Human-Machine Interaction: EEG Electrode and Feature Selection Exploiting Evolutionary Algorithms in Motor Imagery Tasks

Aurora Saibene

Multi Media Signal Processing Laboratory
Department of Informatics, Systems and Communications
University of Milano-Bicocca
Milan, Italy
Email: a.saibene2@campus.unimib.it

Francesca Gasparini

Multi Media Signal Processing Laboratory
Department of Informatics, Systems and Communications
University of Milano-Bicocca
Milan, Italy
Email: francesca.gasparini@unimib.it

Abstract—**Brain Computer Interfaces (BCIs) based on the recording of electroencephalographic signals have revolutionized the human-machine interaction. Being in presence of heterogeneous electrophysiological data, that come with a low number of instances and a great number of features, it is necessary to find a solution that can achieve good performances with respect to all the subjects, having as input a restricted feature subset. Firstly, we propose a population-based approach that allows to mitigate the data heterogeneity. Secondly, not wanting to make assumptions on the feature types, we propose the application of genetic algorithm, particle swarm optimization and simulated annealing as evolutionary feature selection techniques. We present the results of our proposal on a motor movement/imagery experiment. From these results, we verified that each feature type contributes differently depending on the task and on the sensor it was computed on, thus giving a broader view of the different type of analyses that can be performed to allow a better interaction between a user-centric system like a BCI based on motor imagery and its human user.**

Keywords–Brain Computer Interface; Electroencephalography; Evolutionary Feature Selection.

I. Introduction

The combination of Brain Computer Interfaces (BCIs) and Electroencephalography (EEG) has allowed the development of a plethora of applications directly based on the translation of human brain responses into machine understandable instructions. These responses are usually due to natural neurological processes or elicited by external stimuli and interactions and can be easily recorded in a non-invasive way by placing electrodes (sensors) on a volunteer's scalp.

Each electrode returns an electroencephalographic signal of a peculiar brain area, deputed to specific brain activities and functions [1]. Thus, the EEG signal representing the responses has a spatial connotation in addition to its temporal resolution. It is also characterized by different frequency bands [2], each of which is associated to a peculiar set of brain states, summarized in Table I.

Moreover, the EEG signal is easily affected by noise and is heterogeneous, having variations inter-volunteers, but also intra-volunteer. In fact, depending on the volunteer's physiological and psychological conditions, on external factors like the environmental temperature or on the type of recording that is performed (e.g., clinical analysis, experimental setting and so on) the EEG signal could drastically change.

The described characteristics must be taken into account when the recorded EEG signals are used as inputs to a BCI, which provides a user-centric system able to recognize the brain activity patterns coming from the EEG signals and consequently allows a human-machine interaction [3], following two steps [4]: (1) offline training for system calibration and (2) online translation of brain responses.

One of the most widely studied BCI applications is based on Motor Imagery (MI), i.e., the imagination of movement, mainly for rehabilitation purposes: from moving a prosthetic arm to controlling a wheelchair. Focusing on left/right-handed MI tasks, it has been proved that the brain activation coming from the imagination of the left/right hand movement mimics the one necessary to perform a real movement of the left/right hand. This activation involves a specific brain area, called motor cortex, which in a modified 10/10 electrode configuration is covered by the sensors highlighted (light-blue) in Figure 1 [5]. However, most of the literature works reduces the analyses on the electrodes enclosed by the red line (Figure 1), being this choice bounded to experimental design or made a priori. The sensors placed on the right hemisphere records the motor left-handed movement/imagination, while on the left, the motor right-handed movement/imagination.

Notice that mainly two frequency bands are involved during a motor imagery task [6]: the power spectrum in the α band (also called μ band when observed in the motor cortex) decreases, while in the β band increases.

Having this field knowledge in mind, the aim of the various researches conducted on this topic is to discriminate the left/right-handed MI tasks in order to have reliable and efficient brain computer interface systems. Different classification techniques have been applied to the electroencephalographic signals [4] and recently deep learning models [7] [8] have been developed to move from hand-crafted features, i.e., custom computed signal characteristics, to learned features.

Most of the state-of-the-art works dealing with standard classification techniques (e.g., support vector machines, neural networks and so on), have mainly concentrated their efforts in refining the classification performances. They also compute hand-crafted features limited to the previously described field knowledge. Moreover, the computed features usually take into account only a subset of the various combinations that could be made, especially using the spatial information, power spectra on the frequency bands of interest or some statistical measures.

Having a limited amount of instances per task, the proposed approaches could be considered a good compromise to maintain a low computational complexity while obtaining good accuracy values without incurring in the overfitting and curse-of-dimensionality issues.

