

TREE BASED WAVELET TRANSFORM AND DAG SVM FOR SEIZURE DETECTION

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ABSTRACT

In this paper, we have proposed a new tree based wavelet transform (TBWT) for feature extraction scheme for epileptic seizure detection. Also this paper uses the Directed Acyclic Graph Support Vector Machine (DAGSVM) for the multi-class electroencephalogram (EEG) signals classification. The main aim was to determine the effective features for this problem. Wavelets have played an important role in biomedical signal processing for its ability to capture localized spatial-frequency information of EEG signals. The TBWT works well for high dimensional, multi-class data streams. Decision making was performed in two stages: feature extraction by computing the approximate and detailed wavelet coefficients and classification using the classifiers trained on the extracted features. We have compared the TBWT with wavelet based transform by evaluating with the benchmark EEG dataset. Our experimental results show that the TBWT with DAGSVM gives higher classification accuracy such as 97% than the existing classifier.

KEYWORDS

Electroencephalogram (EEG) signals classification, epileptic seizure detection, Tree based Wavelet Transform, Directed Acyclic Graph Multi-Class Support Vector Machine (DAGSVM)

1. INTRODUCTION

The electroencephalogram (EEG) is a complex and aperiodic time series, which is a sum over a very large number of neuronal membrane potentials. Despite rapid advances of neuroimaging techniques, EEG recordings continue to play an important role in both the diagnosis of neurological diseases and understanding the psychophysiological processes. In order to extract relevant information from recordings of brain electrical activity, a variety of computerized-analysis methods have been developed. Most methods are based on the assumption that the EEG is generated by a highly complex linear system, resulting in characteristic signal features like nonstationary or unpredictability [1]. Much research with nonlinear methods revealed that the EEG is generated by a chaotic neural process of low dimension [2]–[4]. As in traditional pattern recognition systems, classification of biomedical signals consists of two main modules namely Feature Extraction and Feature Classification. In recent papers, for studying and analyzing the behaviour of EEG signals, chaos theory was used [1]–[4]. To quantify the complexity of EEG signals, numbers of entropy estimators are available. This proposed technique uses wavelet coefficients, which are generated using new generalized tree based wavelet approach as the input feature. The general structure of developed EEG signals classification model has two modules

(Figure.1). A significant contribution of our work is the composition of composite features, which are used to train novel classifier. We use the Directed Acyclic Graph SVM for the classification mechanism. For the classification and comparison we are using the benchmarked datasets (EEG Signals) which includes three classes. The paper is organized as follows. In Section 2, we briefly presented the literature survey that has been performed. In Section 3 we described about the benchmark dataset, our proposed methodology with feature extraction method and classification techniques that are considered. In Section 4, we compared the results of the proposed classifiers using the features with other existing classifier. And Section 5 concludes the paper.

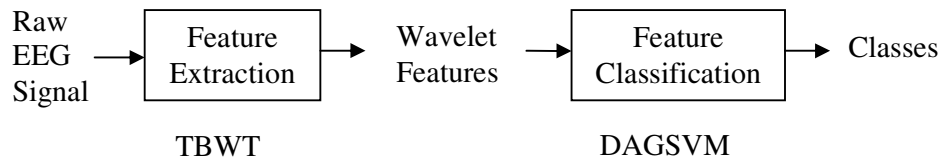


Figure 1. General Structure of developed EEG-signals classification

2. LITERATURE SURVEY

Automatic analysis and diagnosis of epilepsy based on EEG recordings is started in the early 1970s. Today, computer-based analysis addresses two major problems: 1) interictal event detection 2) epileptic seizure analysis [1]. Various feature extraction techniques have been used for the classification of EEG signals with the emphasis on seizure detection. Non-linear based feature extraction technique uses Correlation Dimension, Lyapunov Exponent and Standard Deviation for extracting the features of EEG signals [1][2]. Entropy is a term of thermodynamics that is used to describe amount of disorder in a system. Entropy based technique uses Approximate Entropy (ApEn) as the input feature [4] [6]. Wavelet based technique uses Max, Min, Mean and Standard Deviation [2] [7] [8] [9]. Time Frequency based technique, Feature extraction based on Local Variance [3]. The benchmarked dataset that have been used in the existing works was used to compare the proposed method with the existing methods. The EEG signal classification techniques are divided into three broader categories: Conventional classifiers such as Linear Discriminant Analysis [10], Support Vector Machine [8], and Naïve Bayes [1]. Neural Networks such as MLPNN [8], PNN [10], and RBFNN [6], Combinational classifiers such as Boosting, Voting and Stacking [11].

