We propose a fusion approach that combines features from simultaneously recorded electroencephalog-raphic (EEG) and magnetoencephalographic (MEG) signals to improve classification performances in motor imagery-based brain-computer interfaces (BCIs). We applied our approach to a group of 15 healthy subjects and found a significant classification performance enhancement as compared to standard single-modality approaches in the alpha and beta bands. Taken together, our findings demonstrate the advantage of considering multimodal approaches as complementary tools for improving the impact of non-invasive BCIs.

**Keywords:** classifier fusion; EEG; MEG; brain-computer interface; motor imagery.

1. **Introduction**

Non-invasive brain-computer interfaces (BCIs) exploit the ability of subjects to modulate their brain activity through intentional mental effort, such as in motor imagery (MI). BCIs are increasingly used for control and communication and for the treatment of neurological disorders. Despite their societal and clinical impact, many engineering challenges remain, from the optimization of the control features to the identification of the best mental strategy to code the user’s intent. Furthermore, between 15
and 30% of the users are affected by a phenomenon called "BCI illiteracy" which consists in not being able to control properly a BCI even after several training sessions. These challenges critically affect the usability of MI-based BCIs and have motivated, on the one hand, a deeper understanding of mechanisms associated with MI, and on the other hand the research of new features to enhance BCI performance for both healthy subjects and patients.

In the latter case context, promising results have been obtained by integrating EEG spectra with features derived from other types of signals, such as manual control or bodily signals as well as brain activity recorded from functional magnetic resonance imaging (fMRI) or near-infrared spectroscopy (NIRS) as well as brain activity recorded from functional magnetic resonance imaging (fMRI) or near-infrared spectroscopy (NIRS).

Here, we consider magnetoencephalography (MEG), which carries complementary information in terms of source depth sensitivities, but also radially/tangentially oriented dipole detection. While previous studies have demonstrated the feasibility of BCI based on MEG activity, the potential benefit of the combination with EEG signals has been poorly explored. Indeed, such integration might have practical consequences in the light of the recent development of portable MEG sensors, based on optically pumped magnetometers.

To address this gap in knowledge, we considered high-density EEG and MEG signals simultaneously recorded in a group of healthy subjects during a MI-based BCI task. We then propose a matching-score fusion approach to test the ability to improve the classification of motor-imagery associated with BCI performance.

2. Materials and Methods

2.1. Simultaneous E/MEG recordings

Fifteen healthy subjects (aged 28.13 ± 4.10 years, 7 women), all right-handed, participated in the study. None presented with medical or psychological disorders. According to the declaration of Helsinki, written informed consent was obtained from subjects after explanation of the study, which was approved by the by ethical committee CPP-IDF-VI of Paris. All participants received financial compensation at the end of their participation. MEG and EEG data were simultaneously recorded with, respectively, an Elekt Neuromag TRIUX® machine (which includes 204 planar gradiometers and 102 magnetometers) and with a 74-channel system (referenced to mastoid signals, with the ground electrode located at the left scapula, and impedances kept lower than 20 kOhms). Recordings were performed in a magnetically shielded room with a sample frequency of 1 kHz and a bandwidth of [0.01 - 300] Hz. We carried out BCI sessions with EEG signals transmitted to the BCI2000 toolbox via the Fieldtrip buffer.

2.2. BCI protocol

We used the one-dimensional, two-target, right-justified box task where subjects had to perform a sustained MI (grasping) of the right hand to hit up-targets, while remaining at rest to hit down-targets. Each run consisted of 32 trials with up and down targets equally and randomly distributed across trials. The experiment was divided into two phases:

(i) Training: The training phase consisted of five consecutive runs without any feedback. For a given trial, the first second corresponded to the inter-stimulus interval (ISI), while the target was presented during the subsequent five seconds.

(ii) Testing: The testing phase consisted of six runs with cursor feedback. For a given trial, the first second corresponded to the ISI, while the target was presented during the subsequent five seconds (i.e., two seconds for target presentation and three seconds for feedback).

2.3. Features extraction

We considered both EEG and MEG activity, the latter consisting of magnetometer (MAG) and gradiometer (GRAD) signals. All signals were first downsampled to 250 Hz and segmented into epochs of five seconds corresponding to the target period. To simulate online scenarios, no artifact removal method was applied. Expert bioengineers visually inspected the recorded traces to ensure that no major artifacts were present. We then computed for each channel the power spectra between 4 and 40 Hz, with a 1 Hz frequency resolution, for both MI and rest epochs. To this end, we used a multi-taper frequency transformation based on discrete prolate spheroidal sequences (Slepian sequences) considered as tapers through the use of the Fieldtrip toolbox.
± 0.5 Hz spectral smoothing through multi-tapering was applied. For each modality, the feature space was finally given by the power of the signal across channels and frequency bins.