TABLE I. FREQUENCY BAND BRAIN ACTIVITY ASSOCIATION [2].

Name	*Range (Hz)*	*Association*
δ	0.5 - 4	present during sleep
θ	4 - 7	present during sleep
α	8 - 13	present in a relaxed state while awake
β	13 - 30	present in a focused/alert state
γ	30 - $<$ 100	present during insight/problem solving phenomena

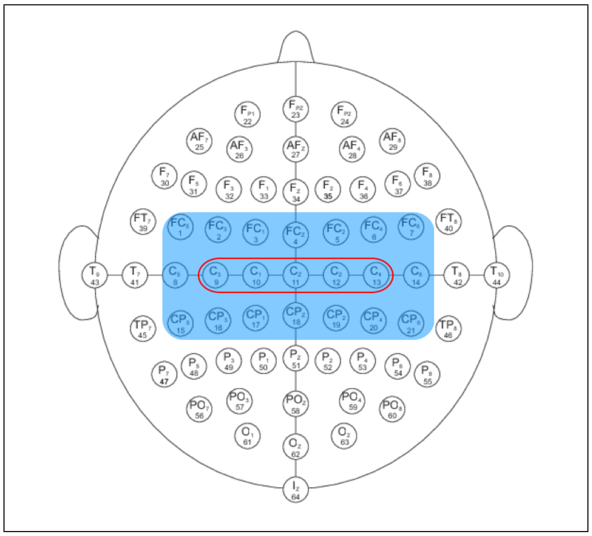

Figure 1. Electrodes covering the motor cortex brain area.

However, some information that could have an impact on the interpretation of the recorded brain responses could be ignored and the various contribution of different electrodes and feature types being lost.

A solution to this loss of information could be the computation of different feature types and a subsequent feature selection, unbiased by a priori knowledge.

Therefore, in our work we compute heterogeneous features on the signal obtained by each available electrode and a set of Evolutionary Feature Selection (EFS) methods, based on Genetic Algorithm (GA), Particle Swarm Optimization (PSO) and Simulated Annealing (SA). We compare the performances obtained by applying different Support Vector Machines (SVMs) models on the resulting subset of features against the classical a priori selection and Principal Component Analysis (PCA) computation.

Our aim is to provide a benchmark that will highlight the contribution given by the spatial (i.e., electrode) and feature type information and that will be exploited for the future development of more complex and possibly efficient classification models for a better interaction between a MI-based BCI and its human user.

To this hand our contributions can be summarized as follows:

1) analysis of the motor left/right hand movement/imagination tasks with a population-based approach instead of limiting the analysis on a single-subject;
2) consider a combination of heterogeneous features in the time, frequency and time-frequency domains, through statistical measures, not wanting to be limited by the field knowledge;
3) apply different feature selection techniques in order to verify the efficacy of methods that do not make assumptions on the features, passing from a priori knowledge selection and extracting dimensions with PCA, to the original application of EFS algorithms;
4) original analyses on the agreement between the EFS resulting feature subset, considering both the electrode and feature type contributions.

The rest of the contribution is organized as follows. Section II provides the background information on the state-of-the-art and the exploited characteristics of EFS algorithms. Also, the used dataset is described. In Section III, we provide a detailed explanation of the proposed approach, while in Section IV, we discuss the obtained results from different tests. Section V concludes the paper highlighting our contributions, some notes on the obtained results and the future work.

II. BACKGROUND

The core of our proposal is the feature selection performed by evolutionary computation algorithms. This process consists in the search of a relevant subset of features with a multi-objective approach: find the minimum number of features needed to obtain the maximum classification accuracy.

Generally, an evolutionary feature selection method starts with the initialization of its parameters and a random selection of the features. Afterwards, the feature subset search and the evaluation of its quality are performed until a stopping criterion is met. The evaluation step, represented by the fitness function, could follow different approaches [9], i.e., the wrapper and filter approaches. In particular, we use a wrapper approach [10], which includes a classification algorithm for the evaluation of the feature subset. Therefore, we discarded the filter approach, which ignores the classification performance, being it not suitable for our purpose. As a final step, the obtained results are validated.

The EFS algorithms are appealing due to the fact that they do not require field knowledge and can return different solutions in a single execution, without making any assumption on the features [11].

We exploit these advantages in an offline configuration knowing that these techniques have as major drawbacks the high computational complexity and cost. Moreover, there could be a stability issue due to the random nature of the processes [11], which we mitigate by investigating the agreement between the applied EFS algorithms on the selected features.

