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<https://doi.org/10.1016/j.combiomed.2019.103596>

Phase-Synchrony Evaluation of EEG Signals for Multiple Sclerosis Diagnosis Based on Bivariate Empirical Mode Decomposition during a Visual Task

Khadijeh Raeisi ^a, Maryam Mohebbi ^{a*}, Mohammad Khazaei ^b, Masoud Seraji ^c, Ali Younesi ^d

^a School of Electrical Engineering, K.N.Toosi University of Technology, Tehran, Iran.

^b School of Electrical Engineering, Iran University of Science and Technology, Tehran, Iran.

^c Center for Molecular and Behavioral Neuroscience, Rutgers, The State University of New Jersey, Newark, NJ.

^d School of Advanced Medical Technologies and Eye Research Center, Tehran University of Medical Sciences, Tehran, Iran.

Email addresses: kh.reisi68@gmail.com (Kh. Raeisi), mkhazaei@alumni.iust.ac.ir (M. Khazaei), m.seraji@rutgers.edu (M. Seraji), m.mohebbi@kntu.ac.ir (M. Mohebbi), a-yoonessi@tums.ac.ir (A. Younesi).

* Corresponding author.

Tel.: +98(21)8406-2240

Fax: +98(21)8846-2066

P.O. Box: 16315-1355,

Abstract

Spatial synchrony evaluation among neural networks of the brain would play an important role in decoding of complicated brain interactions in healthy subjects and the ones with neurological disease such as Multiple Sclerosis (MS). Despite the widespread prevalence of this disease, as well as the importance of identifying any MS-related damage in the central nervous system, the study of brain interactions is still poorly investigated. Moreover, there has always been a vital need to automate the MS diagnosis procedure. This automation would yield to eliminate the evaluation errors and, consequently, improve its consistency and reliability. To address these issues, in this work, we proposed a robust pattern recognition algorithm as a computer-aided diagnosis system. This method is based on the calculation of pairwise phase-synchrony of EEG recordings during a visual task. In order to calculate the phase-synchrony, the bivariate empirical mode decomposition (BEMD) was applied to extract the intrinsic mode functions (IMFs). The phases of these IMFs were obtained using the Hilbert transform to be utilized in the mean phase coherence (MPC), a measure for phase-synchrony calculation. After construction of the feature space using MPC values, the ReliefF algorithm was applied for dimension reduction, which results in lower computational complexity and cost. Finally, the best distinguishing features were fed to the K-Nearest Neighbors (KNN) classifier. The results demonstrated a higher level of networks synchronization in the posterior regions of the brain and desynchronization in the anterior regions among MS group in comparison with the normal subjects. In the validation phase, the leave-one-subject-out cross-

validation (LOOCV) method was used to assess the validity of the proposed algorithm. This led to the accuracy, sensitivity and specificity of 93.09%, 91.07% and 95.24% for red-green, 90.44%, 88.39% and 92.62% for luminance and 87.44%, 87.05% and 87.86% for blue-yellow tasks. Using the proposed algorithm, the pairwise phase-synchrony differences of EEG signals between MS and normal subjects were extracted. The experimental results demonstrate the reliability of the presented method to be generalized in the field of early and automated MS diagnosis systems.

Keywords: Bivariate Empirical Mode Decomposition, Electroencephalography, Multiple Sclerosis, Mean Phase Coherence, Phase-synchrony, Visual Task.

1. Introduction

Multiple sclerosis (MS) is known as a chronic inflammatory disease characterized by widespread lesions of the central nervous system. Due to demyelination and progressive axonal damage, MS leads to several long-lasting neurological disorders [1].

Recently, several types of research on the electrophysiological assessment of the central nervous system of MS patients have been conducted. They have aimed to provide a tool for monitoring and diagnosis of MS in groups of patients with physical disabilities and cognitive problems. A quick look at the previous studies indicates that there are many impairments associated with MS including: cognitive disorders of memory [2], attention [3], information processing speed [4, 5], physical disability, fatigue, depression [6-8] and abnormal brainstem auditory [9, 10], somatosensory, motor [10, 11], and visual evoked potentials (VEPs) [10-18].

Visual problems are among the most common and early symptoms that an MS patient will notice. Therefore, assessing the

function of optic nerves using visual stimuli is thought to be a proper tool for early MS detection. Almost in all conventional VEP-based diagnostic methods, the latency prolongation and abnormal P100 amplitude are reported [10-12, 14, 16]. These metrics are believed to be the indicators of conduction velocity within the optic nerve [19] and its axons, respectively [20].

