Human implicit intent recognition based on the phase synchrony of EEG signals

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Abstract

This paper proposes a human implicit intent recognition system based on electroencephalography (EEG) signals, for developing an advanced interactive web service engine. We focus on identifying brain state transitions between intentions, and classifying a user’s implicit intentions while viewing an image on a web page, based on an EEG experiment. We measure brain state changes between a navigational intention and an informational intention by using phase synchrony; i.e., the phase locking value (PLV) in an EEG. Comparing PLVs that correspond to the two intention states is useful for determining a human’s implicit intention. In order to discriminate between a user’s implicit intentions using a PLV, we must extract features based on an EEG analysis. For this purpose, we identify the most reactive band within the full band of brain signals. Theta (4–7 Hz), alpha (8–13 Hz), beta-1 (14–22 Hz), and beta-2 (23–30 Hz) bands are used to extract the EEG features from the most reactive EEG band. Subsequently, we select the most significant pairs (MSPs) that are highly reactive and correspond to the intention. According to the proposed method, these features are useful for: (i) showing the brain state transitions regarding intentions, and (ii) classifying a human’s implicit intention using several classifiers such as a support vector machine (SVM), Gaussian Mixture Model (GMM), and Naïve Bayes. We then compare the results of these classifiers. This study demonstrates the potential uses of these identified brain electrode pairs for cognitive detection and task classification in future brain-computer interface (BCI) applications.

1. Introduction

Brain cognitive fusion technology is an emerging floating technology and the most promising [4]. In addition, information and communication technology (ICT) systems serve as empathic cognitive extensions of their users. ICT is an active and instrumental technology for driving interactions with computers as well as with other humans, and can learn and adapt with the user. For human development, it is important to establish interactions between humans and machines. Brain plasticity and behavior are required to establish this interaction [4]. According to [23], human beings have a natural method to represent, predict, and interpret intentions that are expressed either explicitly or implicitly. If we aim to design an efficient intention-based human-computer interaction model, we must identify a technique to understand human intentions. Intention recognition is a relatively new field that is being widely used in web applications [2] and internet security [26]. Many researchers have investigated decision discrimination using a variety of methods. Particularly in neuroscience, electroencephalography (EEG) collected non-invasively can be used to study intent discrimination. EEG is a measurement of the brain’s electrical activity and provides good temporal resolution. To understand brain cognition, it is important to understand the differences in brain activities in different regions of the brain that correspond to an intention. For this purpose, connectivity plays an important role and can be identified using measures described in neuroscience literature. Phase synchronization (PS) is one of those measures; it has successfully demonstrated that it can infer functional connectivity using multichannel neural signals, e.g., EEG [27]. In this paper, a particular PS is selected because it is more discriminative than amplitude measures in recognizing the implicit intentions of humans.

We propose the classification of a user’s navigational and informational intentions with a phase estimation based on collected EEG data. In particular, we identify brain connectivity patterns related to the user’s navigational and informational intentions through visual experiments based on static web images that closely match practical scenarios. We analyze differences in phase locking values (PLV) to determine the user’s navigational and informational intentions defined by [11]. A support vector machine (SVM) using a radial basis
kernel (RBF) function is employed to classify the user’s intention as either an informational search or a navigational search in an image based on the PLVs. The proposed intent recognition system based on EEG signals is useful for understanding what users intend to do with an object. Therefore, this result can be used for developing an advanced brain-computer interaction application, such as a new interactive web service. Further, our proposed method also includes the selection of the most reactive brain signal bands. An EEG can be more discriminative within particular selected bands, compared to utilizing entire frequency bands [33]; using particular bands increases performance when classifying a user’s implicit intentions.

This paper is organized as follows: in Section 2, we explain previous research efforts related to the study of human intentions using an EEG. In Section 3, we present a brief background on intent recognition. Our proposed method is discussed in Section 4. We explain the experimental details and present our results in Section 5. Section 6 concludes the paper.

2. Related works

In recent years, a substantial amount of research related to the detection of human intentions based on EEGs has been performed [3,5,7]. However, the specific connectivity patterns and the functional brain activity changes corresponding to intentions have not been reported. The functional brain connectivity changes related to human intentions is subject-specific, and the process required to identify fixed patterns is complicated, because there is no evidence of specific changes corresponding to an intention from the brain science perspective.

