Preliminary findings on tools for the analysis of mental activity of programmers using EEG data from portable devices

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***Abstract*—Developers are indeed the most important resource in software production, and the individual developers are hard to substitute. The core of the work of the developers of knowledge intensive systems is in their mind, and this now a growing interest in understanding how to detect and model the state of their mind. Such analysis would enable to determine and model the optimal situation to develop in terms, for instance, of speed of development, minimization of errors, etc., and, to the extent possible, to recreate or to get close to such situation while organizing the work, the processes, the tools, and so on. Furthermore, on the basis of such modeling, tools could be developed to supply the developers what they need in terms of information, instruments, feedback.**

The problem of performing such analysis is that the most refined equipment to model the work of the mind, like the fMRI, is very expensive and not movable. However, a tool, MNE, has been developed who is able to recreate accurate approximations using EEG of the data coming from an accurate wearable device that would come from the fMRI. This is a major enabler of the research in this area and in this paper details on why to select it and how to use it are provided. Moreover, first-hand information about its usage is supplied.

I. Introduction

This paper discusses a tool used to analyse the mind of developers while programming using a source of data a wearable, multichannel EEG; the role of such tool is pivotal, as it supports more refined analysis than the usual coming from traditional EEG, and thus enables the development of models and tools to describe and optimize the highly intellectual work of software and hardware engineers.

Developers are indeed the most important resource in software production, and the individual developers are hard to substitute. People have always been aware of this, but such awareness has increased significantly in the last few years, especially with the widespread adoption of Lean approaches to the development of knowledge-intensive systems, like software and hardware systems [7].

Needless to say, the core of the work of the developers of knowledge intensive systems is in their mind, and there is now a growing interest in understanding how to detect and model the state of their mind, which has evolved mostly in two directions. On one side there has been a growing acknowledgement of the importance of the cognitive structure of developers, starting from their psychological profiles, a study that originated more than half a century ago [42], to their overall state of mind [1], [34], [4], [3], [26] including their emotions and feelings [50], [19]. This has been noted particularly true in the context of agile development [9], [15], [11]. Emotions have been also considered and also how people collaborate and interact [47], [41], [10], [20], [39].

On the other side, there has been an increase in the use of biophysical signals to understand better the state of the minds of developers [8], using a variety of approaches, including fMRI, MEG, and complete EEG devices. Such understanding would enable to determine and model the optimal situation to develop in terms, for instance, of speed of development, minimization of errors, etc., and, to the extent possible, to recreate or to get close to such situation while organizing the work, the processes, the tools, and so on. To this end, it is important to mention the work of Apel with colleagues study the work of the brain using very accurate techniques, like the functional magnetic resonance imaging (fMRI). They detected activation specific Broadmann-areas during code comprehension [45]. In their follow up work, they investigated the difference between bottom-up program comprehension and comprehension with semantic cues in terms of brain areas involved [46].

fMRI provides a very careful description of the dynamics inside the brain. However, fMRI poses the challenge that developers have to work lying using mirrors, a hardly comparable environment with the real one, therefore alternative less disruptive approaches would be preferable. There have been works employing single channel EEG devices. Fritz at al. [51] and Müller and Fritz [38] have collected, among others, once channel EEG signals. However, the single channel electroencephalogram (EEG) device was used, which may result in an error of up to fifty percent [36].

There have been recent works using multi channel EEG signals [31], [6], [8], which indeed provide a more comprehensive view of what happens in the brain, still using wearable devices, so being able to record the activities in quite standard working situations. Moreover, the technical development of computed analysis of spectral EEG data has allowed quali-quantitative assessment of localized brain functional areas as well as of connectivity networks [49], [32], a fact which indicates that the objective evaluation specific brain functional capacity, both in physiological and in pathological conditions.

EEG offers in comparison to other diagnostic neuroimaging modalities such s fMRI, the advantage to providing adequate real-time information about the ongoing activity of virtually all the brain areas [25]. This would suggest that high-intellectual activity tasks, such as software conception and implementation, can be objectively measured and compared between different individuals, as well as in the same individual albeit in different moments in which emotional and psychological conditions can change [24]. There are recent reports of EEG demonstration of specific brain areas deactivation (following transient global amnesia for example) and reactivation a few days after the clinical recovery which again could indicate that memory, as well as social cognition, can be objectively screened. Moreover, default-mode network (DMN), a well-known pattern of resting state studies of brain connectivity, could also be utilizied for evaluating high-task brain activities since it is closely related to high intellectual processes such as mind/mentalization and long-term memory [23].

