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Entropy-based feature extraction for classification of EEG signal using Lifting Wavelet Transform

Abstract. *In the realm of Brain-Computer Interface (BCI), a crucial hurdle lies in effectively classifying Motor Imagery (MI) signals. Numerous techniques have been developed for Electroencephalogram (EEG) signal-based MI classification. The proposed system transforms EEG signals into various representations through Lifting Wavelet Transform (LWT). Long Short Term Memory (LSTM) is employed for classifying the extracted feature vectors in each line. The performance of this method is evaluated on the PhysioNet database, specifically for distinguishing between right and left hand imagery move. The strategy,resulting in 100% accuracy in 19 out of 72 wavelet families of LWT. This combination proves to be a highly efficient tool for BCI-based EEG analysis, showcasing its potential as a resourceful solution in this domain.*

Streszczenie. *W obszarze interfejsu mózg-komputer (BCI) kluczową przeszkodą jest skuteczna klasyfikacja sygnałów obrazowania motorycznego (MI). Opracowano liczne techniki klasyfikacji MI na podstawie sygnału elektroencefalogramu (EEG). Proponowany system przekształca sygnały EEG na różne reprezentacje za pomocą transformacji falkowej Lifting Wavelet Transform (LWT). Pamięć długoterminowa Long Short Term Memory (LSTM) jest wykorzystywana do klasyfikowania wyodrębnionych wektorów cech w każdej linii. Wydajność tej metody jest oceniana w bazie danych PhysioNet, w szczególności w celu rozróżnienia ruchu obrazowania prawej i lewej ręki. Strategia ta zapewnia 100% dokładność w 19 z 72 rodzin falek LWT. Ta kombinacja okazuje się wysoce wydajnym narzędziem do analizy EEG opartej na BCI, pokazując swój potencjał jako zasobnego rozwiązania w tej dziedzinie.* (***Ekstrakcja cech oparta na entropii do klasyfikacji sygnału EEG przy użyciu transformacji falkowej Lifting Wavelet***)

Keywords: Brain Computer Interface, EEG, Lifting Wavelet Transform, LSTM.
Słowa kluczowe: Interfejs mózg-komputer, EEG, transformacja falkowa typu Lifting Wavelet Transform, LSTM.

Introduction

Motor Imagery (MI) represents one approach for implementing Brain-Computer Interface (BCI). Typically, it employs electroencephalography (EEG) for capturing brain activities, which is a non-intrusive and easily applicable method. The suggestion is to utilize a support vector machine (SVM) for generating a non-linear decision boundary. Additionally, specific kernel functions are defined to handle situations where the datasets lack linear separability [1]. The researchers have undergone many works in motor imagery based brain computer interface EEG signal classification in various applications [2-7]. In the context of BCI, the common spatial pattern (CSP) stands out as one of the frequently employed features. Selim et al. [8] presented a hybrid approach incorporating the attractor metagene algorithm and the Bat optimization algorithm. This hybrid method was employed to choose the optimal features of CSP and simultaneously enhance the parameters of the SVM. Other investigations have explored the use of CSP filter to derive a novel time-series. The authors [9], following pre-processing techniques such as Band Pass Filter (BPF) and independent component analysis (ICA) to eliminate noise. They attained a exactness of 81±8% and 83±3% for explicit and implicit MI methods respectively in distinguishing between left fist and right fist movements. Additionally, various studies have proposed the combination of different methods to enhance overall performance. In [10], a fusion procedure designed for the classification of binary-class MI. It employed a cross-correlation technique to extract features and utilized a Least Squares SVM (LS-SVM) for classification. Performance assessments were conducted through a 10CV method, and the outcomes were compared with eight alternative methods, showing a notable improvement of 7.4%. Another crucial approach for extracting features and performing classification involves the utilization of a convolutional neural network (CNN) [11]. The performance of BCI was enhanced through the integration of a LSTM network with a spatial CNN. Subsequently, a feature vector was obtained using a Discrete Wavelet Transform (DWT). The outcomes demonstrated a notable level of accuracy.

