency of 10 Hz, where we found incoherence between the time series from MEG channels in the vicinity of the inferior parietal lobe (in both hemispheres) and their contralateral counterpart, or at least the most prominent ERD region in the KI-dominant group. This means that indeed the loss of communication is reciprocated in the same regions that show ERD.

The coherence studies indeed support our hypothesis by highlighting how the carrier waves are not communicating between different parts of the brain for KI. Incoherence in gamma waves at 45 Hz (that are being carried) further validates this hypothesis. The results for VI do not show such suppression of both the carrier and the carried waves.

Validation from the ANN studies

The results from ANN studies first highlight the higher accuracy for machine learning in case of KI as compared to VI, as one would expect.

Also, finding better ANN accuracy for differentiating between left and right hand MI after including mu band frequency (carrier frequency) and the channels corresponding to the most significant ERS/ERD activity indicates how indeed MI specifically communicates at this frequency and through these regions.

Furthermore, the accuracy versus cut off frequency curves indicates that inclusion of mu band tends to improve the performance for the KI group and deteriorates the performance for VI group. This is because additional redundant information is being fed to the ANN which increases the learning burden at the cost of new and relevant data to learn from.

Figure 17 - Homunculus: Mapping of muscles on motor cortex. (Gold 2009)

Interestingly, the analysis for ANN performance to differentiate between the legs reveals the opposite results as for the hands. We believe it happens because the legs occupy a significantly smaller region (Penfield and Boldrey 1937) on the motor cortex as compared to hands and so the requirement of motor-associated areas in KI causes the subjects to have a very small brain region participating in the MI, whereas, VI involves visually seeing the image which remains the same for both hands and legs. Also, perhaps it takes a stronger visualisation for legs than hands to perform MI and so for a few VI subjects, the ANN performance is quite high.

Involvement of ventrolateral PFC

Observing distinct ERS for KI and the absence of any significant ERS/ERD seems to indicate that a KI-specific process is happening at the ventrolateral PFC and ERS is associated with the mechanism behind that process.

Observing suppressed communication between the inferior parietal lobe and the contralateral ventrolateral PFC for KI as opposed to VI, which maintains a communication in this neural pathway, reflects that information exchange between the two aforementioned contralateral regions does take place and it is suppressed in KI.

The frontal cortex is often associated with abstract thinking and decision making tasks (Coutlee and Huettel 2013) and we think that here it also plays a similar role. As we mentioned earlier, lesions in the parietal cortex can lead to execution of movements during MI without the knowledge of it. This leads us to think that the inhibitory control failure at the parietal lobe results in transparent and hurdle-free mediation of the movement signal. Therefore, it only makes sense to observe ERS at the ventral PFC which is mediating the signal for all subjects. However, there is distributed delta activity for VI, and areas other than the ventral PFC are also active.

45 Hz

Along with the hypothesis developed, our results also provide us with this specific gamma frequency being utilized for MI. The improvement in ANN performance after its inclusion for 6 out of 8 subjects validates its special role and also suggests that its role is the same for both KI and VI. The only difference must be in the carrier wave (mu waves) which is being suppressed in the case of KI.

Future work

The hypothesis that we propose in this work needs to be validated using rigorous analysis and argumentation before it can be accepted as a mechanism to study MI and other neural processes. Some steps towards it are as follows.

- ANN analysis with notch-pass filter centred on 45 Hz.
- More number of subjects.
- More number of trials for each subject.
- Classification of KI/VI using ANN.
- Classification accuracy between hands and legs MEG data.
- Training ANN for one subject in KI/VI and testing with other subjects.

The chosen ANN parameters are arbitrary and can be further improved upon. Finding a systematic way to choose the parameters for optimal results can be one of the new objectives.

The briefly discussed alternate mixing strategies for the ANN training can be further looked upon to get an even better machine learning performance. The current hypothesis does not include the effect of the MI content on inhibition as discussed in the state-of-the-art section and can be further explored in future studies.

