# Motor Imagery signal Classification for BCI System Using Empirical Mode Décomposition and Bandpower Feature Extraction

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**Abstract**

The idea that brain activity could be used as a communication channel has rapidly developed. Indeed, Electroencephalography (EEG) is the most common technique to measure the brain activity on the scalp and in real-time. In this study we examine the use of EEG signals in Brain Computer Interface (BCI). This approach consists of combining the Empirical Mode Decomposition (EMD) and band power (BP) for the extraction of EEG signals in order to classify motor imagery (MI). This new feature extraction approach is intended for non-stationary and non-linear characteristics MI EEG. The EMD method is proposed to decompose the EEG signal into a set of stationary time series called Intrinsic Mode Functions (IMF). These IMFs are analyzed with the bandpower (BP) to detect the characteristics of sensorimotor rhythms (mu and beta) when a subject imagines a left or right hand movement. Finally, the data were just reconstructed with the specific IMFs and the bandpower is applied on the new database. Once the new feature vector is rebuilt, the classification of MI is performed using two types of classifiers: generative and discriminant. The results obtained show that the EMD allows the most reliable features to be extracted from EEG and that the classification rate obtained is higher and better than using the direct BP approach only. Such a system is a promising communication channel for people suffering from severe paralysis, for instance, people with myopathic diseases or muscular dystrophy (MD) in order to help them move a joystick to a desired direction corresponding to the specific motor imagery.

**Keywords:** Brain Computer Interface, motor imagery, Bandpower, Empirical Mode Decomposition, Hidden Markov Model, Support Vector Machines, Cohens kappa coefficient.

## 1. Introduction

A BCI system is a communication and control pathway between a brain and an external device. It does not require any external devices or muscle intervention to issue commands and complete the interaction (Abdulkader et al., 2015). This system primarily concerns the medical domain and mainly the field of disability. So, the major goal of the BCI research is to provide severely disabled people with a new communication channel, which is not based on the traditional motor output channels (Van Erp et al., 2012).

A BCI system is represented as a system in a continuous closed, generally composed of six steps, (see fig 1): 1. Brain activity measurement, 2. Preprocessing, 3. Feature Extraction, 4. Classification, 5. Translation into a command and Feedback.

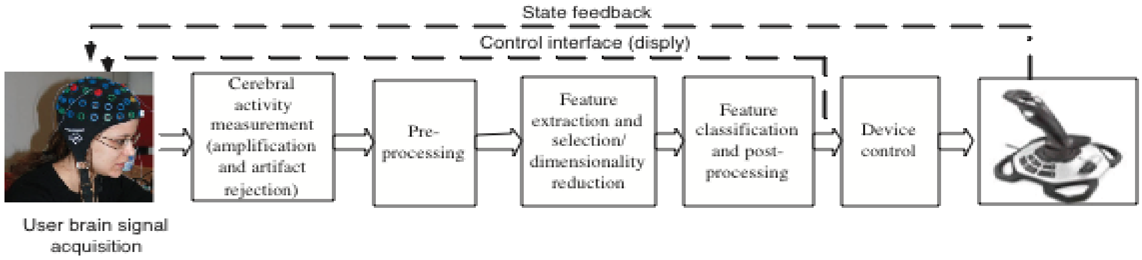



*Figure 1. General architecture of an online (BCI)*

One major challenge of our BCI system is to describe the signals EEG by a few relevant values called features i.e. step 3 in Fig (1). The success of the mental imagery classification depends on the choice of features used to characterize the raw EEG signals. These features can then be used in step 4 in order to classify the user's mental state. Several approaches for feature extraction have been proposed in literature.

These approaches are based on time, frequency or time-frequency methods (Al-ani & Trad, 2010; Pfurtscheller, 2004). A common way to gain BCI control is to use motor imagery of left and right hand movement, which is based on Event-related desynchronization/synchronisation (ERD/ERS) in specific frequency bands. For instance, imagination of left or right hand movement results in amplitude causes an attenuation (Event-related desynchronization (ERD)) of $\mu$ (8-13Hz) and central $\beta$ (13-30Hz) rhythms at the contra-lateral sensorimotor representation area and, in an amplitude increase (event-related synchronization (ERS)) within the $\gamma$ band (30-40Hz) at the ipsi-lateral hemisphere (Pfurtscheller, 1999; Neuper & Pfurtscheller, 1999). Several common band power techniques were employed in the BCI literature. Herman et al. (Herman et al., 2008) demonstrated that the Yule and Welch PSD approaches, mainly dominate the other studied ones.

These approaches are based essentially on some linearity and stationary hypothesis such as the use of fast Fourier transform (FFT) spectrum in a short-time segment of data. The accuracy of the FFT calculation is closely related to the choice of the duration of the signal segment. However, the nature of the EEG signal is non stationary and nonlinear. The main non-stationary and nonlinear feature extraction technique is the Wavelet Transform (WT) (Samar et al., 1999). Various kinds of wavelets have been used for BCI, such as Morlet wavelets (Lemm et al., 2004) and wavelet packet decomposition (Hettiarachchi et al. 2014). Despite being more effective than the FFT, WT approach shows a much bigger ambiguity in signal decomposition. However, it cannot provide higher resolution both in time and frequency domain, besides, the decomposition of signal is not adaptive.