To our knowledge, we are the first to apply three different EFS techniques, i.e., genetic algorithm, particle swarm optimization and simulated annealing, and analyze their agreement on the selected features considering both the electrode and feature type contributions.

In fact, some works have proposed the usage of evolutionary computation for feature selection in the context of BCIs, focusing their attention on one aspect and technique at a time. Also, the concept of feature subset is mostly considered as an electrode set reduction.

On this topic, *Atyabi et al.* [12] propose the separate usage of GA, PSO and random search to find the best electrode locations that guarantee the maximum classification accuracy using a sigmoid extreme learning machine. *Amarasinghe et al.* [13] also apply the GA technique on their BCI data for robot control to obtain the best classification accuracy from a support vector machine by selecting the minimum number of electrodes. Instead, *Gonzalez et al.* [14] apply the NSGA-II optimization technique and change the fitness function using a combination of Kappa index and error distribution. They also propose a feature ranking procedure to address the stability issue, but they make an a priori choice on the sensors set.

Even though these researches have relevance in the field of EFS, the authors test their techniques with a subject-based approach and with a small amount of instances per class. Here, we propose a population-based approach to assess the possibility of having a generalized procedure, that we can apply on a greater number of instances and subsequently use to make some assumptions when analyzing the data coming from a new single volunteer.

To this hand, we test our methods on the PhysioNet *EEG Motor Movement/Imagery Dataset* (https://physionet.org/content/eegmmidb/1.0.0/) [15] [16] dealing with it in three different ways: Non-Normalizing the Data (NN-DS), performing a Min-Max score normalization (MM-DS) and applying the Z-Score normalization (ZS-DS).

In this dataset are collected the EEG recordings of 109 subjects, who performed an experiment consisting of real and imagined movements of hands and feet. We focus our attention on the motor movement/imagery tasks of the left/right hand. The signal was recorded from the electrodes presented in Figure 1, with a sampling rate of 160 Hz. We reorganized the data, obtaining 4924 instances (2469 for the left hand) for the Motor Movement Task (MM-T) and 4915 (2479 for the left hand) for the Motor Imagery Task (MI-T).

III. Proposed Approach

The proposed pipeline (Figure 2) is divided in three main modules: feature computation, feature selection and classification through different support vector machine models.

All the data that are passed to the first module have been pre-processed with a notch filter (50 Hz) to remove the direct current interference and with a finite impulse response filter in the range 7 - 31 Hz. In this specific case, we used the field knowledge to retain only the frequency bands of interest (μ and β), trying to have as less noise as possible without applying other noise removal techniques.

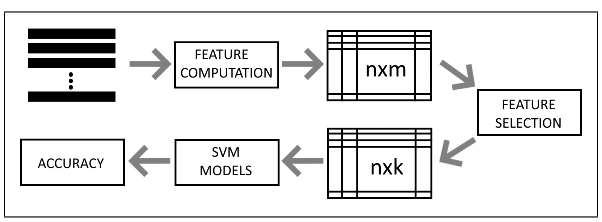

Figure 2. Proposed pipeline scheme.

Different tests are conducted on the considered PhysioNet dataset with the previously cited configurations: NN-DS, MM-DS, ZS-DS.

In the following, we describe the main modules in more details.

A. Feature Computation

Our proposal includes features computed on each electrode in the time, frequency and time-frequency domains and also some statistical measures, in order to access the contributions given by different type of analyses. All the procedures are developed in MATLAB.

The Hjorth activity, mobility and complexity parameters [17] represent respectively the EEG signal power, the proportion of power spectrum standard deviation and the signal similarity to a sine wave [18]. Thus, they characterize the EEG signal in the time domain and they also have low computational cost. We developed the parameters following the formulae reported by *Oh et al.* [18].

Wanting to also have a representation of the data in the frequency and time-frequency domains, we estimate the power spectral density (PSD) using the Welch's method [19] and the complex Morlet wavelet [20] on the previously cited frequency bands of interest, i.e., μ and β. The Welch's method divides the signal into windows on which are computed the periodograms. Their average represents the PSD estimation. Instead, the complex Morlet wavelet is convolved with the EEG signal, obtaining the data power and phase. The idea underlying the development proposed by *Cohen* [20] is about being able to control the trade-off between time and frequency precision with the *cycle* parameter; thus, we exploit this characteristic and perform the feature computation with a better time-precision (3 cycles), a better frequency precision (7 cycles) and a trade-off between the two modalities (3 - 7 cycles).

Finally, we use the function provided by the MATLAB tool EEGLAB [21] to compute the mean, standard deviation, skewness, excess kurtosis, median, low/high percentile and trimmed mean/standard deviation on the signal obtained from each electrode.