Indeed, the description of the activity of the brain provided by the EEG is less accurate than the one by the fMRI. However, in the last 20 years the medical discipline has evolved and software tools have been produced to provide a description of the brain similar to the one obtained via fMRI but using the EEG. This paper reports on the feasibility of using such tools in the context of software engineering research. In particular we focus on the use of the tool MNE (Minimum Norm Estimates) [18]. In our experience, these tools enable very accurate analysis, still using a wearable, multichannel EEG devices, as the major source of information. As such the role of this tool is pivotal, since it enables analyses otherwise impossible and further provides the ground for followup research and development.

As a matter of fact it is very important to emphasize that on the base of such modeling, tools could be developed to supply the developers what they need in terms of information, instruments, feedback. Using an analogy, now cars have mechanisms detecting when a driver is falling a sleep and providing a signal to wake up, for instance on the steering wheel or on the dashboard; likewise, we could imagine mechanisms to alert developers that they are loosing concentration and are likely to inject mistakes in their code or to loose their productivity significantly. As mentioned, the initial modeling of the work of the mind requires quite refined tools, the simplest being EGG devices with at least a dozen of sensors, but it is not difficult to hypothesize that after the initial modeling, to spot specific state of minds requiring feedback, like the lack of attention, simpler devices could be employed, such as one channel EEG, simple galvanic skin response, or simple eye tracking devices: all tools that could cost something of the order of 7.000 roubles or 100 euros. Even more, we could hypothesize further that, after modeling, suitable correlations could be made by levels of attention and how keystrokes occur or the mouse is moved, and then using such information as input for the tools.

The paper is organized as follows. Section II summarizes the current approaches in measuring the activity of the brain. Section III provides a short background on how to collect the data from EEG and of the software used to analyse it. Section IV details the research settings used in our research. Section V outlines the results of the analysis of the collected data. Sections VI review the results and the possible limitations and draws some conclusions.

II. Measuring the brain activity

Currently, many studies use biological signal measurements and questionnaires to measure the brain activity. However, there is a lack of research related to the analysis of the mind of programmers and their concentration. In this section we briefly summarize methods used elsewhere, but applicable to programmers.

There are a lot of studies using he EEG as a primary method for measuring brain activities. In [33] researches used EEG signals for Attention Recognition (AR) and extended previous research that used other techniques such as eye-gaze, face-detection, head pose and distance from the monitor to track the subject's attention. AR is a promising field that can be applied in many areas such as e-learning, driving, and most relevant - in measuring awareness during video conferences, which is import for the current study, because some programmers participate in multiple video conferences per day. In [21] EEG was used to determine the attention level, while the subject was performing a learning task. In [5] EEG was used to estimate alertness in real-time, which could be applicable during coding. In [29] presented a single channel wireless EEG device which can detect driver's fatigue level in real-time on a mobile device such as smartphone or tablet.

Apart from EEG, attention also could be measured via [28], [44]:

- heart rate variability,
- galvanic skin response,
- pupil diameter and eye blink frequency,
- brain activity measurement, such as MEG (Magnetoencephalogram), fNIRS (functional near-infrared spectroscopy), ECoG (electrocorticogram), fMRI (functional magnetic resonance imaging), etc.), positron emission tomography (PET), transcranial magnetic stimulation (TMS), near-infrared spectroscopy (NIRS) [44], [28].

Among tests to measure the brain activity there are [16], [13], [5], [28]:

- Conner's Continuous Performance Test (CPT), a simple examination technique where the subject has to react in case a rare signal appears,
- the test of variables attention (T. O. V. A.), an objective neuropsychological assessment of attention organized quite like a very simple computer game.