In this paper, we applied a recent technique proposed by Huang et al. (Huang et al. 1998), called the empirical mode decomposition (EMD) for nonlinear and non-stationary time series data for pattern extraction from motor imagery EEG of left and right hand imaginary movement. This method EMD is a data driven approach (i.e. one does not need to define a mother wavelet beforehand) that can be used to decompose adaptively a signal into a finite number of mono-component signals, which are known as intrinsic mode functions (IMF s) or modes. It considers signals at their local oscillations, but they are not necessarily considered in the sense of Fourier harmonics. Their extraction is non-linear, whereas their recombination for exact reconstruction of the signal is linear. The IMFs admit well-behaved Hilbert transforms (HT) (Long et al. 1995) and they satisfy the following properties: they are symmetric, different IMFs yield different instantaneous local frequencies as functions of time that give sharp identifications of embedded structures. In this work, we propose a hybrid approach combining the EMD and BP for feature extraction from the EEG signals. We first apply the EMD to select only the IMFs corresponding to sensorimotor rhythms (mu and beta) using Welch-based PSD to extract the reliable information of EEG during left and right hand movement imagination. Based on these new features, the experimental using two classifiers hidden Markov models (HMMs) and Support Vector Machines (SVM) results show that the proposed method improves recognition rate greatly.

## 2. Methods

### *2.1. Participants and experimental paradigm*

The EEG signals used for this experiment were recorded by a real-time EEG acquisition hardware g.GAMMAsys active electrode System along with a g.USBamp amplifier g.tec, Guger Technologies. In this study, the EEG data of ten subjects (two young females and seven young males with ages ranging from about 22 to 35 years), recorded during imagination of the left and right hand movements. A subject training session in our work consisted of one experimental run of 40 trials with randomized direction of the cues (20 left-hand imagination and 20 right-hand imagination). For each subject, we used only 4 out of the best sessions (i.e. 160 trials/subject). Therefore, each subject is seated in a comfortable armchair 150 cm in front of a computer screen.

At the beginning of each trial (t = 0 s), a fixation cross-appeared on the black screen. After two seconds a warning stimulus was given in the form of a beep. From 3 to 4.25s, an arrow (cue stimulus), pointing to the left or right, was shown on the screen. The subject was instructed to imagine a left or right hand movement until the end of the trial, depending on the direction of the arrow. The EEG was sampled and classified on-line throughout the session. Between 4.25 and 8s, the classification result was used to give a continuously updated feedback stimulus in the form of a horizontal bar that appeared in the center of the screen. The paradigm is illustrated in fig (2).

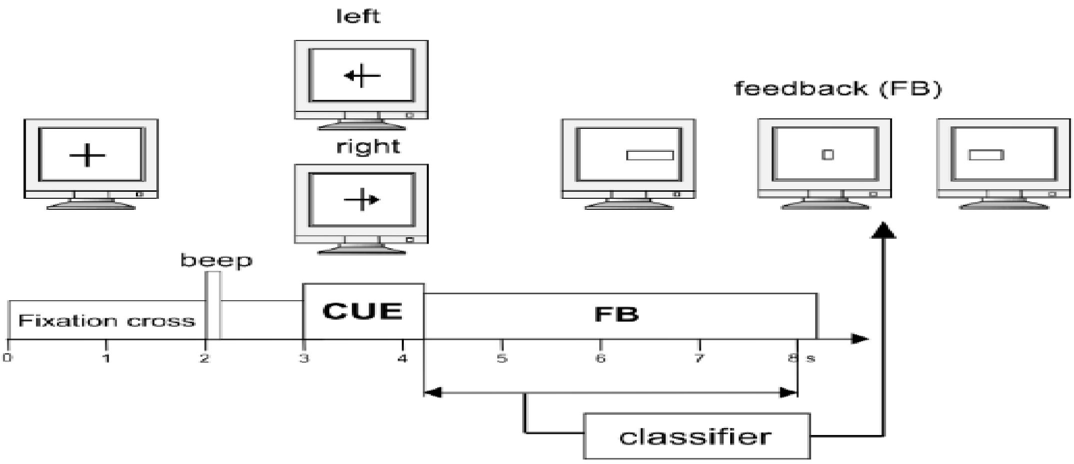



*Figure 2. Timing of one trial of the experiment with continuous feedback (Guger et al, 2001)*

### *2.2. Preprocessing*

Two bipolar EEG channels were measured over C3 and C4 according to the international 10-20 System (Jasper 1958). The left ear served as reference and the FPz as ground. The signals were sampled at 256 Hz and bandpass-filtered between 0.5 Hz and 30 Hz. An additional 50 Hz notch filter was enabled to suppress line noise.

### *2.3. Feature extraction*

Once the raw EEG data is recorded and pre-processed, the following step is to extract its intrinsic features. This step is essential in the functioning of BCIs due to the important measured amount of brain activities. The aim of this step is then to find a better representation of the EEG signal while keeping the most relevant properties corresponding to the performed mental imagery. This information is called features. In this work, we propose a robust method bases on BP and EMD to extract the relevant EEG features corresponding to MI.