Empirical Mode Decomposition (EMD) is employed in BCI [12,13] to derive Intrinsic Mode Function (IMF)-based features for the sorting of imagery EEG signal. In [14], IMF's Band Power (BP) utilized to identify μ and β rhythms. Subsequently, other signals were rebuilt using BP on IMFs. Here classifier was hidden Markov model (HMM). Outcomes demonstrated that EMD facilitated the extraction of suitable features. Another study focused on removing artefacts and retaining suitable data from MI based EEG signals [15]. A novel de-noising approach was developed as a method, involving the decomposition of the signal using Ensemble Empirical Mode Decomposition (EEMD). Subsequently, an improved wavelet threshold technique was used to remove the artefacts of high frequency (HF) modules. Finally, de-noise signals were generated using superimposing of IMFs. The outcomes indicated a greater Signal-to-Noise Ratio (SNR) and lower Root Mean Square Error (RMSE) by comparing state of art approaches, such as EMD and EEMD. In other study, a hybrid approach of ICA and complete EEMD (CEEMD) were employed to eliminate noise [16]. Additionally, in [17] researchers suggested an efficient distribution method and utilized naïve Bayes for categorizing signals. The deep learning (DL) technique has the benefit of not requiring manual feature extraction. Through training, the neural network understands end-to-end classifiers that includes CNN [18-22], DCNN- mVGG [23], QNET [24], G-CRAM [25], Triplet Network model [26] and LightGBM [27]. EEGNet [28] process EEG data for categorization he activities using convolutional networks. The author [29] proposes a deep ConvNet with a variation of diverse architectures that outperforms the extensively utilised filter bank widely utilised spatial pattern decrypting approaches. One-Dimentional CNN layers helps to gain knowledge of temporal and spatial filters to extract the features [18]. All such techniques eliminated the need for manual feature obtaining and outperformed conventional machine learning (ML) techniques and reviews of these techniques have been done[30]. However, the exactness in the cross-individual motor imagery categorization activity requires an improvement. In EEG evaluation, the substance of the t-f data plays a significant role. The t-f based wavelet domain represents complicated EEG data more efficiently than the Fourier domain because the frequency data varies with time.

Research Gap and objective

Following the literature review, many wavelet transforms were utilized to increase the classification performance of BCI-based EEG signals. Although features had a high computing cost associated with feature estimate, which has its own limitations for classification of signals. According to the study, entropy-based features guarantee better classification outcomes than other t-f domain features; however, in order to choose the right entropy-based features that balance classification accuracy and computational complexity, in-depth research is required.

Researches have the limitations of detailed study on using the right features to improve accuracy of classification with suitable classifier. Wavelet Transform can preserve the signals' time and frequency precision, resulting in efficient feature extraction that influences the BCI's classification accuracy. The research is required in terms of fast computation, better numerical stability, In-Place computation, Flexibility and Efficient implantation.

Unique method to classify the EEG signal using Log energy entropy, sure entropy and Shannon entropy. While there are indeed many other feature extraction algorithms available in the literature, entropy-based techniques offer unique advantages in terms of dimensionality reduction, information content, robustness, interpretability, and generalization. Depending on the specific characteristics of the data and the requirements of the problem at hand, entropy-based feature extraction methods can be a valuable tool in the data analysis and modeling process. By way of a single feature, it is capable to fetch better classification accuracy. The proposed technique starts with LWT-based feature extraction from EEG signals. Then the classification technique LSTM is used in our work. The proposed LWT-based log energy entropy as a single feature to classify EEG signals for left and right fists shows much better accuracy. In this paper, we propose an LWT method and LSTM for the classification of EEG data.

Material & Methodology

Dataset

The EEG database sourced from [31,32] contains 1500 signals recorded through 64-electrode EEG recordings, adhering to the 10-10 Electrode placement systems [33], and involving 109 participants. Each participant engaged in tasks that involved imagining the movement of either the left hand or right hand in response to a target appearing on the corresponding side of the screen. Some trials did not involve a target and were labelled as rest. The task involved imagining the opening and closing of the hand till the object vanished from the monitor or display. Each and every trial had a duration of 4 seconds, followed by a brief period of inactivity. On average, each user contributed around 150 EEG trials, with a relatively equal distribution of right label, left label or rest label.

EEG Pre-Processing And Feature Extraction

The EEG signal is picked up from the brain. The raw brain signals contain noise and so the redundant noises are eliminated, and then the features of signals are extracted by LWT, after which the two-class data is classified using LSTM. Fig. 1 shows the block diagram of MI Tasks BCIs based EEG Classification.