The distinctive structural, morphological, and physiological features of the three major types of ganglion cells of the brain have led to a new method for VEP studies in MS patients [21, 22]. In such studies, presenting a specific stimulus to provoke a response from a selected type of ganglion cells have been under scrutiny. These stimuli have been designed based on the different chromatic and contrast features of ganglion cells. Some researches were conducted to identify the ganglion cells and find the most appropriate stimuli for them. For instance, in an attempt, Denison and her colleagues [23] succeeded to identify the ganglion cells in the human lateral geniculate nucleus (LGN) and their corresponding stimulus. Their results show

that the luminance stimulus with low spatial and high temporal frequency is responsible for eliciting magno cells. Parvo cells respond to isoluminant red-green stimulus with high spatial and low temporal frequency. Besides, when a blue-yellow isoluminant stimulus with medium spatial and temporal frequency is presented, konio cells can be stimulated. Using these stimuli results show that the demyelination process in MS patients affects magno and parvo cells significantly [24]. Therefore, it can be claimed that presenting these kinds of stimulus can help to develop a suitable method for MS diagnosis.

Despite a variety of reported researches on VEP, especially for monitoring and diagnosis of MS, there are still some weaknesses in this field. Firstly, the correlation of VEP measures with the visual function is claimed to be weak because the VEP morphological components depend on various factors and experiment conditions. Secondly, despite the complete or near complete recovery of visual performance, a significant latency prolongation remains unchanged [25]. Lastly, a fundamental assumption in evoked potentials (EPs) is to consider the ongoing electroencephalogram (EEG) as an uncorrelated noise. In contrast to EPs, EEG is known as a non-phase-locked activity. This feature causes the elimination of the background EEG (or even some information associated with EPs [26]) in the ensemble averaging process. This process would yield to improve the signal to noise ratio and subsequently, the extraction of ERP components. However, the real situation is

more complicated than this weak and widely used assumption. In other words, the phase reorganization of the background EEG during the presence of a stimulus would also result in EPs [27]. It was also shown that a visual stimulus could cause a significant reduction in the amplitude of the ongoing EEG [28]. Therefore, it could be claimed that a presented visual event results in not only the generation of an ERP but also a change in the background EEG. This is due to the interactions between neurons during a particular task or event. Therefore, assuming EEG as an uncorrelated noise and eliminating it cannot be fully trusted [29]. This assumption will cause the loss of useful and informative recorded responses of the brain for further analysis. It is worth mentioning that Babiloni et al, [30] have recently studied the effect of MS on the topological characteristics of different frequency bands of EEG signals. The results showed that there is a significant difference in alpha amplitude of studied groups: the healthy controls and two subtypes of MS, namely relapsing remitting and secondary progressive. These results would reconfirm the accurate choice of EEG signals as a tool for diagnostic aims in MS.

Aside from the type of data used, to have a reliable diagnostic system, the interpretation process is also of great importance. Traditionally, interpretation of the EEG for diagnostic aims was limited to the decision of a trained individual to distinguish between regular EEG activity and abnormalities contained within recorded signals. In respect to the recent advances in the field of pattern

recognition and machine learning, the advantage of applying a host of successful methods, as the computer-aided diagnosis systems, has been achieved. These automated techniques would undoubtedly provide a more accurate generalization in the diagnosis process. Before the presented work, a limited number of studies tried to develop an automated algorithm to diagnose MS from EEG signals. For instance, Ahmadi et al.[31] could diagnose MS with the accuracy of about 90% using a cognitive stimulus. Their proposed method was based of cross-frequency coupling and online sequential extreme learning machine classifier. In another study, employing a pattern recognition system (based on neural networks) and red-green and black-white stimuli led to the proper classification of MS and healthy controls [21].

The current study fulfills the above-mentioned advantages (the use of cortical recordings without eliminating the background EEG, engaging three examined visual tasks and being automated) of a reliable electrophysiological procedure in the MS diagnosis. Although the main contribution of this paper is meant to be diagnostic, any interaction changes between different regions of the brain were also visualized to represent better insight. To evaluate these interactions, which are poorly investigated in the framework of MS, several criteria in the task design and the processing level were met. From the point of the task design, three different stimuli were engaged like the ones used in [23]. This is the first

time that all of these three tasks are used in the study of MS with the utilization of EEG signals. As a result, this would yield to select the best distinguishing stimulus between normal and MS subjects. It is worth mentioning that, these kinds of task cause a more reliable and applicable diagnostic tool in comparison with other cognitive ones, due to the less prevalence of cognitive problems (about 40-65%) among MS patients [32].