#### *2.3.1. Bandpower*

The features may be extracted from the EEG signals by estimating the power distribution of the EEG in predefined frequency bands. In general, the band power is estimated by digitally bandpass filtering a signal in a given frequency band, then squaring the filtered signal and finally averaging the obtained values over a given time window. Pfurtscheller et al. (Pfurtscheller et al.,1997) used the BP and demonstrated that for each subject, different frequency components were found in the μ and $\beta$ bands which provided best discrimination between left and right hand movement imagination. These frequency bands varied between 9 and 14 Hz and between 18 and 26 Hz. Such features have been notably used with success for motor imagery classification.

*2.3.2. Empirical mode decomposition (EMD):*

The traditional EMD was recently proposed as an adaptive time-frequency data analysis method (Huang et al., 1998). An algorithm based on an empirical framework defines it. The basic EMD is defined by a process called sifting to break down any multimodal signal to a sum of basis components called intrinsic mode functions (IMFs). The IMFs are zero-mean AM-FM signals which must satisfy two conditions: the first one is that the number of extrema and that of zero-crossing must differ at most by one; the second one is that the mean value between the upper and lower envelopes are equal to zero at any point. Conceptually, the establishment of this method is quite simple: one needs to consider a signal at its local oscillation level, remove the fastest oscillation and iterate the process on the residue considered as a new signal. At the end of the sifting processes, a given signal $x(t)$ can be written as a sum of a finite number of IMFs, $I_m(t)$, m = *1. 2, .... M*, and a final residue $r_M(t)$ (Equation1):

$$x(t) = \sum_{m=1}^{M} I_m(t) + r_M(t) \quad (1)$$

The decomposition is stopped at step M, if either the residue is a mono-component signal or has only 2 extrema. The stopping criterion must be set to ensure that the obtained signal satisfies the properties of an IMF while limiting the number of iterations. For more details about the different steps of the sifting process for the calculation of the IMFi as well as the stopping criterion definition see (Huang et al., 1998). Since the decomposition into IMFs is based on the local characteristic time scale of the data, it applies to nonlinear and non-stationary processes. The IMFs admit well-behaved Hilbert transforms (HT) and they satisfy the following properties: they are symmetric, different IMFs yield different instantaneous local frequencies as functions of time that give sharp identifications of embedded structures. The decomposition is done linearly or non-linearly depending on the data. This complete and almost orthogonal decomposition is empirically realized by identifying the physical local characteristic time scales intrinsic to these data, which is the lapse between successive extrema.

*2.3.3. EMD and BP for motor imagery*

In this work, we propose a direct nonlinear approach to extract the more relevant IMFs corresponding to the different frequency components in the $\mu$ and $\beta$ bands and then obtain the BP in order to use them as features for mental task classification (see Fig. 3). The feature vector $p_i$ used for the demonstration in this paper is composed, for each sample *I*, $1 < i < 2048$, in a given trial (among a total of 160 trials) of four bandpower, calculated of the rhythms $\mu$ and $\beta$ in positions C3 and C4 (Trad et al., 2011).

Fig. 4 shows the EMD decomposition result of one-trial (left hand movement imagination) for subject 2 in the channels C3 and C4 respectively (the pre-filtered EEG signal used for this illustration is not corrupted by blinking artifact.). Each channel is decomposed into ten IMFs and one residue.

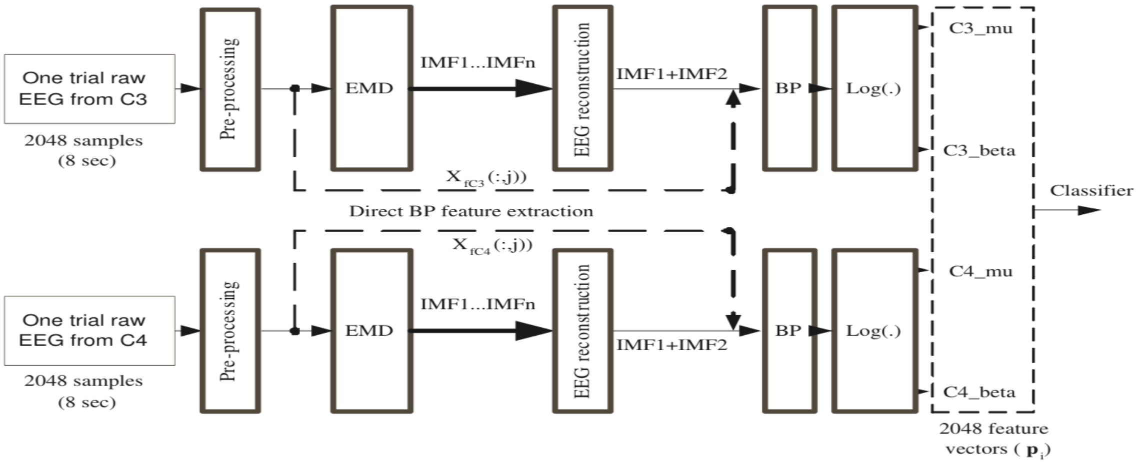
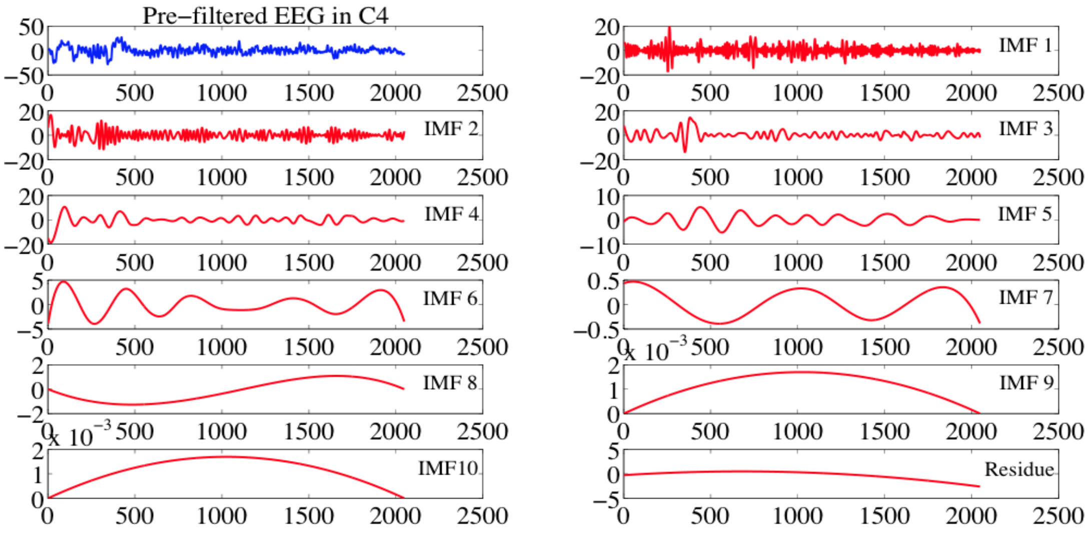