2.4. Classification and fusion

We adopted a semi-automatic procedure to extract the relevant features in the training phase. First, we restricted our focus to the channels in the motor area contralateral to the movement (see Appendix A.1). Second, we statistically compared the power spectra of the MI epochs versus the resting epochs for each frequency bin within the standard bands: theta (4-7 Hz), alpha (8-13 Hz), beta (14-29 Hz) and gamma (30-40 Hz). To this end, we performed a non-parametric cluster-based permutation t-test, with a statistical threshold of $p < 0.05$, false-discovery rate corrected, and 500 permutations. Finally, for each modality, we retained the ten most significant features for the testing phase. Given their relatively small number, we used a five-fold cross-validation in a linear discriminant analysis-based (LDA) classification. LDAs are particularly suited for two-class MI-based BCIs.

44 To assess the classifier performance, we measured the area under the curve (AUC). To integrate the information from different modalities we used a Bayesian fusion approach based on the weighted average method. To assess the classifier performance, we measured the area under the curve (AUC). To integrate the information from different modalities we used a Bayesian fusion approach based on the weighted average method. Similar to what has been proposed for hybrid-BCI systems, we linearly combined the posterior probabilities obtained from the classification of each modality $i = \text{EEG, MAG, GRAD}$ weighted by a parameter $\lambda_i = p_i / p_{\text{tot}}$, where $p_{\text{tot}}$ is the sum of the posterior probabilities from all the modalities (see Figure 1).

2.5. Statistical analysis

We evaluated our fusion approach with respect to the results obtained in each single modality separately (EEG, MAG, GRAD). In addition, we tested the effect of including an increasing number of most significant features. To statistically compare the results, we input the corresponding AUC values into a nonparametric permutation-based ANOVA with two factors: modality (EEG, MAG, GRAD, Fusion) and features ($N_f = 1, 2, ..., 10$). A statistical threshold of $p < 0.05$ and 5000 permutations were fixed. We finally used a Tukey-Kramer method to perform a post-hoc analysis with a statistical threshold of $p < 0.05$.

3. Results

Figure 2 shows the grand-average time-frequency representation of the event-related de/synchronization (ERD/S) for the MI in the testing phase. In all modalities, we reported significant changes for the alpha (ERD around -100 %) and beta band (ERD around -60 %). ERDs started to appear just after the target appearance ($t = 1 \text{s}$) and became stronger during the feedback period ($t = 3-6 \text{s}$). Notably, ERDs tended to appear early in the MEG signals as compared to the EEG signals. Figure 3 illustrates the candidate features that were selected through the semi-automatic procedure for each modality in the training phase. Features obtained from MEG signals tended to be more focused both in space (around the primary motor areas of the hand) and in frequency (mostly in the alpha band). This finding was in line with the fact that lower ERDs were observed in the beta band (see Figure 2).

Fusion improves classification performance

In all frequency bands, the type of modality significantly affected the AUC values (ANOVA, $p < 10^{-3}$), whereas the number of features did not have a significant impact ($p > 0.05$). The AUC values obtained with the fusion approach were significantly higher than those obtained with any other modality (Tukey-Kramer post-hoc, $p < 0.016$), except for theta and gamma bands for which we did not observe significant improvements with respect to EEG. The highest classification performance was obtained in the alpha band (Figure 4), for which we also reported a significant interaction effect between modality and number of features (ANOVA, $p = 0.0069$). In this case, the AUC values with the fusion were significantly higher than those obtained with EEG, MAG, or GRAD separately (Tukey-Kramer post-hoc, $p = 4.3 \times 10^{-9}$, $3.9 \times 10^{-7}$, and $0.012$).

To evaluate the classification performance in every subject, we considered for each modality the optimal number of features and the optimal frequency band (between alpha and beta) associated with the highest AUC. Results showed that in thirteen subjects, the fusion led to a better performance as compared to single modalities, with AUC values ranging from...
0.55 to 0.85, and relative increments ranging from 1.3 % to 50.9 % (with an average of 12.8 ± 6.0 %). In only three subjects, the fusion gave equivalent performance (see Table 1). Notably, the contribution of the different modalities to the fusion's performance was highly variable across subjects, as illustrated by the parameters measured from the respective posterior probabilities (see Figure 5).

4. Discussion and Conclusion

Improving performance remains one of the most challenging issues of non-invasive BCI systems. High performance would allow effective control and feedback to the subject that is crucial to establish an optimal interaction user-machine. BCI performance depends on several human and technological factors, including the ability of subjects to generate distinguishable brain features, as well as the robustness of signal processing and classification algorithms.

Here, we focused on a complementary angle aiming to integrate information from different neuroimaging modalities. To that end, we recorded simultaneous EEG and MEG signals in a group of healthy subjects performing a motor imagery-based BCI task. Both EEG and MEG exhibit a high temporal resolution and the sensory motor-related changes are well known in the literature, as is their utility in standard BCI applications.