As a final result, we obtain a vector of 1280 features: 64 electrodes $\times$ [2 frequency bands $\times$ (PSD estimate through Welch's method + 3 modalities $\times$ PSD extraction through Morlet wavelets) + statistical measures].

B. Feature Selection

As described in the previous sections, the evolutionary computation algorithms applied for feature selection have the advantage of being decoupled from the field knowledge and do not make any assumption on the features.

The developed EFS techniques are the genetic algorithm, particle swarm optimization and simulated annealing. They are Python coded and while the first two are modified versions of pre-existing codes, we developed the SA procedure following the pseudo-code provided by *Jeong et al.* [22]. Also, notice that we update the PSO velocity and position at each iteration exploiting the cognitive, social and inertia parameters presented by *Clerc et al.* [23]. All the parameters, reported in Table II, are empirically adapted to the presented problem, starting from the default values.

The EFS algorithms follow a wrapper approach, thus a SVM classification with radial basis kernel [24] and gamma scaled to $1/(N_{features} * variance(data))$ is applied on the dataset divided in training (80%) and test (20%) set. Moreover, we developed two different fitness functions for the evaluation step. The first one takes into consideration only the accuracy obtained by applying a SVM as the classifier, while the second one is meant to find the best trade-off between the number of

TABLE II. EVOLUTIONARY FEATURE SELECTION ALGORITHM PARAMETERS AND CONSTRUCTION COEFFICIENTS [23].

Algorithm	*Parameters and construction coefficients*
GA	iterations = 100; population size = 8; # parents = 4; # mutations = 3
PSO	construction coefficients: kappa = 1; $\phi_1 = \phi_2$ = 2.05; $\phi = \phi_1 + \phi 2$; $\chi = 2 \times \frac{kappa}{\lvert 2-\phi-\sqrt{\phi^2-4\phi}\rvert}$ parameters: iterations = 100; # particles = 30; # neighbors = 5; cognitive = $\chi \times \phi_1$; social = $\chi \times \phi_2$; inertia = χ; euclidean distance = 2
SA	initial temperature = 100000; temperature reduction = 0.9

selected features and the SVM accuracy, following the function presented by *Vieira et al.* [25]:

$$f(x) = \alpha(1 - acc) + (1 - \alpha)\left(1 - \frac{N_{sf}}{N_{if}}\right) \tag{1}$$

where $\alpha \in [0, 1]$ is a constant weighting the feature number/accuracy trade-off and is set to 0.88 after verifying that with lower/higher values, α does not provide better results; acc is the accuracy obtained by the SVM model; N_{sf} corresponds to the number of selected features, while N_{if} corresponds to the initial number of features.

The final result obtained by the EFS algorithms is a binary vector $1 \times N_{if}$, where 1s represent the selected features, 0s otherwise.

C. SVM Classifiers

The last main module is the one that performs the binary classification of left/right hand motor movement/imagination by applying the SVM models (Linear, Quadratic, Cubic, Fine/Medium/Coarse Gaussian) provided by the Classification Learner MATLAB application [26]. The SVMs are trained using a 5-fold cross-validation.

We use as benchmarks the models performed on the dataset retaining (1) all the computed features, (2) the feature subset selected a priori, consisting of the feature computed on the electrodes *C5, C3, Cz, C2, C4* (highlighted by the red line in Figure 1) and (3) the dimensions explaining at least the 95% of the data variance obtained by the principal component analysis, a standard procedure to reduce the feature number.

Afterwards, we apply the SVM models on the datasets obtained by the EFS techniques and using the feature subset representing the agreement between the evolutionary computation algorithms.

Finally, we compute the accuracy obtained by the various models.

IV. DISCUSSION

Following the previously described pipeline, we conducted 11 tests, whose best results are summarized in Table III and in Table IV. The benchmark corresponds to the first three entries of the tables, while the tests on the proposed EFS methods are reported in the remaining rows.

The benchmark consists of the results obtained by applying the Classification Learner SVM models to all the dataset types, i.e., non-normalized (NN-DS), min-max score (MM-DS) and z-score (ZS-DS) normalized.

Notice that the best result achieved by the benchmark (67.8% of accuracy) for the motor left/right hand movement task (from now on called MM-T) is obtained by the cubic SVM on the ZS-DS retaining all the computed features. The dataset consisting of the features selected a priori and of the dimension extracted by the PCA do not have comparable results.