III. Background on EEG recording devices and the associated software

EEG recordings from the surface of the scalp represent the electrical activity coming from the different parts of the brain. Scalp EEG activity shows oscillations at a variety of frequencies. This rhythmic activity is divided into frequency bands, such delta, theta, alpha, beta and gamma. This electrical activity is generated by a large numbers of electrically charged neurons moving within the central nervous system and causing small electrical currents. The amount of current flow is characterized by the volume conduction, i.e., the electromagnetic properties of the tissues inside the brain. EEG frequency bands have been noted to have certain biological significance and can be associated to different states of brain functioning[23], [24]. There are still uncertainties about exactly where various frequencies are generated from. On the contrary there is largely recognised evidence about the activated areas within the brain that generate specific spectral activity along the scalp.

Many algorithms have been developed so far for processing these signals at the scalp-level and to produce a visual image of them, similar for easiness of use to MRI and fMRI, starting about 30 years ago [14].

A. Loreta

The first software aiming at using EEG signal to reconstruct the function of the brain was Loreta and its evolutions. In 1994 Pascual-Marqui, Michel and Lehman have published a new method for localizing the electrical activity in the brain based on scalp multiple-channel EEG recording. This revolutionary technique was called LORETA, (abbreviation for LOw-REsolution brain electromagnetic TomogrAphy) [35].

LORETA computes a three-dimensional distribution of 2394 voxels of 7x7x7 mm of the generated electric neuronal activity in the grey matter. It enables to estimate the activity distributed throughout the brain volume by decomposing the overlapping EEG voltage patterns into their underlying sources and by localizing them within the brain. A great advantage of this technique is that it is not restricted to a certain number of electrodes or electrode locations, therefore it self-adapts to almost every electrode set-up and EEG measuring device. LORETA analysis of limited frequency bands can be used to determine which regions of the brain are activated during different states or mental tasks, thus helping in determining whether the brain is operating in an optimal way or not.

LORETA is not only answering the question of where the sources are located, but it also provides you with the time courses of each source functioning. LORETA voxels are located in fixed positions within the brain's grey matter. It is always interesting to analyze not only the activation of single voxels but also the entire regions associated with specific brain functions. Broadmann areas are regions of the cerebral cortex that were introduced in the field of neurology/neuroanatomy at the beginning of the 20th century based on their cell organization and that later on were proven to be directly related to certain brain activities such as audition, vision and motor functions.

Since the beginning of 2001 LORETA has also been used for Neurofeedback and its use is expanding. So far studies based on EEG recordings are replicating others obtained using fMRI in either voluntaries either clinical populations, and they appear to be more cost-effective than fMRI for investigating deep cortical structures.

There are two different kinds of LORETA:

- sLORETA: standardized low resolution brain electromagnetic tomography [30], [40], that has no localization bias in the presence of measurement and biological noise.
- eLORETA: exact low resolution brain electromagnetic tomography [2], [22]. The first ever 3D, discrete, distributed linear solution to the inverse problem of EEG/MEG with exact localization (zero localization error).

The source estimation with LORETA requires several complex steps.

1) *Valid head coordinates:* Valid head coordinates (standard or realistic) are needed, matching the international 10-20 electrode system and its derivatives (i.e., 10-10 and 10-5 systems). Moreover, it is also recommended to have a uniform distribution of the electrodes throughout the scalp with the number of electrodes being at least 64 (Michel CM et al., 2004). However studies have been published with using also 32 channels EEG recordings (Imperatori et al. 2016)
2) *Accuraste voltage measurements in the EEG data:* The most important prerequisite which, highly specific of LORETA, is that only timed-domain voltage values are valid input for the algorithm. Source analysis also benefits from a high signal-to-noise ratio, which can be achieved by managing well pre-processed data. There are two different domains in the analysis:
   a) the electrode space where you have the voltage measurements;
   b) the source space, where the neuronal current sources are confined inside the brain.

   LORETA computes the electrical potentials based on the information about channel coordinates from the electrode space and the source parameters (position, orientation and magnitude of the neuronal current sources) from the source space.

3) *Source model:* A predefined source space is crucially important as for model sources. The source space is restricted to the regions of the cortical grey matter and hippocampus in the Talairach atlas, (a widespread internationally recognized anatomical atlas used for stereotactic neurosurgery) discretized into a total of 2394 voxels at 7 mm spatial resolution. These sources are then modeled using equivalent current dipoles.
4) *Volume conductor model:* it describes the geometrical and conductive properties of the head. A standard brain model which is based on the MNI-305 brain template (Evans AC, et al. 1993) could be used. The MNI images are co-registered to the Talairach brain atlas in order to map the detailed brain structures into the MNI space.