From a signal processing point of view, research trends for detecting human intentions based on EEGs are mainly focused on two methods: (i) employing magnitude information and (ii) using the EEG signal’s phase information.

In general, it is important to identify the specific locations of brain function connectivity changes that correspond to a particular task. For instance, there is a well-known motor imagery activity study analyzing human concentration between the left and right frontal lobes [13,30]. Once the specific locations and corresponding changes in brain activity are located, further analysis becomes easier. However, there has been no such evidence reported in the field of intent recognition. Therefore, the entire brain is generally taken into account for intent recognition [1,25]. However, this approach makes analysis more complicated and connectivity pattern identification more tedious. Therefore, it is important to limit the analysis to specific regions or specific connectivity patterns [1,25]. For this purpose, we must understand the information communications between EEG data collected in the channels and the location of each EEG electrode change that corresponds to an event. Several works have identified the information exchanged between electrodes in EEG montages that correspond to human intention states [15,24]. These works have contributed to the realization of BCI systems.

Psychological research related to the identification of human intentions has a significant influence on previous intention research [11]. Nevertheless, research that attempted to classify human implicit intentions using EEG signals is insufficient. In this paper, we propose a method to classify human implicit intentions (which are defined as informational search intentions and navigational search intentions) based on psychological background using EEG signal analysis.

3. Background of proposed method

3.1. Humans’ implicit intention

Human intentions can be explicit or implicit by nature. Humans express their explicit intentions using different action sequences. In contrast to explicit intentions, implicit intentions are vague and often difficult to interpret [6,8]. According to [9,11], human implicit intentions that occur during a visual search can be classified as either navigational or informational intentions. The different human implicit intentions that occur during a visual stimulus can be defined as follows.

Navigational intention: refers to the human idea to find some interesting objects in a visual input without a particular goal. In other words, the subject glances over the input scene to get an overall picture.

Informational intention: refers to the human aspiration to find a particular object of interest. In other words, the subject searches the input scene for a particular object assuming that it exists.

Fig. 1 shows heat distribution maps that indicate the human gaze preference [10] corresponding to navigational and informational intentions. This heat map, which can be generated with a Tobii eye tracker, shows human gaze activity for a specific stimulus. The colored region indicates the subject’s gaze position while viewing the stimuli; those positions gradually turn red when the subject focuses on them. In Fig. 1(a), it can be observed that the subject’s gaze is spreading all over the map during a navigational intent, while Fig. 1(b) demonstrates that the gaze is more focused or confined to some particular areas of the visual stimulus during an informational intent. Hence, the gaze maps corresponding to navigational and informational intentions are in accordance with the definitions given above.

3.2. Why do we select the phase synchrony method?

Human cognition studies that aim to measure the intentions of users represent a new and challenging field. Such studies are necessary to realize brain–computer interaction (BCI) systems. Researchers have been attempting to classify human intentions using both EEG and multiple biological signals [17]. In human implicit intention research, some works in the literature employ bio-signals [10]. However, few research efforts have identified human implicit intentions using EEG signals. It will be easier to show the human intent transitions between navigational intentions and informational intentions and to classify the intention type, if we use EEG signals and PS. Among the methods using EEG signals, the phase synchrony method has an advantage over other measures because it is more discriminative when corresponding to an event [15]. By comparing measures from the two brain states corresponding to navigational intentions and informational intentions, we can classify the intention of the parts. By using the phase of the EEG, we can measure the strength of the synchrony between any two locations over the surface of the brain. In general, we quantify the strength between two locations by using the synchrony measure PS, which is normalized from 0 to 1; 1 represents perfectly synchronized and 0 represents no synchronization at all.

Fig. 1. Gaze position by heat map for each intent: (a)Navigational intention: to focus on the image present on the screen, (b) Informational intention: to search for the specific object in the displayed image.
4. Method

PLV synchronization measures the EEG synchronization level at every time instant between any two electrode pairs, and ranges from 0 to 1 [15,27]. Therefore, the aim of this study is to represent user intentions that change over time as a quantitative representation of PLV.