Comparable accuracy values are achieved by some of the evolutionary feature selection models, which are computed only on the normalized dataset, noticing that the best results achieved by the benchmark tests are on ZS-DS and MM-DS. In particular, the GA and SA algorithms obtained the same result as the best benchmark test using as fitness function the trade-off between the feature number and accuracy value, while the PSO using the trade-off function exceeds the best result with the 68.0% of accuracy. Even though the SA with the only accuracy fitness function achieves the best result (68.3%) on MM-T, we highlight the fact that the technique retains 1117 of the 1280 total features. Thus, we consider the SA result not fitting our purpose, i.e., having a minimum feature subset that can guarantee a comparable/better accuracy on the original dataset. Therefore, we elect the GA and PSO with the trade-off function as the best methods.

As a final remark on MM-T, we highlight that the results obtained by the SVM models applied on the feature subset generated by the EFS algorithms approach the best accuracy values returned by the previous tests. Also, notice that the ZS-DS is the most present dataset in Table III, suggesting that in a population-based analysis a z-score normalization seems to be the best approach.

Concerning the motor left/right hand imagination task (from now on called MI-T), surprisingly the best accuracy (64.3%) is obtained by the linear SVM on the NN-DS retaining all the computed features. The observations on the a priori feature selection and PCA tests for MI-T are the same reported for the MM-T.

A comparable result is achieved by PSO with the trade-off function (64.0% of accuracy), which selects 714 of the 1280 features on the ZS-DS. On the feature agreement, the quadratic SVM model obtains 63.3% of accuracy when applied on the ZS-DS with the trade-off fitness function. The z-score normalization seems to be confirmed as the best approach in a population-based analysis.

A possible reason behind the decrease in all the accuracy values on MI-T compared with MM-T, is represented by the inability of accessing if the subject performed correctly the imagination of the left/right hand movement, thus causing an uncontrolled introduction of outliers.

However, notice that there are numerous similarities in the results obtained on both tasks. Focusing on the benchmark, the a priori feature selection and the PCA dimensions are unable to provide an accuracy comparable to the result

TABLE III. BEST RESULTS OBTAINED IN EACH TEST ON MOTOR LEFT/RIGHT HAND MOVEMENT (MM-T).

Test	*SVM model*	*Dataset*	*# features*	*Accuracy (%)*
all features	cubic	ZS-DS	1280	67.8
a priori	mean Gaussian	ZS-DS	100	62.7
PCA	quadratic	MM-DS	43	62.3
GA accuracy	cubic	ZS-DS	662	67.2
GA trade-off	cubic	ZS-DS	646	67.8
PSO accuracy	cubic	ZS-DS	620	67.3
PSO trade-off	quadratic	ZS-DS	675	68.0
SA accuracy	cubic	ZS-DS	1117	68.3
SA trade-off	cubic	ZS-DS	1116	67.8
agreement accuracy	quadratic	ZS-DS	264	66.4
agreement trade-off	cubic	ZS-DS	308	67.5

TABLE IV. BEST RESULTS OBTAINED IN EACH TEST ON MOTOR LEFT/RIGHT HAND IMAGINATION (MI-T).

Test	*SVM model*	*Dataset*	*# features*	*Accuracy (%)*
all features	linear	NN-DS	1280	64.3
a priori	linear	ZS-DS	100	59.7
PCA	quadratic	MM-DS	41	59.5
GA accuracy	cubic	ZS-DS	641	63.8
GA trade-off	quadratic	ZS-DS	608	63.7
PSO accuracy	cubic	MM-DS	622	61.7
PSO trade-off	quadratic	ZS-DS	714	64.0
SA accuracy	cubic	ZS-DS	1114	63.6
SA trade-off	cubic	ZS-DS	1117	63.8
agreement accuracy	cubic	ZS-DS	272	62.4
agreement trade-off	quadratic	ZS-DS	313	63.3

obtained by the test retaining all the features. Moving to the proposed EFS techniques, observe that: (1) the various models generally achieve the best accuracy on the ZS-DS; (2) the activation function exploiting the trade-off between the number of selected features and the accuracy, allows the EFS methods to achieve a better accuracy compared to the accuracy-only activation function; (3) the best methods are GA and PSO, which maintain good performances with a restricted feature subset; (4) the SA technique retains about the 87% of the original features on average, thus not representing a good solution for the feature minimization and accuracy maximization problem.

Having a general description of the best results, we now focus our attention on the EFS agreement; in particular on the feature subset selected through the trade-off fitness function.

Figure 3 and Figure 4 report the number of features selected for each electrode on MM-T and MI-T respectively. Table V summarizes how frequently a specific feature type is selected in the EFS feature selection agreement on the motor left/right hand movement/imagination tasks.