Once all these steps are completed the lead-field matrix is ready to be analyzed by computing. This matrix serves as a mapping mechanism from the neuronal current sources within the brain which are recorded by the electrical potentials on the head surface.

B. MNE

MNE is a software that has been very recently introduced in the clinical use [17], [18] and still has received several upgrades and improvements together with a very handy API in Python (MNE Python) [27], [12]. The latest version features several options for better EEG recording cleaning and it is used in the present study.

MNE Python allows time-frequency analysis as well as non-parametric and connectivity studies. Raw data are cleaned from artifacts by using its signal space separation technology [48]. Pre-stimulus intervals in the evoked responses during registration are used for optimizing signal-to-noise ratio. Sensor-level data show the active sources of signals to be amplified, and MNE software uses a current dipole which can be measured in both EEG and MEG technology. As a matter of fact, a small number of equivalent current dipoles (ECDs) evoke a specific signal (a spatial recognition of the original source in the brain) whilst time-varying dipole setting warrants a time-related proper analysis. In this manner either complex cognitive processes either "resting state" activities con be recorded.

MNE software analysis chooses the current distribution of best quality as representative of all the registered currents, and in this way it combines the best spatial with the best possible temporal resolution. In fact sensor-space and source-space frequencies are processed simultaneously, and artifacts are cleaned using a signal-processing technique [43], MNE Python is automatized with free-surface power spectrum software coupled with fast Fourier transfer (FTT) algorithms for automatically performing Fourier's analysis of recorded data. A 250 MB power is the minimum requirement. The final result is a spatial reconstruction of the activated areas of the brain on real time.

The most used techniques to study brain activation are fMRI, MRI and EEG. The first two techniques allow researchers and medical workers to inspect internal activations of the brain and provide high-resolution images of it. However, they are not suitable for usual programming tasks, because they require the subjects to lay down in the scanner, which is not a convenient environment to program. EEG, on the other side, is more suitable for such tasks, because it is portable and can be used while the subject is moving and performing different actions. Moreover, the MNE tool [18] can be used to interpret EEG signals and transform them into MRI-like images which allows analysing the brain activity of the programmers in more details without the use of fMRI and MRI scanners.

The goal of the research is to assess the MNE tool [18] and interpret the EEG signals of developers programming in different circumstances. Moreover, we aim to understand whether it is suitable to explain the differences in patterns of activation of brain activity during programming in different environments and conditions.

IV. Typical Settings

In our research, we have collected data to validate different research questions, such as if there are remarkable differences in brain waves when developers are programming while listening to music, when coding in open spaces, when working in pairs, and so on; moreover we have then tried to link the structure of the brain waves to the different mental states to determine the most effective situation in which people can program and how to achieve such situation.

In this section, we present the typical setting of our experimentation to understand the context in which we used the tool.

A. Preparation and running of the experiment

Before the experiment, each subject answered questions about their working preferences and programming experience. Programmers were divided into three groups of experience: elementary, intermediate and advanced to take into account partially the difference in experience. They, they were given tasks to solve, which depended on their experience. If needed, they could select the program of their choice.

The EEG device was then calibrated as follows:

- Eyes closed: 2 minutes
- Eyes opened: 2 minutes
- Main experiment: test subject solving given task

The time for solving task was different for each person, and it ranged from 10 to 20 minutes. If the test subject did not solve the task in the given time, the researcher stopped the experiment.

B. Tools

For the software side, we used different tools. We used the software tools first to collect and archive the data properly, and then to analyse it.

Specifically we:

- recorded EEG data in Mitsar EEG Studio (1.23.1),
- preprocessed, analysed and visualized data using MNE 0.19.2 on Python 3.7.4,
- we used Jupyter Notebook 6.0.1 as a working environment.

V. What we achieved using MNE

We have found that MNE has been particularly effective in our needs and specifically because:

- it allows to work with raw EEG data, which could be collected directly from programmers during their work and show the current state of the brain, unlike MRI or fMRI that require subject to lie still in the machine and do not give an opportunity to conduct research during the working process
- ease of installation and use with the help of documentation and numerous tutorials with clear instructions and examples on the web site
- it allows to visualize and present EEG data in three-dimensional fMRI-like representation with using built-in averaged brain structure and mathematical transformation data

In the remaining of this section, we are going to discuss more in details how we used it and the results that we have collected.