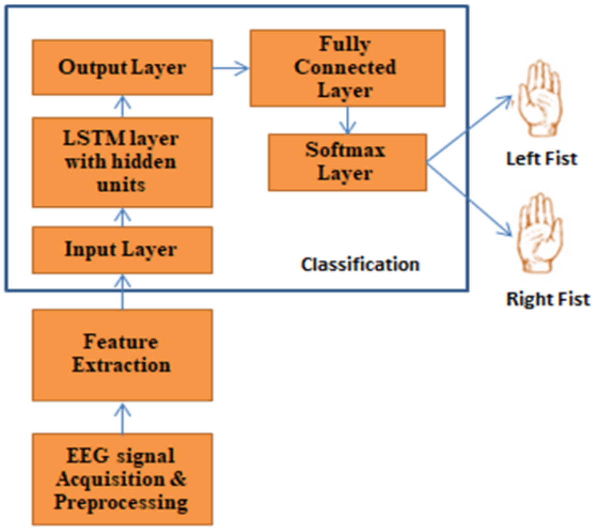

Fig. 1. Block diagram for classification of Left and Right fist

Lifting Wavelet Transform

A lifting system was suggested to minimize calculation time as well as memory necessity this system takes on an in-place execution of WT. LWT makes the system simpler by directly examining the systems in the integer domain. The LW minimizes time as well overwhelms the weakness of the previous wavelet it contains a frequency localization feature. The fundamental idea behind wavelet lifting was to create a distinct wavelet with enhanced features compared to the existing one, embodying the core concept of lifting. In the framework of the Integer Wavelet Transform (IWT), the LW method typically encompasses three stages: splitting or merging, prediction, and updating [34].

The reconstruction of LWT is a counter-step of decomposition. The decomposition and reconstruction of the Lifting Wavelet Transform are shown in Fig 2.

1.Split step: This step is known to be a lazy wavelet transform. This operation simply splits input signal y (*m*) into odd and even samples as shown in (1), Yo(m) and Ye(m) respectively.

(1) $$Ye(n) = y(2m)Yo(m) = y(2m+1)$$

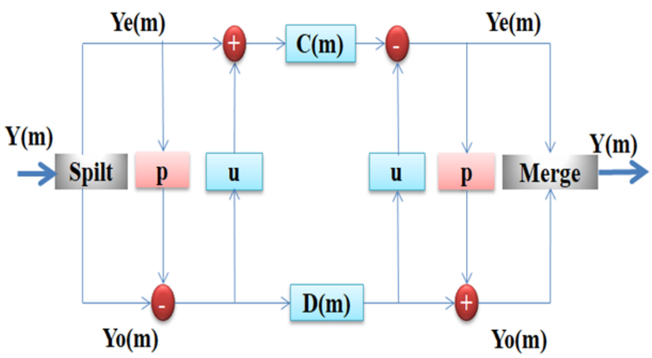

Fig. 2. Decomposition and reconstruction of LWT

2.Prediction Step: This Step involves unchanged even samples and for prediction utilize Ye(m) and Yo(m). The 2 signal subsets from the split step are most closely associated. The detailed signal D(m) is given in (2):

(2) $$D(m) = Yo(m)- p[Ye(m)]$$

here p[.] = predict operator. The detailed signal D(m) is the high-frequency component of Signal y(m). Therefore, the prediction step functions as a high-pass filter.
3.Update step: Introduce the update operator u[], and contemplate using it on the detailed signal D(m) to update even samples Ye(m). The approximate signal A(m) denotes the low-frequency component of signal y(m) as in (3). Hence, this operation serves as a low-pass filter.