Observe that the set of electrodes that are usually selected a priori (*C5, C3, Cz, C2, C4*) contribute minimally to the classification in both tasks. Their contribution is also not symmetrical, i.e., if one of these electrodes is selected in the left hemisphere of the brain, most probably the corresponding one in the right hemisphere is not selected. This could actually be an optimal configuration, knowing that each of these electrodes is at least coupled with a feature in the time-frequency domain. As stated in the introduction, we know that the power spectrum decreases on the μ band, while it increases in the β band when dealing with a motor related task and also it has a spatial connotation depending on the fact that the movement/imagination is intended for the left/right hand.

Concerning the other electrodes related to the motor cortex (light-blue highlighted in Figure 1), the number of contributions is greater for MI-T than for MM-T, which reports some specifically localized contributions.

The frontal (*Fp, AF, F*) sensors are involved in the motor tasks, probably due to the experimental settings. In fact, a subject had to perform the motor left/right hand movement/imagination following a visual cue, thus involving the specific brain area coupled with the previously cited electrodes.

The parietal (*P*) sensors make some contributions, especially with the statistical features. This brain area is deputed to sensory information and thus could be involved in the motor tasks.

Finally, the temporal, parieto-occipital and occipital (*T, PO, O*) electrodes give some information, mostly through Hjorth parameters and statistical measures. This could be due to their brain area activities concerning memory and visual processing.

We finally report the selection frequency of the various feature types (Table V).

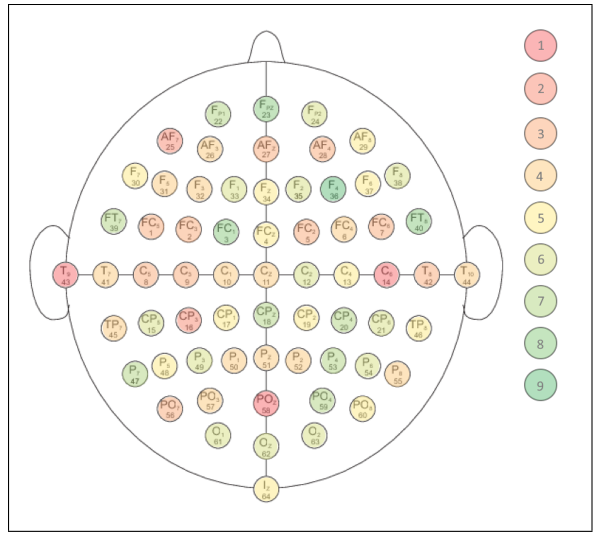

Figure 3. Agreement electrode contributions for the motor left/right hand movement (MM-T) task.

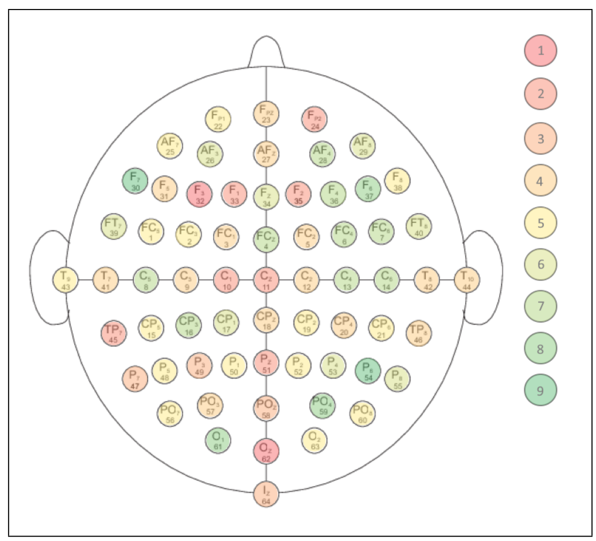

Figure 4. Agreement electrode contributions for the motor left/right hand imagination (MI-T) task.

In MM-T there is a balanced selection of the features involving the information in the frequency domain. Between the Morlet wavelet related features, the most selected is the power spectral density extracted using this technique on the μ band with a time-frequency trade-off. There is also a good balance in the same type of features selected for MI-T.

The Hjorth parameters have a big impact especially for MI-T, where the activity parameter appears 27 times and thus with the highest frequency in respect to the other feature types.

The standard deviation and median features give a great contribution especially for MM-T.

The rest of the feature types are balanced for both tasks.

TABLE V. FREQUENCY OF FEATURE TYPE SELECTION FOR MM-T AND MI-T.