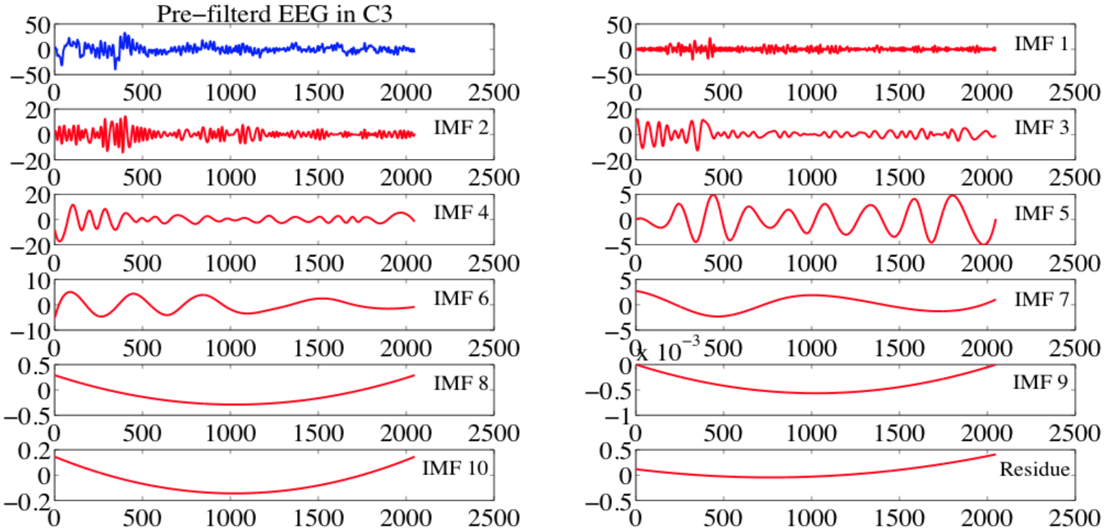

*Figure 3. Hybrid EMD-BP approach for one trail feature extraction*

Welch based PSD method was applied to analyze the different characteristics of each IMF. This method was applied to each IMF to find the active frequency bands such as the $\mu$ and $\beta$ rhythms. Fig. 5 shows the PSD in each IMF shown in Fig.4. The major advantage of EMD is that the input signal may be decomposed directly and adaptively to basic functions (IMFs), each with a distinct time scale. The IMFs are ordered in increasing time scales, i.e., decreasing frequency. Based on this property, we can notice that the characteristics of the active frequency bands corresponding to $\mu$ [8-12Hz] and $\beta$ [13-30Hz] are located only in IMF 1, IMF 2 on C3 and C4.

Therefore, the new signal is reconstructed by keeping only the two first IMFs. EMD also allows eliminating the artifacts in the EEG during the recording sessions like eye blinks and eyeball movements. In Fig 5, we noted that ocular artifact frequency is generally low around 5Hz with high amplitude. This artifact appears mainly in IMF3 and IMF4. Finally, band power was applied for the new signal. As a last step, the logarithm of the BP is calculated in order to transform the distribution of this feature to a more Gaussian like shape, because the classifiers we used, such as HMMs and SVM assume normally distributed features.