In this paper, to diagnose the MS, phase coupling strengths between different areas of the brain were extracted. A quick look at the literature indicates that synchronization measures have been widely employed in the researches based on EEG [31, 33-41]. All these measures aim to seek the quantity of interaction between two or more signals and so, the corresponding sources they represent. In this study, to measure this type of coupling, firstly, different neural oscillations were extracted by bivariate empirical mode decomposition (BEMD) from electrode pairs. Considering the nonlinear nature of neural oscillators, BEMD would be a more suitable choice than frequency or time-frequency decompositions and has been successfully employed in the researches based on EEG [37, 42]. Then, using the Hilbert transform and mean phase coherence (MPC), the phase synchronization was calculated. In the feature selection and classification stages, the distance-based ReliefF algorithm and k-nearest neighbors (KNN) method were used, both of which are well-known and have been widely used in practical or clinical studies of biological signals. To the best of our

knowledge, this diagnostic method, including BEMD and MPC, have not been applied to classify EEG signals in the framework of MS yet.

The rest of this paper is organized as follows. In Section 2, the specifications of the experimental setup are described, and then the proposed methodology including feature extraction, feature selection, and classification are comprehensively introduced. In Section 3, the experimental results are expressed and finally, the last section discusses the results and provides conclusions to this paper.

2. Materials and Methods

The block diagram of the proposed MS detection method is depicted in figure 1. In this work, three visual stimuli were employed to differentiate between MS and healthy groups. The EEG data, recorded during the presentation of each visual stimulus through a 32-channel EEG acquisition system, was used as the input to the proposed signal processing procedure. Following a pre-processing step, five pairs of IMFs were extracted from each possible pair of EEG recordings using BEMD method. Then, the phase obtained from the Hilbert transform of each IMFs pair was used to calculate MPC indexes. The feature space was constructed from these indexes. Finally, ReliefF and KNN classification method were applied to classify healthy and MS subjects. The leave-one-subject-out cross-validation (LOOCV)

was used to evaluate the performance of the proposed method.

2.1 Data collection

A total of 16 Relapsing-Remitting MS patients (10 women and 6 men) aged 34.54 ± 7.61 years were compared with 15 age- and sex-matched healthy controls. The diagnosis was made by McDonald criteria [43]. Those with psychiatric, neurologic, or medical disorders other than MS were excluded from the experiment. All of the participants also had a normal or correct-to-normal vision, with no color-blindness. Using g.HIamp from gtech Company, 32 channels of EEG based on 10-20 system were recorded. The sampling rate of recorded signals was 512 Hz.

The Bioethics Committee of the Iran University of Medical Science approved this study. All of the participants took part voluntarily in the experiment and were fully informed about the study and written informed consent was obtained from them.

2.2 Visual Stimulus

The stimuli were designed using Python-based PsychoPy software [44]. Three subtypes of the stimulus were considered in the experiment, including red-green, blue-yellow (greenish yellow), and luminance. They were all sinusoidal grating with a sinusoidal counterphase flicker in a constant orientation. The properties of these three stimuli are presented in Table 1. [23, 45]. The outer borders and the interval screen between trials were set to be a grey color with mean

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luminance. By using these tasks, each experiment included 84 randomly trials (28 luminance, 28 red-green, 28 blue-yellow) each lasting for 1000 ms.

Table 1. Characteristic of three generated tasks.

Stimuli	Luminance Contrast	Flicker Frequency (Hz)	Spatial Frequency (cpd)
Luminance (Black-white gratings)	100%	15	0.5
Red-Green (Red-Green gratings)	isoluminant	5	2
Blue-Yellow (Blue-Yellow gratings)	isoluminant	10	1.25

2.3 Preprocessing

In order to prepare the recorded signals for further processing, firstly, a 50 Hz notch filter was applied to signals to eliminate the effects of the power frequency interference. Then, epochs corresponding to each specific trial, including 100 ms before and 1000 ms after stimulus triggering, were extracted.