Feature type	*Frequency on MM-T*	*Frequency on MI-T*
Hjorth activity	13	27
Hjorth mobility	13	14
Hjorth complexity	15	8
PSD Welch on μ	17	17
PSD Welch on β	14	12
PSD Morlet time-prec on μ	13	11
PSD Morlet time-prec on β	14	15
PSD Morlet freq-prec on μ	15	16
PSD Morlet freq-prec on β	14	16
PSD Morlet trade-off on μ	17	13
PSD Morlet trade-off on β	10	16
Mean	16	15
Standard deviation	20	18
Skewness	15	19
Excess kurtosis	16	17
Median	25	17
Low percentile	17	16
High percentile	14	18
Trimmed mean	18	15
Trimmed standard deviation	11	12

V. CONCLUSION AND FUTURE WORK

In this work we investigated the possibility of conducting a preliminary analysis on the data provided by a MI-based BCI, to improve the interaction between this peculiar kind of system and its users. In particular, we concentrated our efforts on the PhysioNet *EEG Motor Movement/Imagery Dataset* tasks concerning the motor left/right hand movement/imagination.

Firstly, we noticed that most of the data normalized by the z-score normalization technique achieves better results and thus allow a population-based analysis. We can assume that by applying the data normalization, the data heterogeneity due to inter- and intra-subject variability is mitigated. Therefore, we can exploit this results to have a higher number of instances per class when dealing with a MI-based BCI.

Secondly, we computed different feature types in the time, frequency and time-frequency domains and also as statistical measures, wanting to have a broad insight on their contributions.

We verify on this specific dataset that the feature types contribute in the task discrimination depending on the electrodes on which they are computed. Thus, the brain area localization is an important information.

We notice that not only the electrodes covering the motor cortex are involved in the motor tasks with their time-frequency related features, but also the other brain areas contribute with different types of features, especially the Hjorth parameters and the statistical measures.

The evolutionary feature selection algorithms represented great allies in the optimal feature subset search. In particular, the genetic and particle swarm optimization algorithm obtained the best results, having the support vector machine models (applied on the reduced datasets) obtained comparable or better results in respect to the benchmark ones.

Finally, the agreement of the EFS techniques on the selected features has highlighted the various contribution from each electrode and from each feature type, without decreasing drastically the accuracy values.

As future work, we would like to test the EFS techniques with different fitness functions and on different datasets. Using data obtained by experimental protocols that do not only involve the motor imagery, but also cognitive workload, emotion recognition and so on, we could simulate a real-life scenario and verify if our approach is generalizable.

We would also like to define our own experimental protocol for a live MI-based BCI, taking into account the ergonomic issues that could be involved in this user-centric system modeling. In fact, as stated by *Baek et al.* [27], most of the BCI related works do not consider the importance of having user-friendly, flexible and accessible systems, which could allow a better EEG recording in absence of stress and discomfort.

REFERENCES

[1] S. Ackerman et al., Discovering the brain. National Academies Press, 1992.

[2] A. Zani, A. Proverbio, G. Mangun, E. Fletcher, E. Brattico, C. Olcese, M. Tervaniemi, R. Näätänen, E. Wilding, K. Federmeier, M. Kutas, R. Knight, D. Scabini, P. Luu, and D. Tucker, Metodi Strumentali nelle Neuroscienze Cognitive. EEG ed ERP- Instrumental Methods in Cognitive Neuroscience. EEG and ERP. Aracne Editrice, 11 2013.

[3] L. F. Nicolas-Alonso and J. Gomez-Gil, “Brain computer interfaces, a review,” sensors, vol. 12, no. 2, 2012, pp. 1211–1279.

[4] F. Lotte, L. Bougrain, A. Cichocki, M. Clerc, M. Congedo, A. Rakotomamonjy, and F. Yger, “A review of classification algorithms for EEG-based brain–computer interfaces: a 10 year update,” Journal of neural engineering, vol. 15, no. 3, 2018, p. 031005.

[5] P. Szczuko, “Real and imaginary motion classification based on rough set analysis of EEG signals for multimedia applications,” Multimedia Tools and Applications, vol. 76, no. 24, 2017, pp. 25 697–25 711.

[6] M. Dai, D. Zheng, R. Na, S. Wang, and S. Zhang, “EEG classification of motor imagery using a novel deep learning framework,” Sensors, vol. 19, no. 3, 2019, p. 551.

[7] A. Craik, Y. He, and J. L. Contreras-Vidal, “Deep learning for electroencephalogram (EEG) classification tasks: a review,” Journal of neural engineering, vol. 16, no. 3, 2019, p. 031001.

[8] B. Rim, N.-J. Sung, S. Min, and M. Hong, “Deep learning in physiological signal data: A survey,” Sensors, vol. 20, no. 4, 2020, p. 969.