Fig. 2 shows an overview of our proposed method. When the subject views some visual stimuli, EEG signals are also acquired simultaneously, in synchronization with the stimuli. Subsequently, we calculate the PLV using the data acquired from all electrode pairs in the brain. After extracting the PLV based on the most significant pairs (MSPs) at each intention period, we use the PLVs from the MSPs to distinguish between navigational and informational intentions. Therefore, these PLVs form useful feature vectors for classifying the user’s implicit intentions in our proposed method.

4.1. Phase locking value (PLV)

EEG phase differences are often used to compute “directed coherence,” which is a measure of the directional flow of information between two EEG electrode sites [12]. EEG phase differences are also used to estimate conduction velocity and synaptic integration time [18,28]. PLVs are a possible means to represent the synchronization phenomena in EEG signals. It is similar to a cross spectrum, but independent of the amplitude of the two signals [27]. With the assistance of the PLV, we can measure the synchronization between all electrode pairs in an EEG collection montage. The PLV is obtained with Eq. (1) [27],

$$\text{PLV} = \frac{1}{N} \sum_{n=1}^{N} \exp \left( j \Delta \Phi(t, n) \right) $$

where \( N \) is the total number of trials, \( \Phi(t, n) \) is the phase difference \( \Phi_1(t, n) - \Phi_2(t, n) \) between pairs of brain nodes, \( t \) is the time of each period, and \( j \) indicates a complex mark. The range of PLV values varies between 0 and 1. A PLV value of 1 indicates perfect coupling of electrode pairs, whereas a PLV value of 0 indicates that the electrode pairs are not coupled at all.

4.2. The most significant pair (MSP) at each intent period

To identify the network map of the brain, we must identify the PLV difference of two events against neutral duration (the difference between informational intention and the rest state, and the difference between navigational intention and the rest state). The PLV differences for all electrode pairs provide the pair information and the brain locations that are responsible for the corresponding event [5]. The PLV obtained during informational and navigational intention periods is used to calculate the PLV differences for all electrode pairs. The difference in the PLV between a navigational and an informational intention period is the key for the classification of human implicit intentions.

The MSP represents the most reactive electrode pairs (electrode pairs/locations) of the brain based on a comparison between the two events (information intention/navigation intention and rest). After determining the PLV of all the electrode pairs for each informational and navigational intention part, we define the MSP as the electrode pair that has the largest PLV difference between these two events [33]. The MSP formulas for both intent types are given in Eqs. (2) and (3).

$$\text{MSP} - N = \arg\max_{\epsilon} \{ \text{PLV}_{\text{navigation}} - \text{PLV}_{\text{rest}} \} $$

$$\text{MSP} - I = \arg\max_{\epsilon} \{ \text{PLV}_{\text{information}} - \text{PLV}_{\text{rest}} \} $$

MSP-I and MSP-N correspond to the MSPs identified for informational intention and navigational intention, respectively. In Eqs. (2) and (3), \( \epsilon \) represents electrode pairs. It is possible to identify both the brain connectivity and the most reactive electrode pairs based on PLV from Eqs. (2) and (3). Recently, the work of [5] identified the five MSPs for classifying moving motor imagery tasks, as shown in Fig. 3. In this figure, we can observe five green rectangles that were selected as the MSPs among all electrode pairs. In this study, we follow a similar procedure for the identification of five MSPs. One may also select a greater number of MSPs (for instance, 10 or 20 MSPs).

4.3. Difference level of PLV (DPLV)

To classify navigational and informational intentions, we selected five MSP-Ns and five MSP-Is identified in the theta band. MSP-Ns and MSP-Is are identified using Eqs. (2) and (3). The average PLV of five MSP-Ns and five MSP-Is can be observed during both of these events for three subjects.

We can easily observe that the MSP-Ns have a higher PLV level compared to MSP-Is during navigational intentions and vice versa during informational intentions. The difference in the PLV levels for navigational intentions and informational intentions is crucial for intent classification. The difference in the PLV levels of the identified MSPs can be calculated using the following equations:

$$\text{DPLV} = \{ \text{PLV}_{N}^{\text{MSP-N}} \} - \{ \text{PLV}_{N}^{\text{MSP-I}} \} $$

Fig. 2. Overview of the proposed method.

Fig. 3. Determining the most significant pairs.
DPLVI = \langle PLV_{MSP-N} \rangle - \langle PLV_{MSP-I} \rangle \tag{5}

where DPLVN is the difference in the average PLV of the five electrode pairs for MSP-N to MSP-I during the navigational intention period, and DPLVI is the difference in the average PLV for MSP-N to MSP-I during the informational intention period. \langle \rangle represents the mean operator.