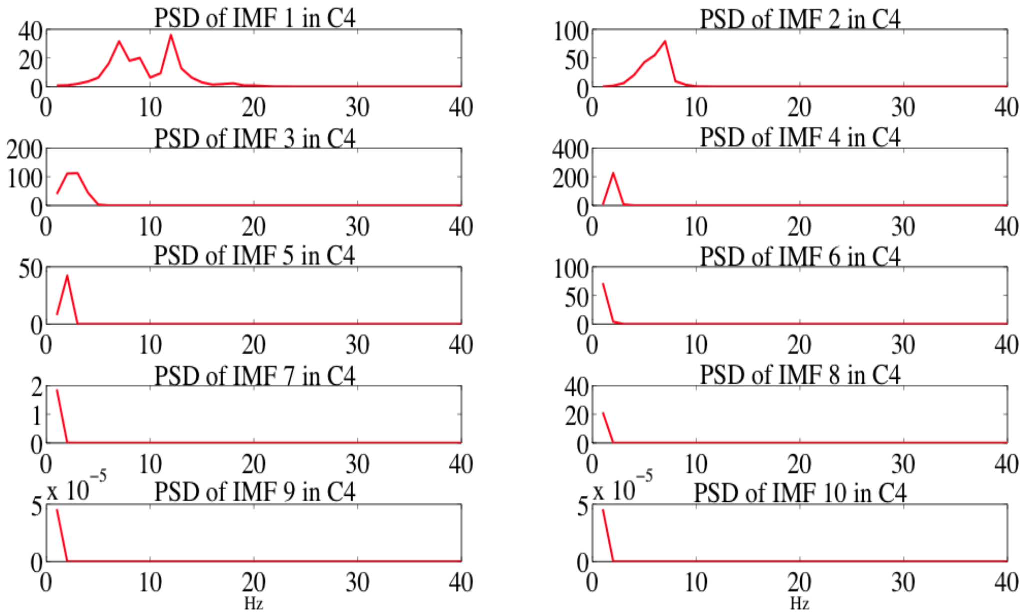



a)

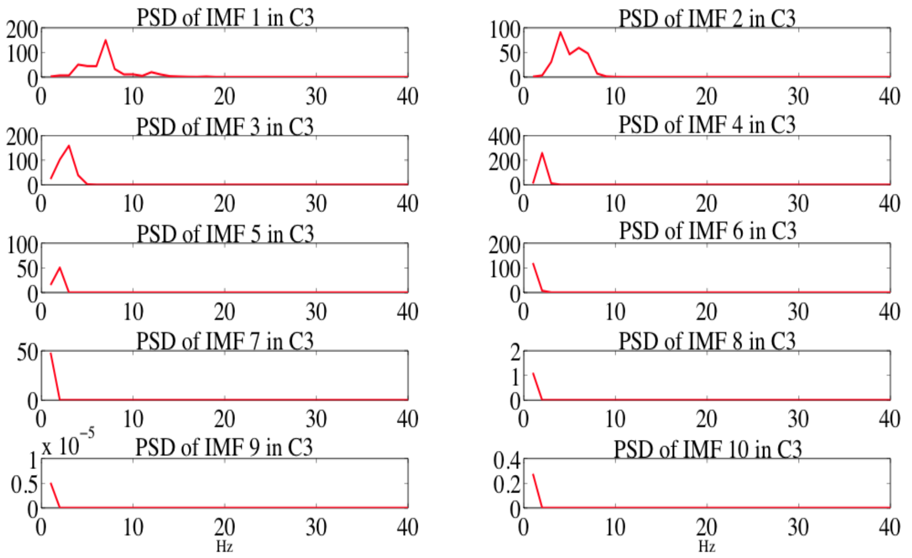



*b)*

*Figure 4. The EMD decomposition results for subject 2 when he imagines left hand movement. From top-left to down-right: the raw signal, the ten IMFs and the residue in channel C4 (a) and in C3 (b)*




a)




b)

*Figure 5. PSD (dB/Hz) vs freaquency (Hz) of each IMF showen in fig 4 in channel C4 (a) and in C3 (b)*

### *2.4. Classification*

The goal of the classification step is to assign automatically a class to the feature vector previously extracted. In this study, four feature sets for each feature extraction approach, BP and EMD+BP, were used for classification and for test. Two sets of feature vectors; one for LMI and the other for RMI were used to train the classifier (creating one model for each MI) while the two other sets of feature vectors, one for left and the other for right MI were used for test. Each set contains 40 feature matrices each of dimension 4x2048. We evaluated our feature extraction approach by using 2 classifiers.

#### *2.4.1. Hidden Markov Model (HMM)*

The *HMMs* approach is very efficient nonlinear technique used for the classification of time series (Rabiner, 1989). It necessitates two stages: a training stage where the stochastic process models are estimated through extensive observation corpus and decoding or detection stage where the model may be used off/on-line to obtain the likelihoods of the given test sequence evaluated by each model. A *HMM* is defined by the following compact notation to indicate the complete parameter set of the model $\lambda = (\Pi, A, B)$, where $\Pi$, $A$ and $B$ are the initial State distribution vector, matrix of State transition probabilities and the set of the observation probability distribution in each State, respectively:

$\Pi = [\Pi_1, \Pi_2, ..., \Pi_{Ns}]$, $\Pi_i = P(q_1 = s_i)$, $\mathbf{A} = [a_{ij}]$, $a_{ij} = P(q_{t+1} = s_j \mid q_t = s_i)$. Where $1 \le i, j \le N$, $s_i, s_j \in S$, $S = \{s_1, s_2, ..., s_N\}$, $t \in \{1, 2, ..., T\}$. The observation at time (or index) t, $\mathbf{O}_t$, is considered in this paper as continuous or real-valued K-dimensional vector $\mathbf{O}_t \in R^K$, $1 \le t \le T$, $1 \le \boldsymbol{t} \le T$.