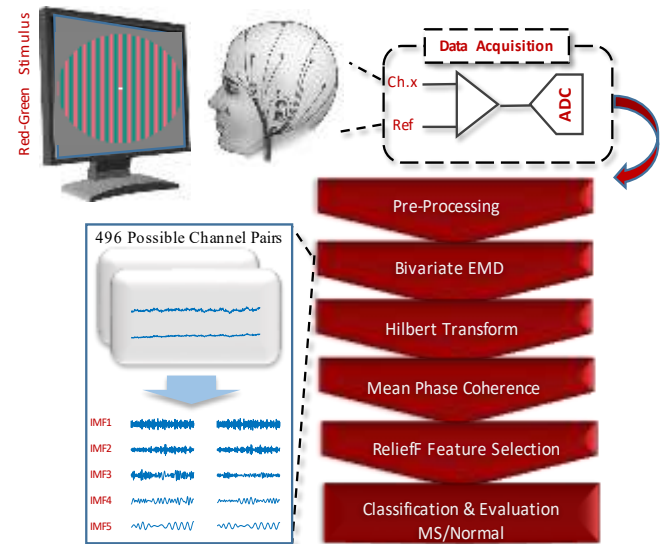


Figure 1. Data acquisition stage and the structure of the proposed method for MS detection.

2.4 Bivariate Empirical Mode Decomposition

Empirical mode decomposition (EMD) is a data-driven decomposition method in which nonstationary and nonlinear time series could adaptively decompose to their intrinsic mode functions (IMFs) with different frequency contents [46]. Unlike frequency-based methods, EMD-based methods do not rely on any basic assumptions about underlying components of the signal, and IMFs are determined from the dynamics of the signals. However, when it comes to multi-channel data, EMD cannot prevent the aliasing among different IMFs [47, 48]. Considering the nonlinear nature of multichannel EEG recordings, in this study, an extension of EMD, called BEMD, was used to decompose a complex (or bivariate) signal for further analysis. This method is applied to the real and imaginary parts of a bivariate signal simultaneously. As a result, dependencies

between these two parts of a signal will be preserved. Based on this method, every bivariate signal consists of fast rotations superimposed on slow rotations. Like EMD, this method also needs an envelope to separate fast rotations from slow ones, but in this situation, the envelope is a three-dimensional tube which encloses the bivariate signal. For this three dimensional tube, there are infinite directions which can set the edge of the tube. Practically, only a set consists of N directions ($\varphi_k = 2k\pi/N, 1 \leq k \leq N$) can be used to detect the envelope. In this study, we considered 10 directions. Having two channels of EEG signals, we can combine them to create a complex-valued signal as $x(t) = ch1(t) + ich2(t)$. Now given this bivariate signal and set of directions, the BEMD algorithm, as proposed in [49], is as follows:

- 1- For $1 \leq k \leq N$
 - a. Project $x(t)$ on the direction φ_k :

$$p_{\varphi_k}(t) = Re(e^{-i\varphi_k}x(t))$$
 - b. Extract the maxima of $p_{\varphi_k}(t) : \{t_j^k, p_j^k\}$
 - c. Interpolate the set $\{t_j^k, e^{i\varphi_k}p_j^k\}$ to obtain the tangent in the direction of φ_k : $e'_{\varphi_k}(t)$
- 2- Compute the mean of all tangents: $m(t) = \frac{2}{N} \sum_k e'_{\varphi_k}(t)$
- 3- Subtract the mean to obtain: $d(t) = x(t) - m(t)$

Now the complex-valued signal can be expressed as:

$$x(t) = \sum_{i=1}^M d_i(t) + r(t)$$

where $d_i(t)$ denotes the i^{th} IMFs and $r(t)$ the residue.

2.5 Mean Phase Coherence

MPC is an appropriate tool to determine the strength of the phase synchronization between two recordings from different areas of the brain [50]. In order to calculate the MPC for each complex-valued IMF, the instantaneous phase of real and imaginary parts must be calculated. To do this using the Hilbert transform, the analytical form of signals are obtained as follows:

$$\begin{aligned} z[t] &= s[t] + ih[t] \\ &= a(t)\exp(i\varphi[t]) \end{aligned} \quad (1)$$

in which $h[t]$ is the Hilbert transform of $s[t]$. Having the analytical signal, the instantaneous phase is obtained using:

$$\varphi[t] = \arctan(h[t]/s[t]) \quad (2)$$

Then, the relative phase between real and imaginary parts of an IMF is calculated using the following formula:

$$\begin{aligned} \varphi_{1,1}(t) \\ &= \varphi_{imag}(t) - \varphi_{real}(t) \end{aligned} \quad (3)$$

Given the relative phase, the MPC can be calculated as follow:

$$R = \left| \frac{1}{N} \sum_{j=0}^{N-1} e^{i\varphi_{1,1}(j\Delta t)} \right| \quad (4)$$

Where $1/\Delta t$ is the sampling rate of recordings. According to (4), it becomes clear that R is limited between 0 and 1. If there is a strict phase locking ($\varphi_{1,1}(j\Delta t) = \text{constant}$) between two oscillators, R reaches the value 1. By contrast, if phases are

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distributed uniformly, R is equal to 0. In this study, for each channel pair, five IMFs were calculated. Then, for each complex-valued IMF, the MPC was measured. As a result, for each pair of electrodes in every trial, five MPCs were determined.