4.4. Intention classification

In order to classify human implicit intentions, we must identify important features not only for human navigational intentions, but also for human informational intentions. For navigational intentions, we select MSP-N based on Eq. (2). We then calculate the PLV of MSP-N for each intention period. Likewise, the PLV for MSP-I can be calculated in the same manner. These extracted features are used as input for the classification process with 10 times cross-validation. Because the PLV transitions of MSP-N/I have opposite shapes for each intention part, we use it to classify changes in the user’s implicit intentions between navigational and informational intentions.

5. Experimental results

5.1. Experimental setup

Ten healthy male subjects participated in the experiment. EEG data from 32 channels were recorded with a BIOSEMI (www.biosemi.com) amplifier. Because, it is difficult to identify the specific region corresponding to human implicit intentions, we consider all channels covering the entire brain surface. The timing scheme of the experiment is shown in Fig. 4. Subjects were required to perform various tasks during each trial. According to the phase synchrony method, we were required to perform repetitive experiments for each subject. This was necessary because EEG signals are difficult to estimate with only one trial.

Each session consists of five trials. In each trial, different navigational and informational intention images that closely emulated real-life scenarios were presented as shown in Fig. 4(a). Five sessions were conducted, implying 25 trials per subject. Blank images were displayed between the two different intention images to prevent mixing of the intentions. Random images from each sequence were presented to avoid the induction of intentions in subjects, owing to the repetitive nature of the experiment. Fig. 4(b) shows the stimuli and areas of interest in the stimuli that were provided to the participants. In order to create informational intent for each participant, they were instructed to look for and continuously find a specific object in each image [10].

5.2. Results

In this section, we present a method to create a feature vector for classifying human implicit intentions using a PLV based on the proposed method. As discussed in Section 4, we calculate the PLVs of the MSPs that are estimated at each intention period. From the PLV differences, we select the most reactive band. Subsequently, we compare the intention change transitions between navigational intentions and informational intentions. Finally, we check the classification performance of the proposed method using various features to classify the user’s implicit intention.

5.2.1. Most reactive band

This section presents a comparison of several frequency bands, from the theta band to the beta band of the EEG signal (theta band (4–7 Hz), alpha (8–13 Hz), beta-1 (14–22 Hz), and beta-2 (23–30 Hz)). Thus, we obtain the PLV differences among several frequency bands for each intention period [22,33]. For example, Fig. 5 shows the different level of PLV at each frequency band in the MSP-N/I for subject #8. Fig. 5(a) shows a PLV average for MSPs at each intention period. In this figure, it is evident that the PLV differences between the navigational intention PLV and the informational intention PLV in the theta
Fig. 5. Band-wise comparison of MSP (Sub#8); An average of PLV over the trials at each band (a) MSP-I, (b) MSP-N.

Fig. 6. PLV of MSP-N/I values of 10 subjects at each band.

Fig. 7. PLV transitions of all participants. As shown in Fig. 7, although each subject has an MSP-N and MSP-I, we obtain similar PLV graphs at each intention period. In Fig. 8, mean PLV of selected number of pairs as MSP over all trials of the subject during informational period was shown. Theta band is used to calculate all the PLV values shown in Fig. 8 as in theta band both the intents are highly discriminant. For all selected number of MSPs the mean PLV of informational intent MSP’s PLV is always higher than the navigational intent MSP’s PLV. Similarly, during navigational intent it is vice versa. This phenomenon is observed in all subjects. This shows that intentions can be discriminated as specific pair combinations of one intent specific network pattern has significantly differed PLV compared to other intent. Hence, PLV difference of MSPs corresponding to intents is selected for classification. There is no significant difference in PLV depending on the number of MSPs (See Fig. 8). We also attempt to classify human intention based on the number of MSPs. In our proposed method, we confirm the transition using five MSPs. This shows a PLV average based on the number of MSPs. This figure was obtained by selecting MSPs in quantities of 5, 10, 20, and 50. To identify the transitions between human intentions, we can adjust the number of input samples. However, we must consider the location of MSPs to classify human implicit intentions (See Fig. 9). In Fig. 9, we can observe the change in PLV at each intention period (5 s). During the navigational period for all subjects in Fig. 7, we can observe that the red dotted graph (PLV of MSP-N) is higher than the blue rectangular graph (PLV of MSP-I). Conversely, in the informational period for all subjects in Fig. 7, we observe that the blue rectangular states (PLV of MSP-N) are higher than the red dotted states (PLV of MSP-N). We can also identify an intercept when human intention changes from a navigational intention to an informational intention.