Results show that independently from the modality and the number of features, the best AUCs were obtained in alpha and (in a more limited way) beta bands, which is consistent with motor imagery's being associated with oscillations in the alpha and beta band. The proposed fusion approach showed that combining the most significant features in each modality led, in a large majority of subjects, to a reduction in the subjects' mental state misclassifications (see Table 1). By optimizing the choice of the features (channels and frequency band) in each individual, we obtained an average classification improvement of 12.8 % as compared to separate EEG, MAG and GRAD classifiers (Table 1), suggesting a viable alternative to reduce the illiteracy phenomenon in non-invasive BCIs.

The core of our approach consisted in weighting automatically the contribution of each modality in an effort to optimize performance. This is an important aspect as the discriminant power of features can indeed change over time depending on many factors, such as impedance fluctuations or the presence of artifacts. Because these changes are also subject-dependent, our approach allowed us to flexibly optimize the feature contribution and to personalize the classifier to compensate for potential misclassifications in one modality. While the average performance values that we reported were relatively low (see Table 1), it is important to mention that subjects were BCI-naïve and that no preprocessing was applied, with the goal of simulating real-life scenarios. What we would like to highlight is that instead, thirteen of our fifteen subjects presented an improvement of their performance with the classifier fusion. Taken together, these results prove the potential advantage of using simultaneous E/MEG signals to enhance BCI performance. By using a rather simple classifier (LDA), we could include in the classification a reduced number of specific features involved in the motor-related neural mechanisms such as ERD in alpha and beta bands.

More sophisticated approaches using the whole feature space, such as support vector machines and Riemannian geometry, as well as alternative fusion strategies, such as boosting, voting, or stacking strategies, but also classification in source space to improve spatial resolution, can be further evaluated to exploit their power in practical applications. Even if current MEG devices are not portable, recent efforts to miniaturize MEG sensors will probably offer practical solutions for the integration of multimodal features. We therefore suggest that the development of E/MEG-based BCIs may turn out to be an effective approach to further enhance performance.

5. Acknowledgements

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Figures and Tables

Figure 1. Classifier fusion approach for a given frequency bin. The variables $p_i$ and $\lambda_i$ stand for the posterior probability and the weight parameter associated with the modality $i$, respectively.
Figure 2. Grand-average time-frequency maps of ERD/S. Dashed lines mark the start of the target presentation and the feedback periods (top panels). We computed ERD/S maps by comparing the target period with a baseline of 1 s before the target presentation. Here, \[ \text{ERD/S} = 100 \times \frac{x_{\text{MI}} - \mu_{\text{baseline}}}{\mu_{\text{baseline}}} \], where \( x_{\text{MI}} \) corresponds to the data to normalize and \( \mu_{\text{baseline}} \) to the mean over the baseline. The time-frequency estimation was computed from Morlet wavelets between 4 and 40 Hz, with a central frequency of 1 Hz associated with a time resolution of 3 s via the Brainstorm toolbox.}

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Figure 3. Spatial and frequency distribution of the features selected for classification in each modality. On the left side, the size of the circles is proportional to the number of subjects exhibiting that specific sensor as the best feature. The color identifies the frequency band of interest (blue = alpha, red = beta). On the right, the histograms detail the occurrences in every frequency bin for the sensor that was most frequently selected.
Figure 4. AUC distributions across the 15 subjects, for different modalities (EEG, MAG, GRAD, Fusion) and for different number of features $N_f$ in the alpha band. White discs represent the associated median values.
Figure 5. Contribution of different modalities to the individual performance obtained with the fusion approach.

Table 1. Individual performances overview across modalities. SD = standard deviation and Avg = average. In bold, the best AUC obtained for a given subject.

|      | S01 | S02 | S03 | S04 | S05 | S06 | S07 | S08 | S09 | S10 | S11 | S12 | S13 | S14 | S15 | Avg | SD |
|------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| Band | alpha | alpha | beta | alpha | alpha | alpha | beta | alpha | alpha | alpha | alpha | alpha | alpha | alpha | alpha | beta | beta | beta | beta | beta | X | X |
| EEG  | 0.53 | 0.55 | 0.48 | 0.56 | 0.57 | 0.55 | 0.57 | 0.60 | 0.53 | 0.55 | 0.70 | 0.73 | 0.60 | 0.58 | 0.71 | 0.58 | 0.09 |     |     |
| MAG  | 0.47 | 0.48 | 0.53 | 0.51 | 0.50 | 0.55 | 0.52 | 0.62 | 0.58 | 0.69 | 0.64 | 0.71 | 0.71 | 0.61 | 0.10 |     |     |
| GRAD | 0.54 | 0.50 | 0.55 | 0.50 | 0.54 | 0.55 | 0.49 | 0.65 | 0.63 | 0.72 | 0.62 | 0.71 | 0.72 | 0.85 |     |     |
| Fusion | 0.55 | 0.55 | 0.56 | 0.57 | 0.58 | 0.59 | 0.57 | 0.67 | 0.66 | 0.80 | 0.77 | 0.76 | 0.79 | 0.85 | 0.66 |     |     |

*In bold, the best AUC obtained for a given subject.*
Appendix A

Figure A.1. Pre-selected EEG and MEG sensors (left motor area)