Bibliography

- Bakker, F.C., M.S.J. Boschker, and T. Chung. "Changes in muscular activity while imagining weight lifting using stimulus or response propositions." *Journal of Sport and Exercise Psychology*, 1996: 313–324.
- Bidet-Caulet, A., J. Voisin, O. Bertrand, and P. Fonlupt. "Listening to a walking human activates the temporal biological motion area." *Neuroimage*, 2005: 132–139.
- Blanke, O., et al. "Linking out-of-body experience and self processing to mental own-body imagery at the temporoparietal junction." *The Journal of Neuroscience*, 2005: 550–557.
- Contributors. *Operative Neurosurgery*. 19 December 2015.
http://operativeneurosurgery.com/doku.php?id=superior_temporal_sulcus.
- Contributors, Wikipedia. *Wikipedia*. 7 April 2018.
https://en.wikipedia.org/w/index.php?title=Ventrolateral_prefrontal_cortex&oldid=835169282.
- Coutlee, C.G., and S.A Huettel. "The Functional Neuroanatomy of Decision Making: Prefrontal Control of Thought and Action." *Brain Research*, 2013: 3-12.
- Dechent, P., K.D. Merboldt, and J. Frahm. "Is the human primary motor cortex involved in motor imagery?" *Brain research. Cognitive brain research.*, 2004: 138–144.
- Dominey, P., J. Decety, E. Broussolle, G. Chazot, and M. Jeannerod. "Motor imagery of a lateralized sequential task is asymmetrically slowed in hemi-Parkinson's patients." *Neuropsychologia*, 1995: 727-741.
- Duque, J., L. Labruna, S. Verset, E. Olivier, and R.B., Ivry. "Dissociating the role of prefrontal and premotor cortices in controlling inhibitory mechanisms during motor preparation." *The Journal of Neuroscience*, 2012: 806-816.
- Ehrsson, H.H., S. Geyer, and E. Naito. "Imagery of voluntary movement of fingers, toes, and tongue activates corresponding body-part-specific motor representations." *Journal of Neurophysiology*, 2003: 3304-3316.
- Gerardin, E., et al. "Partially overlapping neural networks for real and imagined hand movements." *Cerebral Cortex*, 2000: 1093-1104.
- Gold, J. *National Public Radio, Inc.* 18 March 2009.
<https://www.npr.org/templates/story/story.php?storyId=101960403>.
- Guillot, A., and C. Collet. "Construction of the motor imagery integrative model in sport: a review and theoretical investigation of motor imagery use." *International Review of Sport and Exercise Psychology*, 2008: 31–44.
- Guillot, A., C. Collet, V.A. Nguyen, F. Malouin, C. Richards, and J. Doyon. "Brain activity during visual versus kinesthetic imagery: an fMRI study." *Human Brain Mapping*, 2009: 2157–2172.