5.2.2. Transition between human implicit intentions

To identify changes in human implicit intentions, we must capture brain signals in real-time, when brain states change. We use the MSP that is calculated by the proposed method. Therefore, a brain signal transition from navigational intention to informational intention can be observed, as shown in Fig. 7. The blue rectangular graph shows the PLV of MSP-I, and the red dotted graph shows the PLV of MSP-N. According to the experiment’s procedure explained in Section 5, each stimuli image is shown to one subject for every 5 s. For this reason, we can observe the change in PLV at each intention period (5 s). During the navigational period for all subjects in Fig. 7, we can observe that the red dotted graph (PLV of MSP-N) is higher than the blue rectangular graph (PLV of MSP-I). Conversely, in the informational period for all subjects in Fig. 7, we observe that the blue rectangular states (PLV of MSP-N) are higher than the red dotted states (PLV of MSP-N). We can also identify an intercept when human intention changes from a navigational intention to an informational intention.
observe the connectivity in different locations by selecting 5, 10, and 25 MSPs identified in the topology graph that correspond to the intent. Selecting MSPs in quantities greater than five results in a few common MSP pairs present in both intents. When selecting more than five MSPs, all subjects exhibit similar patterns that have a few common MSPs in the topology. However, some differences were noted between the MSPs of different subjects. This result shows that each subject uses different significant brain regions when considering an intention. Therefore, to classify human implicit intentions as either navigational or informational, the PLVs of the MSP-N/Is can be utilized to create an appropriate feature vector for the SVM. If we had considered 10 or 25 MSPs, it would have been difficult to identify the significant differences between navigational intentions and informational intentions, as shown in Fig. 9. Hence, we selected five MSPs in the experiment.

Fig. 9 shows the 5 MSP, 10 MSP, and 25 MSP of Navigational and Informational intents of all the subjects. We obtained distinct patterns corresponding to both intents (navigational and informational) and were named as intent specific network patterns. The identified intent specific pattern is consistent over sessions of a subject, i.e. the patterns are subject specific. Analysis across subjects shows that the patterns are distinctive and common patterns cannot be obtained. This shows the human thinking process/mechanism is highly subject specific and is likely to have highly distinctive network mechanisms corresponding to each task [20]. Hence our focus has been on subject-specific analysis. As shown in Figs. 6, 7 and 9, it is hard to discriminate the navigational and informational intentions based on MSP patterns, but the PLV values of MSP are useful information to discriminate the navigational and informational intentions, which are used as the input features of a classifier.

5.2.3. Classification of intention

In this work, we employed support vector machines (SVM) to classify the EEG signals according to the subject’s implicit intention (either navigational or informational) in real-world environment. For comparison analysis, we employed Gaussian mixture model (GMM) ([31,32]) and Naïve Bayesian classifiers [16,21]. Since the identified
MSPs were subject specific (as shown in Fig. 9), the analysis for formulation of feature vector and training the classifiers are also subject-specific.

For training, 15 random trials from the original 25 trials are selected to form the data set. With this training data set, a feature vector is formulated with the PLV, which is computed from the identified five MSPs of both navigational and informational intentional classes in both theta and alpha bands. Thus, the feature vector dimension per trial of each subject is 2 (bands) X 2 (intentions) X 5 (MSPs). The chosen three classifiers are then trained with the formulated feature vector as the input and the corresponding label as the output.

To obtain a good generalization performance with the classifiers, we employed the following procedure to select the optimal meta-parameters for each classifier.