For a continuous observation, the State conditional probability of the observation $b_i(\boldsymbol{O}_t)$ may be defined by a finite mixture of any log-concave or elliptically symmetric probability density function (pdf), e.g. Gaussian pdf, with State conditional observation mean vector $\mu_i$ and State conditional observation covariance matrix $\mathbf{S}_i$. In this paper we consider only a single multivariate Gaussian pdf, so $B$ may be defined as $B = \{\mu_i, \mathbf{S}_i\}$ $i = 1,2, ... ,N_s$. *At* each instant of time t, the model is in one of the States $i$, $1 \le i \le N_s$. It outputs $\boldsymbol{O}_t$ according to a density function $b_i(\boldsymbol{O}_t)$ and then jumps to State $j$, $1 \le j \le N_s$ with probability $a_{ij}$. The State transition matrix defines the structure of the *HMM* (Rabiner, 1989). The model $\lambda$ may be obtained off-line by a given training procedure. In practice, given an observation sequence $O = \{0_1, O_2, ..., O_t\}$, and an initial model λ, the *HMMs* need three fundamental problems to be solved:

1. How to calculate the likelihood P(O|λ)? The solution to this problem provides a score of how *O* belongs to λ.
2. How to determine the most likely State sequence that corresponds to a given observation sequence *O?* The solution to this problem provides the sequence of the hidden States corresponding to the given observation sequence *O*.
3. How to adjust the model λ in order to maximize P(O|λ)? This is the problem of estimating the model parameters given a corpus of training observations sequences.

Problems 1 and 2 are solved in the decoding or classification stage using the forward or the Viterbi algorithms (Rabiner, 1989), while problem 3 is solved during the training phase using either a conventional algorithm such as the Baum-Welch algorithm (Rabiner, 1989) or other optimization-based algorithm, e.g., (Al-ani & Hamam, 1978).

Our training scheme is based on Baum-Welch training algorithm and the *Bayesian Inference Criterion (BIC).* This scheme makes the training procedure independent of the a priori knowledge of the structure of each *HMM* needed in the Baum-Welch algorithm. The decoding or classification may be realised on-line using the stochastic dynamic programming based Viterbi algorithm. This algorithm needs all the constructed *HMMs* to classify on-line a given observation sequence.

In our work, two *HMMs* were built for *RMI* and *LMI* using 40 training feature sequences from each *MI*. Each sequence is composed of $T$ = 2048 feature vectors of dimension $K$ = 4 each.

*2.4.2. Support Vector Machines (SVM)*

SVM was first introduced by Vapnik (Vapnik, 1998) (Vapnik, 2000). It is based on two fundamental principles:

1. Maximum margin which is the distance between the border of separation and the closest samples. In *SVMs,* the boundary of separation is chosen as the one that maximizes the margin. This is justified by the theory of Vapnik-Chervonenkis (or statistical theory of learning) (Vapnik, 1998). The problem is to find the optimal separating boundary from a given training set. This is done by formulating the problem as a quadratic optimization problem for which there are known algorithms.
2. In order to deal with cases where the data are not linearly separable, we increase of the size of the input space. To be able to handle nonlinear separable data, we transform the space of input data to another space with larger size in which the probability that a linear boundary exists is higher. This transformation is realised by using a nonlinear *kernel function.* Several *kernel functions* may be used to design the *SVMs.* In our work, the Gaussian *Radial Basis Function* (*RBF*):

$$K(x,y) = \exp\left(\frac{||x-y||^2}{\sigma^2}\right) \quad (2)$$

With a scaling factor, $\sigma$, of 1 was selected as it gives the most accurate results.

In our work, two classes *SVM* was built for *RMI* and *LMI* using 40 training feature sequences from each *MI.* Each sequence is composed of $T$ = 2048 feature vectors of dimension $K$ = 4 each.

*2.5. Statistical performance evaluation method: Cohen's kappa coefficient*

Training the classifiers presented above was designed to minimize the classification error or to increase the classification rate usually measured by the rate of correctly classified trials. To interpret the classification performance, we take as reference the percentage rate reached by a random classification. Indeed, evaluating the performance of a classifier, based on a given features, is an important issue since its performance may be used for simplifying human training. The evaluation the performance of our feature extraction is based on the performance of the classification results on *RMI* and *LMI*. In order to compare our new feature extraction method results with the traditional feature extraction method results, we used the Cohen's kappa coefficient (Cohen, 1960). It allows to measure the agreement between two classifiers in classification into two categories. The value of the *Cohens* $\kappa$ ranges between 1 and -1, where 1 corresponds to perfectly correct classification and values less than 1 imply less than perfect agreement.

Let $P_0$ the *observed agreement* among two classifiers and $P_e$ the *expected agreement*. The *Cohens kappa* $\kappa$ is defined by:

$$K = \frac{P_o - P_e}{1 - P_e} \quad (3)$$

## 3. Results and discussion

### *3.1. Confusion matrices*

The recognition rate calculated by HMM and SVM for the 10 subjects is represented by the confusion matrix (Table 1) for the two feature extraction methods direct BP and EMD + BP. It is clearly seen that the combination of the two features methods, EMD and BP gives the best classification rates for almost all subjects. Based on these matrices, the performance of our approach was evaluated using *K* scores.