A. MNE Workflow

MNE tool provides workflow summarized on its webpage. In current work, we will use raw EEG data and go through the following steps: preprocessing, epoched data, averaged data, source estimate.

B. Importing Data

MNE supports importing data from various formats, such as Elekta NeuroMag (`.fif`), European Data Format (`.edf`), General data format (`.gdf`) and many others. Our data was in EDF format with labelled events for calibration and experimentation parts. We split data using MNE save function, and the data automatically converted to `.fif` format.

Except for EEG, MNE can work with different data and channel types such as magnetometer and gradiometer, which could be applied for studying Event-related potentials, electrooculogram (EOG), which could be useful to eye artefacts detection, electrocardiogram (ECG), also used for artefact detection, stimulus trigger channels and many others.

Exported EDF data from EEG Mitsar studio does not contain information about electrodes positions. We added positions manually using the class `mne.channels.Montage` class and its method `set_montage()`.

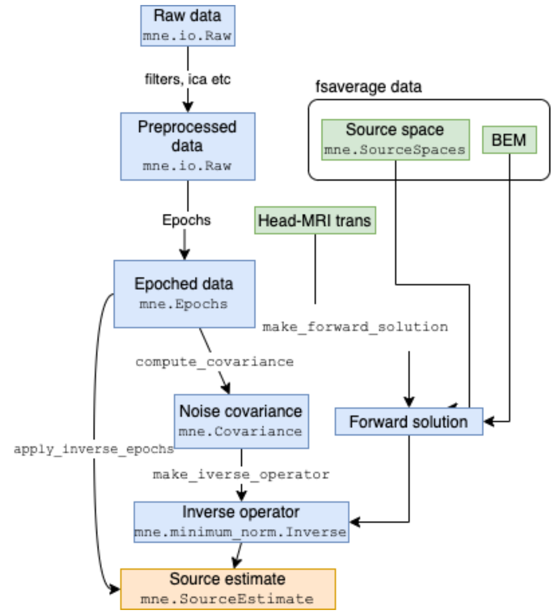


Figure 1: Workflow of the MNE software – Picture inspired by the one in:
https://mne.tools/stable/overview/cookbook.html

C. Preprocessing

One of the problems of EEG data is biological artefacts. We need a technique for estimating independent source signals from a recording in which multiple signals are mixed in unknown ratios. PCA-based preprocessing techniques may not work with non-Gaussian distributed datasets, an example of which is EEG. MNE tool provides implementation of an Independent Component Analysis (ICA) algorithm, which better solution for EEG data preprocessing since it assumes the non-Gaussian distribution of signals.

After the fitting ICA model, resulting components correspond to EEG sensors. They could be visualized as in 2. We can see that the first component (ICA000) captures the EOG (eye blinks). In the remaining sections, we'll look at different ways of choosing which ICs to exclude prior to reconstructing the sensor signals.

Moreover, we can plot an overlay of the original signal against the reconstructed signal with the artifactual ICs excluded (Figure 3).

After we know which component we can exclude, we use the call `ica.apply(reconst_raw)` to exclude it.

D. Epoching data

MNE provides a possibility to extract segments of data (Epochs) from recording using event IDs. The user also can define a hierarchy of events by using tags. During data collection, we marked each event in recording using labels in Mitsar studio (e.g., “eyes opened,” “eyes closed” for calibration). This information could be extracted directly