2.6 Feature Selection

Feature selection, as a significant part of the classification process, is used to identify and select a subset, consists of relevant and informative features, from the original feature set. It can increase the accuracy and reduce the computational complexity in a classification task.

In this study, the ReliefF algorithm [51], an extension of the previous Relief algorithm [52], was used to find a subset of essential features. To deal with feature sets in which there is a strong dependency among features. ReliefF algorithm can be a proper choice because it considers this dependency. This method is comprised of four steps. At first, it samples an instance randomly. Then, it finds k nearest neighbors of the same class, “nearest hits”, and k nearest neighbors of other classes, “nearest misses”. Thirdly, for all features, the difference between the random sample and its nearest hits and nearest misses is calculated. Lastly, the weight vector, which shows the importance of all attributes, is updated based on the measured differences in the third step. If the mean distance from the selected sample to the nearest misses is greater than to nearest hits, the relevancy of features will be increased and vice versa.

2.7 Classification

In this work, the KNN classifier was used to separate normal and MS subjects [53]. This algorithm is a nonlinear method which determines the class of each sample in the test set based on the class of its k nearest neighbors in the training set. Its simplicity and low computational costs are the two key advantages of this algorithm. In order to find k nearest neighbors, some distance metrics such as Euclidean, Chebyshev, Manhattan, and Mahalanobis are considered. In addition to the distance metric, the number of nearest neighbors (k) is the other input parameter which plays an important role in the performance of KNN classifier. In the current study, the highest performance was obtained at $k=6$ for the Mahalanobis distance, so these parameters were set to classify each instance in the test set.

2.8 Performance Analysis

In the proposed scheme, for performance evaluation of the utilized classifier, the LOOCV method was used. In this method, in each iteration, one subject is considered as the validation set and the remaining subjects considered as the training set. The measures, which were used to assess the ability of the classifier in MS detection, are as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100$$

$$Sensitivity = \frac{TP}{TP + FN} \times 100$$

$$Specificity = \frac{TN}{TN + FP} \times 100$$

where *TP*: true positive (cases in which the classifier predicted MS and they do have the disease); *TN*: true negative (cases in which the classifier predicted normal and they do not have the disease); *FP*: false positive (cases in which the classifier predicted MS, but they do not actually have the disease); *FN*: false negative (cases in which the classifier predicted normal, but they do actually have the disease).

3. Results

In this study, in order to achieve an automated MS diagnosis system, 32 EEG channels were recorded from 16 MS patients and 15 healthy controls. Twenty-eight trials were recorded during the presentation of each of the three visual tasks. Totally, the dataset was constructed from 868 trials for each task (448 trials for MS and 420 for control subjects). Using BEMD, five pairs of IMFs were extracted from each possible pair of two different EEG channels (496 pairs). Executing the BEMD, only the IMFs corresponding to the original data were retained. Furthermore, as can be seen in figure 2., IMF1 from each trial contains high-frequency oscillations and has little contribution to the underlying dynamics of the signals. Therefore, it was removed from further processes [54].

Applying the Hilbert transform, the MPC between the extracted IMFs of every channel pairs was determined. The mean difference of these indexes between MS and healthy

groups are shown in a 32*32 matrix in figure 3. As can be seen, unlike the frontal and temporal lobes, the phase synchrony increased between pairs of channels located in the posterior regions of the brain for each of the three tasks.

In order to reduce the feature space and select the best distinguishing features, the extracted MPCs were ranked through the ReliefF algorithm. Top-twenty-ranked features were selected (out of 496 electrode pairs * 4 IMFs) to feed the classifier. These selected features have a significant difference between the two groups in all three tasks (p-value <0.01). As shown in figure 4, these features were mostly extracted from IMF2 and IMF3. None of these features were related to IMF5 which contains lower frequency contents.