(3) A(m) = Ye(m) + u[D(m)]

Classification
Long Short-Term Memory (LSTM) technique

Traditional NN, such as CNNs, excel at extracting features that remain invariant across various input data. Conversely, in tasks requiring the prediction of current outputs based on distant features, Recurrent Neural Networks (RNNs) outperform CNNs according to work [36]. RNN is effective in modeling sequential units due to its ability to retain a memory of historical data. Within each RNN cell, the input pertains to features at time T and possesses a dimensionality equivalent to the size of the features. The hidden state HT-1 in an RNN signifies the memory preceding the current unit. By utilizing HT-1 and the input, we could compute and transmit original memory HT to the subsequent RNN unit. Despite these capabilities, RNN has its limitations it systematically computes sequential information one after the other, disregarding variations in the impact of different pieces of information. Consequently, RNN encounters challenges in identifying and leveraging long-term dependencies within the database [37]. Fig.3 shows the architecture of LSTM cell. Once confronted with consecutive data, RNN may encounter issues such as gradient explosion and vanishing. where I = input gate, O = output gate, F = forget gate, and C = cell vector. The computation of the memory unit is determined using the equations (4-9):

(4) $\sigma(y) = \frac{1}{1+e^{-y}}$

(5) $I_T = \sigma\,(w_{y_I} y_T + w_{H_I} H_{T-1} + w_{C_I} C_{T-1} + B_I$

(6) $F_T = \sigma\,(w_{y_F} y_T + w_{H_F} H_{T-1} + w_{C_F} C_{T-1} + B_F)$

(7) $O_T = \sigma\,(w_{y_O} y_T + w_{H_O} H_{T-1} + w_{C_O} C_{T-1} + B_O)$

(8) $C_T = F_T\, C_{T-1} + I_T\, tanh\,(w_{y_C} y_T + w_{H_C} H_{T-1} + B_c)$

(9) $H_T = O_T \tanh(C_T\,)$

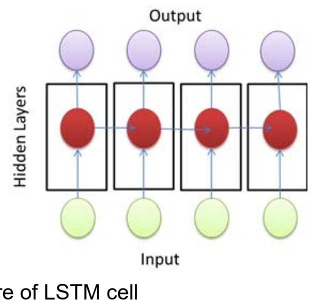

Fig. 3. Architecture of LSTM cell

The matrices in aforementioned equations carry significance consistent with their names. For instance, w_{H_O} = matrix of hidden-input gate. The process within the LSTM division, it transfers the hidden state HT to the subsequent LSTM division, tasked with resolving the EEG signal of the time slice that provides output for subsequent layer. Due to the incorporation of the forget gate, LSTM not only retain crucial long term memory (LTM) but adapt to short term memory (STM) containing vital data.

Results and discussions

The LWT-LSTM algorithm, described in Section 2, was implemented in MATLAB R2018. A set of signals recorded from 109 persons, were used to investigate the proposed classifier performance in classifying from the respective signals. The 1-D LWT features extracted from EEG signals were fed to the classifier, whose performance measures were assessed with a 10 - fold CV.

We selected these metrics to assess the undertaking research work: accuracy (ac), To ensure comprehensive understanding, their precise definitions are provided in (10):
(10) AC = Trp + Trn \ Trp + Trn + Fap + Fan
where Trp = true positive, Trn = true negative,
Fap = false positive, and Fan = false negative.

The EEG Motor Movement Imagery Database (EEGMMIDB), which includes signals corresponding to movements of the right and left fists, was split into a training set (80%) and a test set (20%). After pre-processing the raw EEG signals, extraction of 1-D LWT features were done from EEG signals. These features were then given to the most effective classifiers to assign class labels. The assessment of classification performance, as measured by the previously defined accuracy (AC), involved conducting a 10CV that was repetitive for 10 times. In the dataset, the analysis commenced with the 1st level of LWT and progressed incrementally until the highest accuracy was achieved. Optimal performance was observed at level 9. Considering the mother wavelet, a total of 72 families were taken into consideration. Notably, utilizing all nodes resulted in a superior classification accuracy compared to using only the final node. Following the LWT, the log energy entropy of signals is computed. Subsequently, the extracted features, represented by entropy values, are fed into a LSTM network. The network initialization involves a simple configuration with one hidden layer comprising a single neuron. The architecture is then systematically expanded by increasing the number of neurons and hidden layers until an enhanced classification performance is achieved. The optimal classification accuracy is reached when employing hidden layers totalling 15. In this study, an input size of 1 was employed, and the sequence input layer was linked to an LSTM layer featuring 15 hidden layers. The outcome from the LSTM layer was directed to a fully connected layer, followed by a softmax layer. Ultimately, the output was input into the classification layer to enhance accuracy computation. The optimization process utilized the Adam optimizer with a tanh activation function, and the training was conducted over a maximum of 50 epochs to achieve optimal results. Table 1 shows the wavelet families attained 100 % accuracy with log energy entropy.