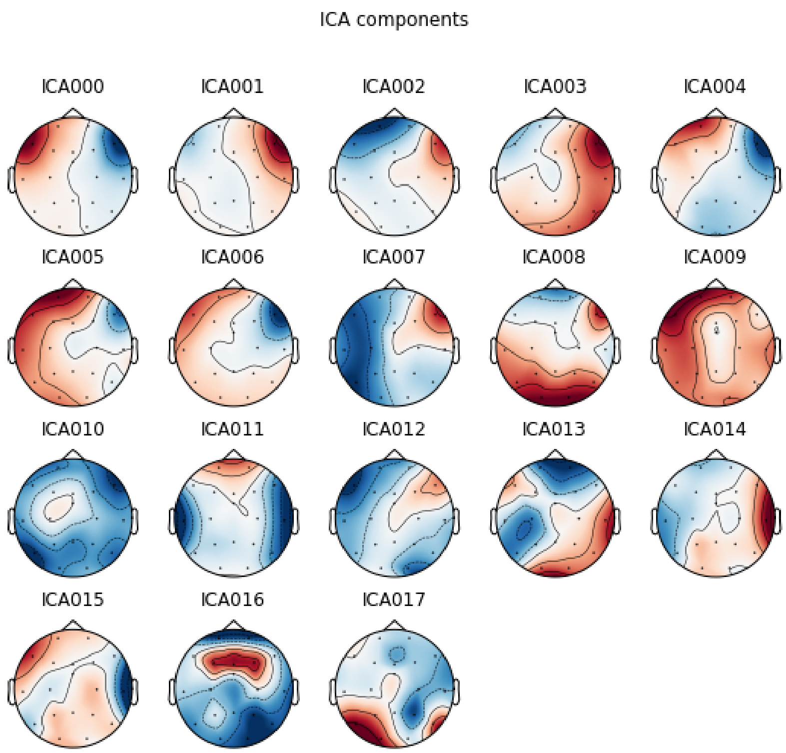


Figure 2: Visualisation of channels after ICA

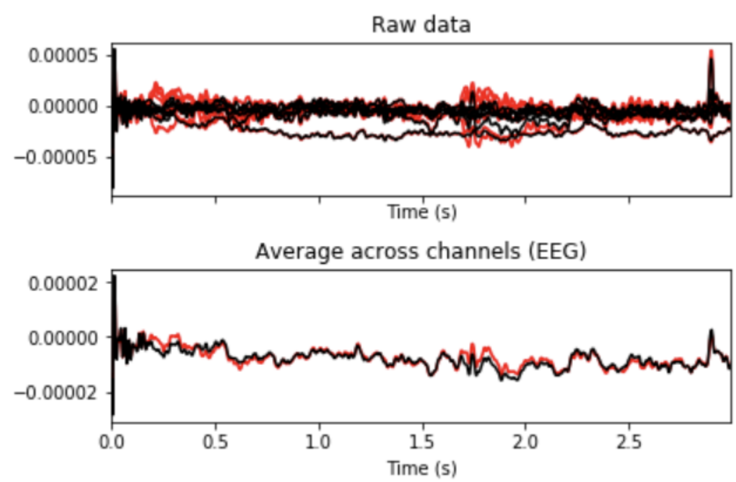


Figure 3: Signals before (red) and after (black) cleaning EOG artifacts using MNE

from raw data. Then we used events data for epoching raw data.

E. Averaged data

The epoched data could be then transformed to evoked data, and this support printing topomaps of interested timestamps as on Figure 5a.

F. Source Estimate

EEG cap used in the current experiment provides whole-head coverage data with accurate electrodes' locations and time courses of the sources. The forward problem is focused on the investigation of the potentials and magnetic fields that result from primary current sources. On the other hand, the inverse problem is to estimate the location of these primary current sources [37]. Processing of

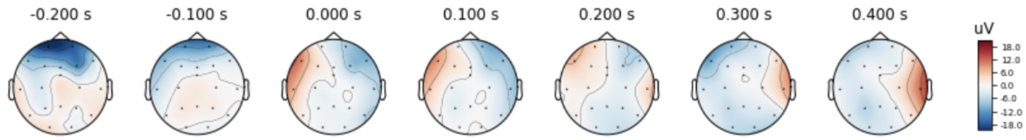
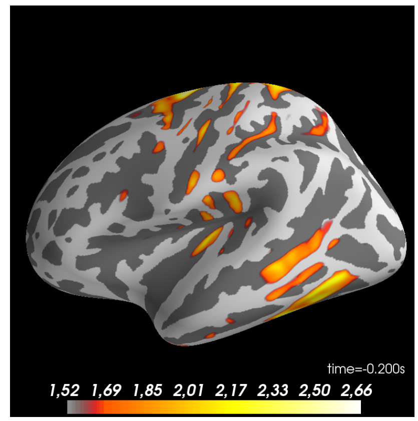