The EEG electrode pairs of the selected features are shown in figure 5. The red arrows in this picture show an increase of synchrony in MS patients in comparison with healthy controls. The green arrows, in contrast, indicate a decline in synchrony strength. In some cases, the MPC indexes from more than one IMF of the same electrode pair were selected to differentiate two groups. Therefore, the number of arrows may be less than twenty. For luminance and blue-yellow, the selected features are mostly from the occipital and frontal regions, so the most effective channels for the proposed method are located in these regions. As can be seen in figure 3., these electrode pairs have the most changes in comparison with the others. Selected features of blue-yellow are placed randomly across the scalp.

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In the classification phase, the KNN classifier was applied and trained to distinguish between two groups. Using the LOOCV method, The best-achieved accuracy, sensitivity, and specificity of the proposed algorithm are depicted in figure 6. for each

task. It is evident that the red-green stimulus results in the highest performance in comparison with two others, with accuracy, sensitivity, and specificity of 93.09%, 91.07%, and 95.24% respectively.

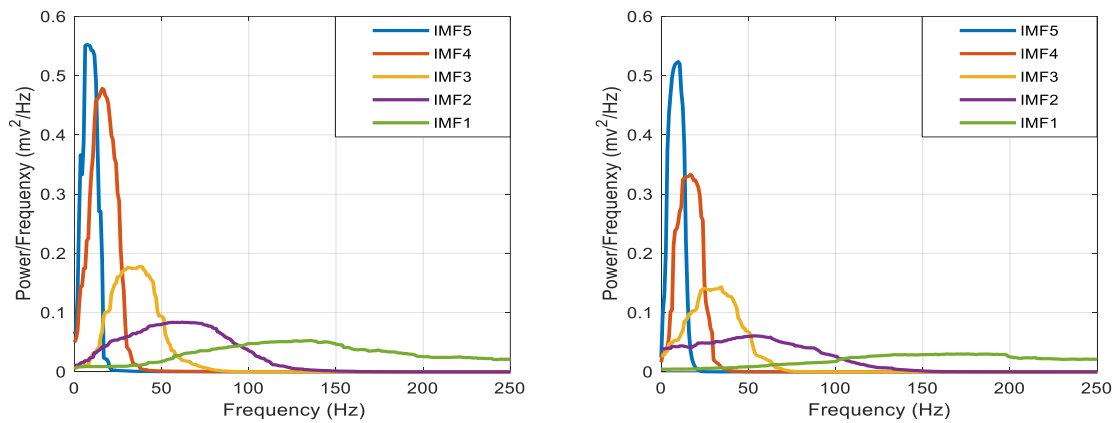


Figure 2. Power Spectral Density of extracted IMFs in two sample channels (CP5 and CP6).

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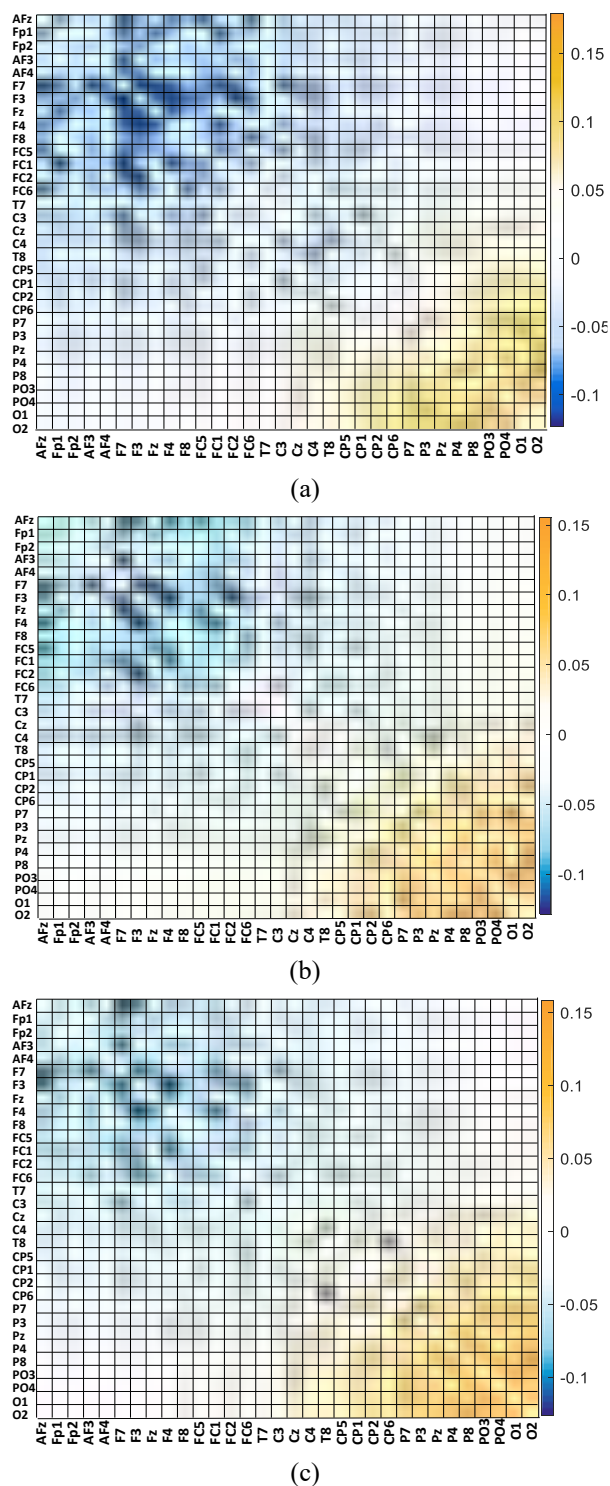