- Guillot, A., F. Lebon, D. Rouffet, S. Champely, J. Doyon, and C. Collet. "Muscular responses during motor imagery as a function of muscle contraction types." *International Journal of Psychophysiology*, 2007: 18–27.
- Guillot, Aymeric, Frank Di Rienzo, Tadhg MacIntyre, Aidan Moran, and Christian Collet. "Imagining is not doing but involves specific motor commands: a review of experimental data related to motor inhibition." *Frontiers in Human Neuroscience*, 2012: 247.
- Hanakawa, T., I. Immisch, K. Toma, M.A. Dimyan, P. van Gelderen, and M. Hallett. "Functional properties of brain areas associated with motor execution and imagery." *Journal of Neurophysiology*, 2003: 989-1002.
- Hanakawa, T., M.A. Dimyan, and M. Hallett. "Motor planning, imagery, and execution in the distributed motor network: a time-course study with functional MRI." *Cerebral Cortex*, 2008: 2775-2788.
- Hanakawa, Takashi. "Organizing motor imageries." *Neuroscience Research*, 2016: 56-63.
- Ionta, S., et al. "Multisensory mechanisms in temporo-parietal cortex support self-location and first-person perspective." *Neuron*, 2011: 363-374.
- Iseki, K., T. Hanakawa, J. Shinozaki, M. Nankaku, and H. Fukuyama. "Neural mechanisms involved in mental imagery and observation of gait." *Neuroimage*, 2008: 1021-1031.
- Izumi, S., T.W. Findley, T. Ikai, J. Andrews, M. Daum, and N. Chino. "Facilitatory effect of thinking about movement on motor-evoked potentials to transcranial magnetic stimulation of the brain." *American journal of physical medicine & rehabilitation*, 1995: 207-213.
- Kameyama, M, K Murakami, and M Jinzaki. "Comparison of [15O] H2O positron emission tomography and functional magnetic resonance imaging in activation studies." *World Journal of Nuclear Medicine*, 2016.
- Kasahara, K., C.S. DaSalla, M. Honda, and T. Hanakawa. "Neuroanatomical correlates of brain-computer interface performance." *Neuroimage*, 2015: 95-100.
- Kasai, T., S. Kawai, M. Kawanishi, and S. Yahagi. "Evidence for facilitation of motor evoked potentials (MEPs) induced by motor imagery." *Brain Research*, 1997: 147–150.
- Kosslyn, S.M., G. Ganis, and W.L. Thompson. "Neural foundations of imagery." *Nature Reviews Neuroscience*, 2001: 635–642.
- Krams, M., M.F. Rushworth, M.P. Deiber, R.S. Frackowiak, and R.E. Passingham. "The preparation, execution and suppression of copied movements in the human brain." *Experimental Brain Research*, 1998: 386-398.
- Kroeger, J., T. Baumer, M. Jonas, J.C. Rothwell, H.R. Siebner, and A Munchau. "Charting the excitability of premotor to motor connections while withholding or initiating a selected movement." *European Journal of Neuroscience*, 2010: 1771-1779.
- Lebon, F., W.D. Byblow, C. Collet, A. Guillot, and C.M. Stinear. "The modulation of motor cortex excitability during motor imagery depends on imagery quality." *European Journal of Neuroscience*, 2012: 323-331.

- Liang, N., et al. "Effects of motor imagery are dependent on motor strategies." *NeuroReport*, 2007: 1241-1245.
- Lisman, J.E., and O. Jensen. "The theta-gamma neural code." *Neuron*, 2013: 1002-1016.
- Lotze, M., et al. "Activation of cortical and cerebellar motor areas during executed and imagined hand movements: an fMRI study." *Journal of Cognitive Neuroscience*, 1999: 491–501.
- Macuga, K.L., and S.H. Frey. "Neural representations involved in observed, imagined, and imitated actions are dissociable and hierarchically organized." *Neuroimage*, 2012: 2798–2807.
- Maksimenko, V., et al. "Nonlinear analysis of brain activity associated with motor action and motor imaginary in untrained subjects." *Nonlinear Dynamics*, 2018: 2803-2817.
- Mizuguchi, N., I. Umehara, H. Nakata, and K. Kanosue. "Modulation of corticospinal excitability dependent upon imagined force level." *Experimental Brain Research*, 2013: 243–249.
- Naito, E., et al. "Internally simulated movement sensations during motorimagery activate cortical motor areas and the cerebellum." *The Journal of Neuroscience*, 2002: 3683-3691.
- Naito, E., P.E. Roland, and H.H. Ehrsson. "I feel my hand moving: a new role of the primary motor cortex in somatic perception of limb movement." *Neuron*, 2002: 979–988.
- Naito, E., R. Matsumoto, N. Hagura, Y. Oouchida, H. Tomimoto, and T. Hanakawa. "Importance of precentral motor regions in human kinesthesia: a single case study." *Neurocase*, 2011: 133–147.
- Park, C.H., et al. "Which motor cortical region best predicts imagined movement?" *Neuroimage*, 2015: 101–110.
- Penfield, W., and E. Boldrey. "Somatic motor and sensory representation in the cerebral cortex of man as studied by electrical stimulation." *Brain*, 1937: 389-443.
- Porro, C.A., V. Cettolo, M. P. Francescato, and P. Baraldi. "Ipsilateral involvement of primary motor cortex during motor imagery." *European Journal of Neuroscience*, 2000: 3059–3063.
- Schwoebel, J., C.B. Boronat, and H Branch Coslett. "The man who executed "imagined" movements: evidence for dissociable components of the body schema." *Brain and Cognition*, 2002: 1-16.
- Sharma, N., V.M. Pomeroy, and J.C. Baron. "Motor imagery: a backdoor to the motor system after stroke?" *Stroke*, 2006: 1941–1952.
- Sirigu, A., et al. "Congruent unilateral impairments for real and imagined hand movements." *NeuroReport*, 1995: 997-1001.
- Sirigu, A., J.R. Duhamel, L. Cohen, B. Pillon, B. Dubois, and Y. Agid. "The mental representation of hand movements after parietal cortex damage." *Science (New York, NY)*, 1996: 1564-1568.

