Enhancing EEG Signals in Brain Computer Interface Using Intrinsic Time-Scale Decomposition

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Abstract. A brain-computer interface (BCI) provides a link between the human brain and a computer. The EEG signal is nonlinear and non-stationary. Feature extraction is one of the most important steps in any BCI system; as such, enhancement to the existing methods has been incorporated in this work. For this, we propose a four-class movement imaginations of the right hand, left hand, both hands, and both feet, and develop feature extraction methods utilizing an intelligent method based on intrinsic time-scale decomposition (ITD) and Artificial neural networks (ANN). Based on the processed electroencephalography (EEG) data recorded from nine subjects, ITD accurately classified and discriminated the four classes of motor imagery; the average accuracy achieved is 92.20%.

1. Introduction
A brain-computer interface (BCI) is a direct communication between the human brain and an output device. BCI has provided persons with locked-in syndrome a substitute form of communication. This improves their quality of life by making them more independent and reduces their health care costs [1, 2]. Many researchers [1-4] showed that the use of BCIs allows paralyzed persons to send commands from their brains to output devices. This is by utilizing only a brain activity instead of a muscle activity. Human brains can generate different mental states, leading to performed imagination of movements (IM) or motor imagery/imagination (MI). The IM or MI can be detected through electroencephalography (EEG). Moreover, it can be implemented as an input signal to control the movement of an output device such as a wheelchair [1].

Different feature extraction techniques had been attempted to detect the mental tasks motor imagery, such as fast Fourier transform [5], autoregressive filter (AR) [6], band power (BP) [7], adaptive autoregressive filter (AAR) [8], power spectral density (PSD) [9] and common spatial patterns (CSP) [10].

In the last decade, various time-frequency techniques were proposed for decomposing non-stationary signals; among them are: Wavelet transform [11, 12], Empirical mode decomposition (EMD) [13-15] and Intrinsic time-scale decomposition (ITD) which is an improved time-frequency version of EMD [16]. ITD was applied to analyze multi-component signals into several proper rotation components (PRCs) [16, 17]. The utilization of more information of a signal and provision of a precise time, frequency, and energy localization for a signal are the advantages of ITD. In this work, the
following question has been addressed: Is it possible to enhance the performance of four class IM/MI involving the right hand, left hand, both hands, or both feet by using a time-frequency technique?

2. Materials and Methods

2.1. Participants and Experimental Tasks
In this study nine healthy right-handed volunteers comprising 2 females and 7 males, aged 20 to 38 years old participated. The wireless Enobio EEG system with eight electrodes was used in the experimental setup. The experiment consisted of one session for performing MI, guided by visual cues. The subject’s screen could be blank or would display an arrow pointing to the left, right, up or down. The participant’s task for each of these periods was to imagine: (1) moving the left hand when a left arrow appeared; (2) moving the right hand when a right arrow was shown; (3) moving both hands when an up arrow appeared; (4) moving both feet when a down arrow appeared. Any imagined movement should involve the continuous opening and closing of the fingers/toes of the respective hand/foot. When a blank screen was shown, the subject was to relax. The total number of runs was five, totalling 120 trials per subject per the whole five runs, with a 1-minute break between each run. The protocol of the data collection and the EEG electrode montage utilized is as shown in Figure 1 below.

![Figure 1. Experimental setup.](image-url)
2.2. Preprocessing
In the pre-processing, we used a temporal filter which is a band-pass filter from 0.5 Hz to 30 Hz, made up of a third order Butterworth filter and a common average reference (CAR) filter [18].

2.3. Feature Extraction
The ITD method is used to decompose the four class MI into proper rotation components (PRCs) consisting of PRC1 to PRC5, and a monotonous trend. PRCs represent the high frequency components of the signal and r5 is the monotonous trend signal. The input signal \( X_t \) can be decomposed as:

\[
X_t = H_t + L_t
\]

Where \( X_t \) is the input signal, \( H_t \) represents the proper rotation components (PRCs), and \( L_t \) is the monotonous trend signal. The procedures for analyzing PRCs and a feature selection vector is shown in Figure 2 below.

![Figure 2. Feature extraction using ITD method.](image)

2.4. Classification
Artificial neural networks (ANN) are comprised of the dense neurons of interconnected but independent entities [19]. The advantage of neural network is in its ability to model and recognize non-linear relationships between data [20].