Table 1. Confusion matrix: recognition rates calculated by HMMs and SVM in the case of RMI and LMI. These results are showen for both methods of feature extraction (BP and EMD+BP) for all subjects.

| Subject | FE | true class | *HMM* - predicted class | | *SVM* –predicted class | |
|---|---|---|---|---|---|---|
| 1 | | | **RMI** | **LMI** | **RMI** | **LMI** |
| | BP | RMI | **70** | 30 | **86.25** | 13.75 |
| | | LMI | 2.5 | **97.5** | 36.25 | **63.75** |
| | EMD+BP | RMI | **90** | 10 | **85** | 15 |
| | | LMI | 2.5 | **97.5** | 2.50 | **97.50** |
| | BP | RMI | **77.5** | 22.5 | **76.25** | 23.75 |
| | | LMI | 7.5 | **923** | 40 | **60** |
| | EMD+BP | RMI | **75** | 25 | **75** | 25 |
| 2 | | LMI | 2.5 | **97.5** | 25 | **75** |
| | BP | RMI | **57.5** | 42.5 | **61.25** | 38.75 |
| 3 | | LMI | 35 | **65** | 33.75 | **66.25** |
| | EMD+BP | RMI | **72.5** | 27.5 | **61.87** | 38.13 |
| | | LMI | 40 | **60** | 25 | **75** |
| | BP | RMI | **71.42** | 28.58 | **55.62** | 44.38 |
| 4 | | LMI | 37.15 | **62.85** | 42.50 | **75.50** |
| | EMD+BP | RMI | **71.42** | 28.58 | **77.50** | 22.50 |
| | | LMI | 42.85 | **57.15** | 82.75 | **71.25** |
| | BP | RMI | **52.5** | 47.5 | **76.25** | 23.75 |
| 5 | | LMI | 42.5 | **57.5** | 33.13 | **61.87** |
| | EMD+BP | RMI | **72.5** | 27.5 | **76.25** | 23.75 |
| | | LMI | 40 | **60** | 27.50 | **72.50** |
| | BP | RMI | **80** | 20 | **67.50** | 32.50 |
| | | LMI | 50 | **50** | 32.50 | **76.50** |
| | EMD+BP | RMI | **85** | 15 | **68.12** | 31.88 |
| 6 | | LMI | 47.5 | **523** | 17.50 | **8230** |
| | | RMI | **80** | 20 | **70.62** | 29.38 |
| | BP | LMI | 35 | **65** | 28.75 | **71.25** |
| | EMD+BP | RMI | **80** | 20 | **78.12** | 21.88 |
| 7 | | LMI | 32.5 | **67.5** | 29.38 | **70.62** |
| | | RMI | **87.5** | 12.5 | **57.50** | 42.50 |
| | BP | LMI | 32.5 | **67.5** | 45.63 | **54.37** |
| | EMD+BP | RMI | **90** | 10 | **38.75** | 16.25 |
| 8 | | LMI | 37.5 | **62.5** | 33.75 | **66.25** |

| | | | | | | |
|---|---|---|---|---|---|---|
| 9 | BP | RMI | **60** | 40 | **78.12** | 21.88 |
| | | LMI | 45 | **55** | 28.13 | **71.87** |
| | EMD+BP | RMI | **82.5** | 17.5 | **77.50** | 22.50 |
| | | LMI | 25 | **75** | 7.50 | **72.50** |
| 10 | BP | RMI | **60** | 40 | **66.87** | 33.13 |
| | | LMI | 42.5 | **57.5** | 36.88 | **63.12** |
| | EMD+BP | RMI | **75** | 25 | **75** | 25 |
| | | LMI | 35 | **65** | 25 | **75** |

*3.2. Cohen's Kappa coefficient*

Table 2 gives the *Kappa*- values for each one of the ten subjects in order to evaluate our method of feature extraction based on EMD+BP. The average score obtained by the HMM classifier when the feature vectors are generated by EMD+BP is equal to 0.54 while that obtained when the feature vectors are generated by BP is equal to 0.4, i.e., an increase of 35%. For the SVM classifier, the average score increases from 0.34 to 0.52, i.e., an increase of 53% using the methods BP and EMD+BP respectively. Therefore, the use of the EMD+BP approach with the two classifiers gives to the *Kappa* scores a significant superiority compared to the direct BP approach.

Table 2. K-values obtained by the two types of classifiers (C) HMMs and SVM with the two types of features extraction (FE) methods: BP and EMD+BP for 10 subjects during RMI and LMI as well as their mean values

| **C** | **FE** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **Mean** *k* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *HMM* | *BP* | 0.6 | 0.8 | 0.4 | 0.2 | 0.2 | 0.4 | 0.4 | 0.6 | 0.2 | 0.2 | **0.40** |
| | *EMD+BP* | 0.8 | 0.8 | 0.6 | 0.4 | 0.4 | 0.4 | 0.4 | 0.6 | 0.6 | 0.4 | **034** |
| *SVM* | *BP* | 0.6 | 0.4 | 0.2 | 0.2 | 0.4 | 0.4 | 0.4 | 0.2 | 0.4 | 0.2 | **0.34** |
| | *EMD+BP* | 0.8 | 0.6 | 0.4 | 0.2 | 0.4 | 0.6 | 0.4 | 0.6 | 0.6 | 0.6 | **032** |

*3.3. Translation into a command*

Once the motor imagery is identified, a command may be associated to this mental task in order to control a machine (Prataksita et al., (2014)) (Guger et al., 1999). In this work, we constructed a new Simuhnk/MathWork model to translate on-line the EEG signals into low-level commands. Fig. 6 shows our experimental EEG-based BCI System (Trad et al., 2015).