- Solodkin, A., P. Hlustik, E.E. Chen, and S.L. Small. "Fine modulation in network activation during motor execution and motor imagery." *Cerebral Cortex*, 2004: 1246–1255.
- Stinear, C.M., and W.D. Byblow. "Motor imagery of phasic thumb abduction temporally and spatially modulates corticospinal excitability." *Clinical Neurophysiology*, 2003: 909–914.
- Takeuchi, N., T. Mori, K. Nishijima, T. Kondo, and S. Izumi. "Inhibitory transcranial direct current stimulation enhances weak beta event-related synchronization after foot motor imagery in patients with lower limb amputation." *Journal of Clinical Neurophysiology*, 2015: 44-50.
- Taulu, S., and R. Hari. "Removal of Magnetoencephalographic Artifacts With Temporal Signal-Space Separation: Demonstration With Single-Trial Auditory-Evoked Responses." *Human Brain Mapping*, 2009: 1524–1534.
- Wolpaw, J.R., and D.J. McFarland. "Control of a two-dimensional movement signal by a noninvasive brain–computer interface in humans." *Proceedings of the National Academy of Sciences of the United States of America*, 2004: 17849–17854.
- Yin, S., Y. Liu, and M. Ding. "Amplitude of Sensorimotor Mu Rhythm Is Correlated with BOLD from Multiple Brain Regions: A Simultaneous EEG-fMRI Study." *Frontiers in Human Neuroscience*, 2017: 356.

Annexure 1 – Impact

This research is aimed at facilitating the development of Brain-computer interfaces (BCI), especially in the context of neurorehabilitation and hands-free control of machines for paraplegic people. The study enables the understanding of the neural circuitry and mechanisms underlying motor imagination and real movements. The proposed model in the study for neural communication and inhibitory control will prove to be fundamental in understanding neural processes, in general, and enable a much better and collective understanding of the plethora of result related to event-related potentials in the scientific literature. This may turn out to be crucial in understanding and tackling areas as wide as drug addiction, character assessment, generalised epilepsy, memory, perception, etc.

Neurorehabilitation	Sharing of neural circuitry between motor imagery and real movements makes neurorehabilitation possible for people who have lost the ability to move using motor imagery.
Hands-free control	Reading directly from brain activity in the head gives way to the possibility of controlling wheelchairs and other devices even after the loss of limbs for paraplegic people.
Drug-addiction	The developed mechanism for motor inhibition may turn out to be applicable even for other kinds of applicable such inhibition to refrain from relapsing to drugs or other kinds of addictions.
Generalised epilepsy	The epileptic activity travelling from one point to another may be controlled if the communication system between the points be hindered.
Perception	Perceiving requires travelling of signals between different brain regions and can be facilitated/impeded as per the requirement.

Catering to such a wide domain of neurophysiological areas with a single study is admittedly quite ambitious. But if it turns out to be true, then it is multiplicatively rewarding and satisfactory. If the findings and discussions of this study can someday turn out to be the cause of paralyzed person walking on his/her feet again or can inhibit the pain perception during childbirth, there can be no bigger gratification than that.

Annexure 2 – Budget

Cost of personnel

Basic salary	16.7€
Social charges	0
Effective cost	16.7€
Total cost	2505€

Cost of material

	Unit price	Quantity	Effective cost
MEG registers	600€	9	5400€
PC	2000€	1	2000€
Poster	50€	1	50€
Total cost			7450€

Material execution budget (PEM)

PEM = Total personnel cost + Total material cost	9955€
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Contract execution budget

PEM + 13% PEM + 6% (PEM + 13%PEM)	11924€
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Total budget

Execution budget (21% VAT included)	14428€
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