We designed and trained feed forward back propagation neural network (FFBP NN) which consisted of one input layer, one hidden layer and one output layer. The hidden layer was varied from 5 to 80 nodes. Different activation functions were investigated such as Tan sigmoid, Log sigmoid and pure linear functions. The feature vector length was 72 while the outputs were set to four (left/right hand, both hands and both feet).

3. Results and Analysis

3.1. ITD Data Analysis
Figure 3 illustrates an example of five PRCs; the first PRC (i.e., PRC1) has the highest frequency content, while the fifth PRC (i.e., PRC5) has the lowest frequency contents from the right-hand MI.
Figure 3. Example illustrating the intrinsic time-scale decomposition of an EEG signal relating to right hand MI.

3.2. Classification Performance

Performance measures namely accuracy, sensitivity and specificity were used to evaluate the discrimination of the four class MI. As shown in Table 1, the mean accuracy of the algorithm based on all the nine subjects in the four-class problem is 92.20%. Based on ITD, the relevant features are useful for preserving class reparability, resulting in a classifier that can accommodate outliers and obtain better generalization properties. The ITD level has a significant effect on classification accuracy of the MI tasks; the accuracy decreased as the ITD level increased.

Table 1. Performance of algorithm based on each participant.

| Participant | Sensitivity (Avg. %) | Specificity (Avg. %) | Accuracy (%) |
|-------------|----------------------|----------------------|--------------|
| S1          | 0.92                 | 0.93                 | 92.65        |
| S2          | 0.914                | 0.94                 | 93.61        |
| S3          | 0.91                 | 0.92                 | 92.24        |
| S4          | 0.96                 | 0.96                 | 95.15        |
| S5          | 0.91                 | 0.9                 | 90.93        |
| S6          | 0.91                 | 0.91                 | 91.32        |
| S7          | 0.91                 | 0.91                 | 93.25        |
| S8          | 0.86                 | 0.86                 | 85.77        |
| S9          | 0.93                 | 0.91                 | 94.88        |
| Mean        | 0.913                | 0.915556             | 92.20        |

3.3. Confusion Matrix

Confusion matrix is a key parameter for a multi class classification analysis used to evaluate the performance of BCIs [21, 22]. The confusion matrix of the four classes using ITD is presented in Table 2 below. The classification accuracy of the right hand, left hand, both hands and both feet were 94.40%, 89.70%, 88.63% and 96.08%, respectively.

The right-hand, left-hand and both hands reduced the classification accuracy by 1.74%, 6.64% and 7.75%, respectively, when compared to both feet. Interestingly, the right hand and both feet MIs were not misclassified as compared to the left-hand and both hand MIs. For the right-hand MIs, the reason
behind it is the handedness; whereas for both feet IMs, the subjects were not confused with other tasks. Both hand IMs were the most misclassified task as they were confused with left-hand or right-hand IMs. The effectiveness of ITD with ROI (region of interest) to predict the MI tasks can be sequenced in the following order, from highest to lowest accuracy: both feet > right-hand > left-hand > both hands.

Table 2. Averaged confusion matrix for all subjects.

| True class | Right hand | Left hand | Both hands | Both feet |
|------------|------------|-----------|------------|-----------|
| Right hand | 94.40%     | 4.03%     | 0.75%      | 0.82%     |
| Left hand  | 7.43%      | 89.70%    | 2.54%      | 0.33%     |
| Both hands | 7.03%      | 3.93%     | 88.63%     | 0.41%     |
| Both feet  | 2.01%      | 1.07%     | 0.84%      | 96.08%    |

4. Conclusion
The aim of this work was to enhance the performance of the four class MIs to be used by completely locked-in people. We demonstrated that the enhancement of the classification performance of the four-class MIs is possible. The ITD based approach yielded an overall accuracy of 92.20%. Our subsequent task was to conclude whether ITD is more suited for a BCI application. Considering the stated statistical features, we propose ITD as a promising feature extractor for real-time applications.

In the future work, the proposed algorithm will be utilized in a power wheelchair to assist the locked-in people to control and maneuver its mobility and direction. To achieve smooth wheelchair controls and movements by the proposed algorithm, we will focus on online signal processing instead of the current offline approach.

5. References
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