Figure 4: Topomaps of Evoked data

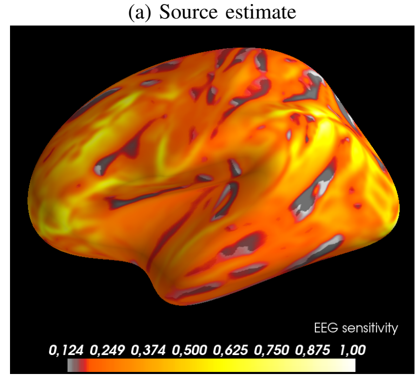
anatomical MRI images implemented in MNE based on the FreeSurfer package [37]. MNE provides an implementation of forward and inverse solutions to reconstruct source from EEG data. The forward solution takes as arguments EEG data, transformation and Boundary element method (BEM) solution surfaces. Transformation (coregistration) is the operation that allows to position the MRI data, the positions of EEG electrodes, and the MEG device data. MRI gives us information about brain structure. We did not use MEG data in computations. The BEM surfaces are the triangulations of the interfaces between different tissues needed for forward computation [18]. Since we do not have fMRI data of our subjects, we used the standard template MRI subject fsaverage. To make inverse solution we used mne.minimum_norm.make_inverse_operator method, which takes raw file info, forward solution and noise-covariance matrix, which could be computed in two ways: auto or using ”empty room” (EEG / MEG cap without a subject) data [18]. Then inverse operator was applied to evoked data and result visualized in 4. The MNE software calculates the inverse operator by computation an SVD of a matrix composed of the noise-covariance matrix, the result of the forward calculation, and the source covariance matrix. This approach has the benefit that the regularization parameter (’SNR’) can be adjusted easily when the final source estimates or dSPMs are computed (Figure 5b).

G. Comparison with information collected with fMRI

Functional magnetic resonance imaging or functional MRI (fMRI) measures brain activity by detecting changes associated with blood flow and provides images using a sampling rate of around one image per second. EEG has a much higher frequency of data collection about a thousand Herz. Thus it allows us to capture a wide range of frequencies and provides more data about brain activations. Also, EEG gives us an opportunity to study the activity of the human brain during various types of activity, while during fMRI, the subject should lie still in the machine. However, preprocessing and analysis of EEG data could be challenging. Except for the functional state of the brain, fMRI provides us with information about its structure, whereas for EEG we have to capture information about brain structure separately using MRI and then connect different types of data together. This task includes various types of activities, such as preprocessing MRI data and solutions of the electromagnetic forward and inverse problems. This way, in the presence of



(a) Source estimate



(b) Visualisation of forward solution

Figure 5: Visualization of on MNE.

MRI and MEG data, EEG can provide a more accurate and detailed picture of brain activity, as it allows to catch a wide range of frequencies, but this requires a high level of data quality and a lot of processing work.

VI. Conclusions

The fMRI provides an accurate model of the activity of the brain, but it is very hard to run experiments using developers because of the physical constraints of such tool, the limit of the frequency of the data acquisition, and its cost. In this paper, we have investigated how we can model the brain activity in a format similar to fMRI using data coming from EEG of software developers during their regular work, removing the constraints mentioned above. We have concentrated our attention to the MNE device. We used the MNE software for preprocessing, analysis and construction of final images.

As a result, MNE allows us to build fMRI-like images of brain activity, like using EEG data, which opens up new possibilities for research. Since the experimental subject should no longer lie motionless in the machine, it is possible to study brain activity in various environments and in different positions of the body. Moreover, the frequency of EEG data capturing is much higher: thousands of hertz versus units using fMRI. Thus we can capture a wide range of frequencies and get more data about brain activations.

Additional advantages of MNE include the presence of a clear workflow, and many training tutorials, examples on the website and precise documentation, which is particularly important for researchers outside medicine, who are not necessarily very familiar with neurological images. Besides, it features interfaces for working with various types of data, many algorithms for use out of the box and averaged examples.

Indeed, additional research is needed to fully understand the suitability of the tool, however, is wide diffusion in the medical area leaves little doubts on the outcome. However, the real goal of the overall research in this area is not on the tool itself, but in using such tool to perform the desired analyses and to create the model of the brain activities with all the corollaries explained before, and, for this purpose, a significant amount of field research is indeed required, which requires probably years if not decades.

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