**1. Off-line phase:** In the first step, the EEG signals are recorded while subjects imagine a right and left hand movement. The second step is the preprocessing and feature extraction of *EEG* data. In this step, we implemented our method to extract the relevant features of the *EEG*. This method is based on the combination of EMD and BP. In the third step, we implemented the *HMM* classifier to assign a model to each motor imagery task: $\lambda$l for LMI and $\lambda$2 for RMI.

**2. On-line phase:** Once the motor imagery is identified by one of the two models, a low-level command can be then associated to this mental task. This mechanism was implemented with Simulink/Mathworks. EMD + BP and Viterbi algorithm (Rabiner 1989) are implemented as an embedded function in Simulink in order to identify the motor imagery on-line. Viterbi algorithm has two inputs data, the first input is the *EEG* data and the second is the two models already constructed in the first step (offline). The Viterbi-based recognition result is translated into a command to reinforce the movement of the joystick (right or left) in order to help persons with myopathic diseases or muscular dystrophy to move this joystick to a desired direction.

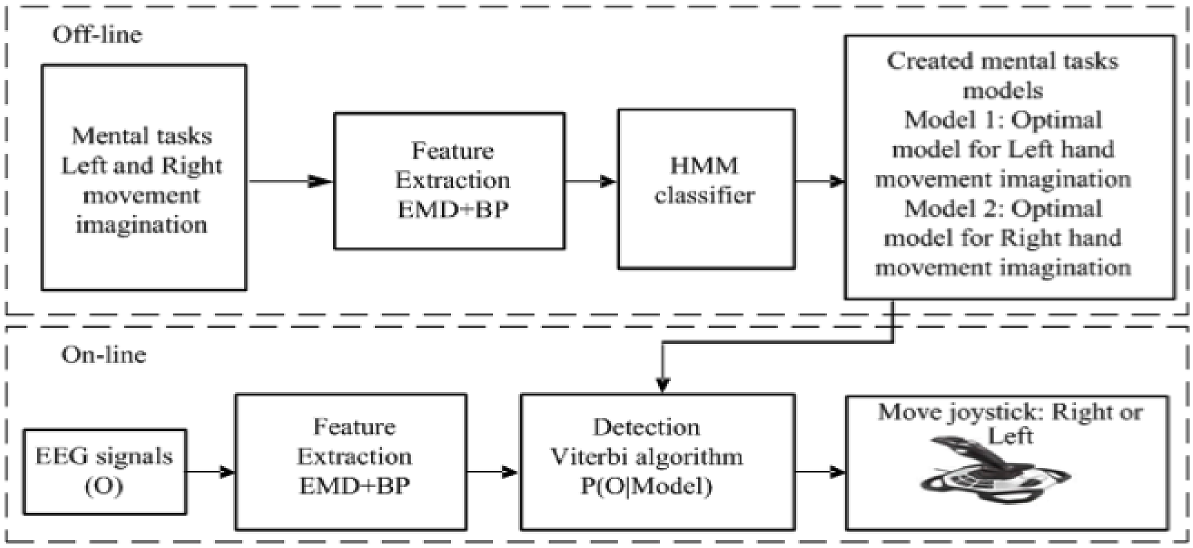



*Figure 6. The general conception of our asynchronous system BCI (offline - online) for reinforcement of a joystick movement*

## 4. Conclusion

The work presented in this paper concerns the steps of feature extraction and classification for ***motor imagery*** in ***BCI*** framework. These steps are essential for the design of ***BCI*** Systems since these Systems represent a direct communication channel between the brain of a subject and a machine without any direct muscular intervention. Our approach is based on indirect, independent and asynchronous *BCI* Systems. Ten healthy subjects participated in the realization of this process by imagining two hand movements. During our work, we have studied the changes in frequency and amplitude of the *EEG* from each subject participating in our experiment. Changes in frequency distribution within the bands of sensorimotor $\mu$ and β rhythms vary from one individual to another and evolve strongly over time. For this reason it is essential to carry a preliminary study for each subject. Once the values of sensorimotor rhythms are determined for each subject, it is easier to control subject's brain activity when one realizes motor imagery. This is achieved through the feedback returned to subject. *EMD* is particularly important in extracting directly from the *EEGs* the time courses of $\mu$ and β rhythms. This facilitates the detection of the reactive *ERD/ERS* bands for individual subjects, i.e., no need to choose an individual subject specific frequency band.

Another advantage of *EMD* is not only that it is a data driven approach but also it has the advantage of removing or reducing the artifacts and the noise affecting the EEG signal.

Therefore, we deduce that the classification rate in the two movements imagination are better using EMD+BP approach than the direct BP approach. When subject motor imagery is recognized, we translated the EEG signal to a low-level command. This System could allow subjects who suffer from severe motor disabilities to better reinforce a joysticks movement to right or left.

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