Figure 3. The difference of mean pairwise phase-synchrony indexes between the extracted IMF2 of EEG recordings of MS and healthy groups for (a) red-green, (b) luminance, (c) blue-yellow tasks.

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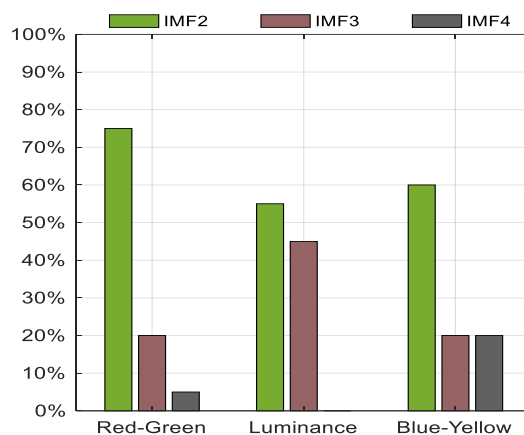


Figure 4. The participation percentage of the IMFs based on the selected features in the red-green, luminance, and blue-yellow tasks.

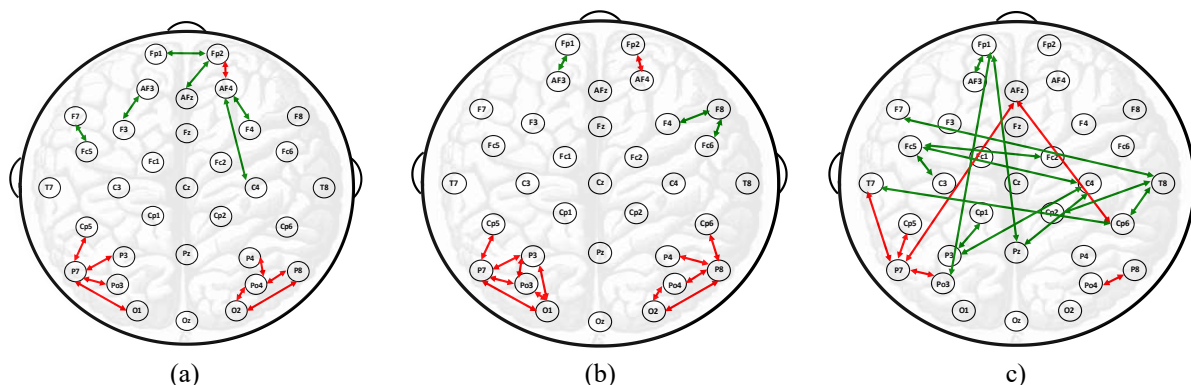


Figure 5. The most effective electrode pairs based on the selected features in the red-green (a), luminance (b), and blue-yellow (c) tasks. The red arrows show increased synchrony in MS patients in comparison with healthy controls, and the green arrows show a decreased synchrony.