[9] B. Xue, M. Zhang, and W. N. Browne, “New fitness functions in binary particle swarm optimisation for feature selection,” in 2012 ieee congress on evolutionary computation. IEEE, 2012, pp. 1–8.

[10] R. Kohavi and G. H. John, “The wrapper approach,” in Feature extraction, construction and selection. Springer, 1998, pp. 33–50.

[11] B. Xue, M. Zhang, W. N. Browne, and X. Yao, “A survey on evolutionary computation approaches to feature selection,” IEEE Transactions on Evolutionary Computation, vol. 20, no. 4, 2015, pp. 606–626.

[12] A. Atyabi, M. Luerssen, S. Fitzgibbon, and D. M. Powers, “Evolutionary feature selection and electrode reduction for EEG classification,” in 2012 IEEE congress on evolutionary computation. IEEE, 2012, pp. 1–8.

[13] K. Amarasinghe, P. Sivils, and M. Manic, “EEG feature selection for thought driven robots using evolutionary algorithms,” in 2016 9th International Conference on Human System Interactions (HSI). IEEE, 2016, pp. 355–361.

[14] J. González, J. Ortega, M. Damas, P. Martín-Smith, and J. Q. Gan, “A new multi-objective wrapper method for feature selection–Accuracy and stability analysis for BCI,” Neurocomputing, vol. 333, 2019, pp. 407–418.

[15] A. L. Goldberger, L. A. Amaral, L. Glass, J. M. Hausdorff, P. C. Ivanov, R. G. Mark, J. E. Mietus, G. B. Moody, C.-K. Peng, and H. E. Stanley, “PhysioBank, PhysioToolkit, and PhysioNet: components of a new research resource for complex physiologic signals,” circulation, vol. 101, no. 23, 2000, pp. e215–e220.

[16] G. Schalk, D. J. McFarland, T. Hinterberger, N. Birbaumer, and J. R. Wolpaw, “BCI2000: a general-purpose brain-computer interface (BCI) system,” IEEE Transactions on biomedical engineering, vol. 51, no. 6, 2004, pp. 1034–1043.

[17] B. Hjorth, “EEG analysis based on time domain properties,” Electroencephalography and clinical neurophysiology, vol. 29, no. 3, 1970, pp. 306–310.

[18] S.-H. Oh, Y.-R. Lee, and H.-N. Kim, “A novel EEG feature extraction method using Hjorth parameter,” International Journal of Electronics and Electrical Engineering, vol. 2, no. 2, 2014, pp. 106–110.

[19] P. Welch, “The use of fast Fourier transform for the estimation of power spectra: a method based on time averaging over short, modified periodograms,” IEEE Transactions on audio and electroacoustics, vol. 15, no. 2, 1967, pp. 70–73.

[20] M. X. Cohen, “A better way to define and describe Morlet wavelets for time-frequency analysis,” NeuroImage, vol. 199, 2019, pp. 81–86.

[21] A. Delorme and S. Makeig, “EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis,” Journal of neuroscience methods, vol. 134, no. 1, 2004, pp. 9–21.

[22] I.-S. Jeong, H.-K. Kim, T.-H. Kim, D. H. Lee, K. J. Kim, and S.-H. Kang, “A feature selection approach based on simulated annealing for detecting various denial of service attacks,” Software Networking, vol. 2018, no. 1, 2018, pp. 173–190.

[23] M. Clerc and J. Kennedy, “The particle swarm-explosion, stability, and convergence in a multidimensional complex space,” IEEE transactions on Evolutionary Computation, vol. 6, no. 1, 2002, pp. 58–73.

[24] R. Bousseta, S. Tayeb, I. El Ouakouak, M. Gharbi, F. Regragui, and M. M. Himmi, “EEG efficient classification of imagined hand movement using RBF kernel SVM,” in 2016 11th International Conference on Intelligent Systems: Theories and Applications (SITA). IEEE, 2016, pp. 1–6.

[25] S. M. Vieira, L. F. Mendonça, G. J. Farinha, and J. M. Sousa, “Modified binary PSO for feature selection using SVM applied to mortality prediction of septic patients,” Applied Soft Computing, vol. 13, no. 8, 2013, pp. 3494–3504.

[26] MATLAB, 9.5.0.1033004 (R2018b) Update 2. Natick, Massachusetts: The MathWorks Inc., 2018.

[27] H. J. Baek, M. H. Chang, J. Heo, and K. S. Park, “Enhancing the usability of brain-computer interface systems,” Computational intelligence and neuroscience, vol. 2019, 2019.

 ISBN: 978-1-61208-829-7