We focussed on entropy-based feature extraction techniques are used in various fields, including signal processing, image analysis, and machine learning, for several reasons: Entropy-based techniques can help in reducing the dimensionality of the feature space by selecting the most informative features. This is particularly useful when dealing with high-dimensional data, as it helps in simplifying the model and reducing computational complexity. Entropy measures the uncertainty or randomness in a dataset. By extracting features based on entropy, we can capture the information content of the data. Features with high entropy are likely to contain more information about the underlying patterns in the data, making them valuable for classification or regression tasks. Entropy-based feature extraction methods are often robust to noise in the data. Features derived from entropy measures can focus on the underlying structure of the data rather than being influenced by noise, leading to more robust models. Entropy-based features are often intuitive and interpretable. They provide insights into the distribution and structure of the data, making it easier to understand the behavior of the model and interpret its predictions. Features extracted using entropy-based techniques can enhance the generalization ability of machine learning models. By focusing on the most informative aspects of the data, these features can help the model generalize well to unseen data, thus improving its performance in real-world scenarios.

To provide a benchmark, we conducted a comparison with previously published results, with a primary focus on accuracy as a key performance measure. Our previous work is based on CWT [38] attained less accuracy comparing state of art techniques. Our proposed approach in this paper applying the LWT followed by Shannon, log energy, and sure entropy computations, culminating in classification using LSTM. Table 2 represents the results of proposed system with previous work done by the researchers. Notably, among the three entropy measures, Log Energy Entropy demonstrated superior performance, achieving 100% accuracy for 19 wavelet families. Moreover, employing LSTM as a classification method contributed to enhanced accuracy. Ultimately, our research systematically explored parameter spaces, including LWT level, wavelet base, number of LWT hidden layers, as well as the quantity of neurons, resulting in a precise methodology that significantly contributes to achieving optimal accuracy.

Table 1: Wavelet Families attaining 100% accuracy with Log Energy Entropy

Wavelet family	Shannon Entropy	Sure Entropy	Log Energy Entropy
Db1	80	81	100
Db5	85	86	100
Haar	85	88	100
Sym8	89	87	100
bior1.1	86	87	100
bior1.5	89	88	100
bior3.5	84	88	100
bior5.5	89	83	100
rbio1.3	88	81	100
rbio2.4	86	82	100
rbio2.6	89	86	100
rbio3.1	80	84	100
Lazy	86	89	100
Cdf2.2	78	83	100
Cdf2.6	78	75	100
Cdf4.6	90	89	100
9.7	90	89	100
r9.7	82	83	100
Coif3	89	91	100

Table 2: Comparison with Previous Work

Title	Methods	Accuracy
Dose et al.,	CNN	80.32%
Li et al .,	DCNN-mVGG	96.48%
Fan et al.,	QNET	82.88 %
Roots et al.,	CNN	83.8%
Li et al.,	CNN-GRU	97.36%
Hou et al .,	scout ESI and CNN	94.51 %
Alwasiti et al.,	Triplet Network	64.7 %
Zhang et al.,	(G-CRAM)	74.71%
Lun et al.,	CNN	97.28%& 98.61%
Abenna et al.,	Delta-CSP-LGBM	98.17
Proposed work	LWT+LSTM	100%

Conclusion

This study outlines a methodology for analyzing EEG data in BCI applications, leveraging the LWT and three different entropies. The classification process is carried out using a LSTM network, and the achieved accuracy is compared to prior research findings. Various factors affecting the technique, including LWT level, wavelet base, and LWT parameters such as the number of neurons and hidden layers, are systematically explored to optimize classification accuracy. The performance of the proposed method is evaluated on the PhysioNet dataset, demonstrating a remarkable 100% accuracy with log energy entropy in the user database. This outcome surpasses existing results on both similar and diverse databases. In summary, the proposed approach, involving LWT, log energy entropy, and LSTM, emerges as a proficient tool for BCI-based EEG analysis and signal classification. Future research endeavors may explore the implementation of a real-time expert system for clinical applications.

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