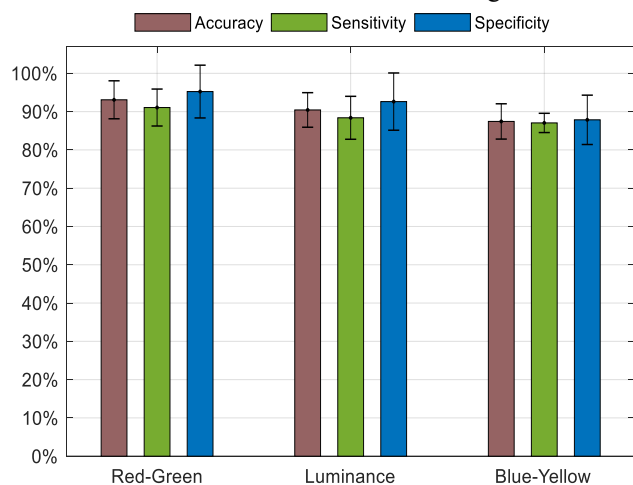


Figure 6. Performance of the proposed algorithm for red-green, luminance, and blue-yellow data.

4. Discussion

In this work, we proposed a signal processing and analysis framework for automated diagnosis of MS using EEG recordings during the presentation of the visual tasks. EEG, as the recording of the electrical potentials produced by the brain, plays an essential role for study and quantifying the human brain activity. Additionally, EEG-based techniques would present a more capable and financially satisfying diagnostic method in comparison with magnetic resonance imaging-

based ones. Despite such advantages of EEG, which made it a reasonable candidate for computer-aided diagnostic systems, there is still a lack of a reliable one in the field of MS. In this paper, we attempt to use visual disorders as a frequent and early symptom of MS, to early diagnosis of this neurologic disease.

Nowadays, analyzing this electrophysical tool for visualizing the synchrony of neural oscillators between different regions of the brain within different frequency bands is becoming a challenging topic in many neurological diseases. However, findings of synchronization in the human brain in the field of MS is still poorly investigated. Understanding how this phase synchrony varies after MS occurrence can help to decipher the complicated electrophysiological mechanisms and brain interactions underlying it during the visual tasks. This may also lead to developing an accurate tool for diagnostic aims. To assess this process, here we measure the phase synchronization between different regions of the brain using EEG recordings.

Assessing MPC indexes, which are extracted from electrode pairs, revealed a significant difference between phase coupling in MS and control subjects' brains. The pairwise MPC coupling changes associated with MS are depicted in figure 3. In all these three states, the increased synchronization of networks in mostly occipital and parietal lobes and desynchronization of frontal oscillators were seen. In the highly distinguishing red-green task, 75% of the most effective MPC indexes were obtained from IMF2 and the remaining from IMF3 which have the same frequency range as beta and gamma waves. Additionally, 75% of the effective features were associated with occipital and parieto-occipital regions. The function of this region of the cerebral cortex, including the primary visual cortex and the

visual association, is mainly related to visual processing. The parietal cortex also is responsible for integrating and processing sensory information, especially complex visual processing, and visual attention. Moreover, this result is in line with the reported abnormalities in the visual function of patients suffering from MS [14, 17, 20, 55, 56].

Previous researches on spatial and non-spatial visual tasks suggested that the prefrontal cortex as the control center for most cognitive functions appears to take charge of the brain's attention and control the parts of the visual cortex, which receives sensory input [57]. Additionally, several studies have reported the attention disabilities among MS patients [58, 59]. As can be seen in figure 3, there is a significant difference in the prefrontal area between two studied groups which confirms the visual attention disabilities among MS patients. Considering these, our results are in line with the mentioned results from other studies.

The classification results indicate that not only the phase synchrony evaluation would reveal the brain interactions underlying the MS, but also can present a powerful tool for diagnostic aims using EEG recordings. Presenting the most distinguishing red-green stimulus, we have achieved a high accuracy of 93.09% in respect to LOOCV, which to the best of our knowledge outperforms the recently reported methods in the literature. It is worth mentioning that due to the broader database samples, the results would be more reliable in comparison with similar studies [31].

5. Conclusion

Despite the huge advances of signal processing and machine learning algorithms, the electrophysiological effects of MS are still poorly

investigated and limited to a range of simple time-based features of VEP signals. In this study, we proposed a new automated method for the diagnosis of MS. For this aim using three visual tasks, 32-channel EEG was recorded. The BEMD method was applied to the EEG trials to decompose each pair to five pairs of IMFs. In order to evaluate the phase information of these IMFs, the phase synchronization between each pair was measured by the MPC method. To avoid the high computational cost and complexity (due to the

high dimensional feature space), ReliefF algorithm was used for dimension reduction. Finally, the twenty top-ranked features were fed to KNN classifier and led us to a subtle distinguishing between MS and healthy controls. As a result, high accuracy was achieved, especially for the red-green task with an accuracy of 93.03%. The results indicated that the proposed scheme has the potential to be generalized and used for the diagnosis of MS disease

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