For SVM classifier, the parameters that influence the classification performance are – regularization constant ($C$) and Kernel parameter. In this work, we chose two Kernel functions, RBF Kernel and polynomial Kernel. For SVM with RBF Kernel (SVM-RBF), the Kernel parameter that requires optimal selection is variance ($\sigma^2$). For this purpose, we performed grid-search on $C$ and $\sigma^2$ for various values ($C$ was varied from $10^{-1}$ to $10^2$ and $\sigma^2$ from $10^{-1}$ to $10^2$). For each pair of $C$ and $\sigma^2$, 10-fold cross validation was performed. The pair that yields the best classification accuracy is identified as the optimal meta-parameters of SVM-RBF. Results obtained for every subject in terms of mean and standard deviation of classification accuracy with identified optimal Kernel parameter ($\sigma^2$) is provided in Table 1. We followed the same procedure to identify the optimal meta-parameter for SVM with polynomial Kernel (SVM-poly). Results obtained for all subject s together with the identified optimal Kernel parameter (order of polynomial) are provided in Table 1.

GMM and Naïve Bayesian classifiers are also trained on the same feature vector formulated from the training dataset. For GMM,
Subject-wise classification performance of all classifiers with identified optimal parameters.

<table>
<thead>
<tr>
<th>Unit (%)</th>
<th>Support vector machine</th>
<th>Naive Bayesian</th>
<th>Gaussian mixture model</th>
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<tr>
<td></td>
<td>%Acc</td>
<td>%Acc</td>
<td>%Acc</td>
</tr>
<tr>
<td>S1</td>
<td>58.92</td>
<td>60.8</td>
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</tr>
<tr>
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<td>63.05</td>
<td>63.1</td>
<td>56.1</td>
</tr>
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<td>73.08</td>
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</tr>
<tr>
<td>S4</td>
<td>60.4</td>
<td>62.4</td>
<td>53.4</td>
</tr>
<tr>
<td>S5</td>
<td>57.1</td>
<td>62.2</td>
<td>64.2</td>
</tr>
<tr>
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<td>58.2</td>
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<tr>
<td>S7</td>
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<td>52.2</td>
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<tr>
<td>S10</td>
<td>61.3</td>
<td>60.6</td>
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%Acc = % Accuracy.

Table 2

Table 2 Subject-wise test performance of all classifiers.

To identify the optimal number of components (N), we trained GMM with various values for N (N = 1–10) and then performed 10-fold cross validation at each instance of N. The value of N which provides the best classification accuracy per subject is identified as the optimal number of components. Subject-wise classification accuracy and identified optimal N for GMM are tabulated in Table 1.

Naive Bayesian classifier was evaluated for two Kernels: (a) Gaussian distribution and (b) Kernel density estimation. The meta-parameters for Naive Bayesian classifier are mean and variance for Gaussian distribution and Kernel bandwidth for Kernel density estimation. These meta-parameters for each subject are empirically estimated from the formulated training dataset of that particular subject. The 10-fold cross validation performance of Naive Bayesian classifier on training dataset is tabulated in Table 1.

The testing dataset for each subject is formulated with the remaining 10 trials out of 25 trials. The feature vector computed from the testing data set is provided to the trained classifiers for classification. All three classifiers’ meta-parameters are initialized with the earlier identified subject-specific parameters provided in Table 1. Subject-wise classification performance of all classifiers for all subjects is tabulated in Table 2. Results show that, SVM-RBF provides best performance compared to the other classifiers. For instance, the classification accuracy obtained with SVM-RBF for S#7 is 77.4%, whereas with SVM-poly, Naive Bayesian and GMM the obtained classification accuracies are 72.4%, 52.2%, 56.8% and 50.5% respectively. The same trend is observed in all subjects.

6. Conclusion

In this paper, we proposed a method to differentiate between a user’s intentions while they viewed a given image based on the phase synchrony of an EEG. Previously, we selected various intention types, in order to adjust to web queries. In web searching, navigational intentions and informational intentions can be matched to the user’s implicit intention while they use a web site [11]. We identified the most significant PLVs in the varying pairs that corresponded to a user’s navigational and informational intention periods. In particular, we identified the most reactive bands by analyzing PLV differences obtained from the different frequency bands of brain signals. By employing the PLV of MSP-N/I, we identified transitions in the user’s implicit intentions and classified them using the SVM. With five MSPs employed for testing, our classification test performance results reached 63.6%.

Our future research will focus on determining the user’s intention based on multi-modal biometric data with our proposed method. We eventually plan to apply these methods for designing human-agent (robot or computer) interaction systems.

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