3. PROPOSED METHODOLOGY

3.1. Dataset Description

This paper uses the already available benchmark EEG dataset described in Andrzejak et al. [8]. There are three classes (denoted A–C) of datasets each containing 100 single-channel EEG segments. Classes A consisted of signals taken from surface EEG recordings that were carried out on five healthy volunteers. The three classes are described briefly in Table 1. The healthy volunteers were relaxed in an awake-state with eyes open. These signals are then categorised into class A. Classes B, and C originated from EEG archive of pre-surgical diagnosis. EEGs from five patients were selected, all of whom had achieved complete seizure control after resection of one of the hippocampal formations, which was therefore correctly diagnosed to be the epileptogenic zone. EEGs from five patients were selected, all of whom had achieved complete seizure control after resection of one of the hippocampal formations, which was therefore correctly diagnosed to be the epileptogenic zone. Segments in class B were recorded from within the epileptogenic zone. And set C only contained seizure activity.

Table 1: Three classes of EEG dataset

Class	Description
A	EEG recordings of five healthy volunteers, with eyes open
B	Seizure-free intervals, from five patients in the epileptogenic zone
C	During Seizure intervals, from five patients in the epileptogenic zone

3.2. Extraction of features

Transforming the input data into the set of features is called feature extraction. Wavelet Transform (WT) is a spectral estimation technique in which any general function can be expressed as an infinite series of wavelets. A major advantage of wavelet methods is their ability to simultaneously localize signal content in both space and frequency. Abnormalities in the EEG in serious psychiatric disorders are many times too subtle to be detected using conventional techniques, such as Fourier transform. We aim at extending the wavelet transform to a generalized tree-based wavelet transform (TBWT). This method is an extension of the Haar like transform introduced by Gavish et al [15], which can also construct data adaptive orthonormal wavelets beyond Haar. This method explains how to construct the data driven-hierarchical tree employed by the extended scheme. The construction of each coarse level of the tree involves finding a path which passes through the set of data points in the finer level. The points order in this path defines the permutation applied to the approximation coefficients of the finer level in the wavelet decomposition scheme.

3.2.1. Tree-Based Haar Wavelets

Let $X = \{x_1, \dots, x_N\}$ be the dataset that contains the different classes of EEG signals, where the samples $x_i \in \mathbb{R}^n$ may be points in high dimension, or feature points associated with the nodes of a weighted graph or network. Also, let $f: X \rightarrow \mathbb{R}$ be a scalar function defined on the dataset, and let $V = \{f | f: X \rightarrow \mathbb{R}\}$ be the space of all functions on the dataset. Here we use the following inner product with the space V :

$$\langle f, g \rangle = \sum_{j=1}^N f(x_j)g(x_j)$$

which is different from the one used by Gavish et al. [15], since it does not contain a normalizing factor before the sum. We note that when the dataset is a weighted graph, but no feature points are available, the diffusion map framework [16],[17] can be employed in order to obtain such points from the graph. The Euclidean distance between the points produced by this framework approximates the "diffusion distance" [16], [17], which describes the relationship between the graph nodes in terms of their connectivity.

Gavish et al. assume that the geometry and structure of the data X are captured by one or several hierarchical trees. They do not insist on any specific construction method for these trees, but only that they will be balanced [15]. Given such a tree, a multiscale wavelet-like orthonormal basis for the space V is to be constructed. They start by showing that such a tree induces a multi-resolution analysis with an associated Haar-like wavelet.

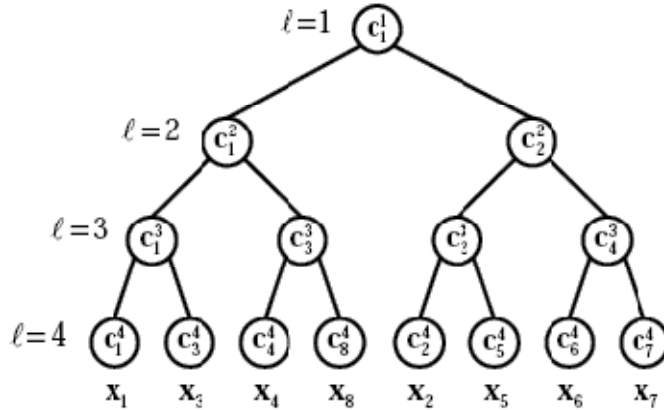


Figure 2. Illustration of a complete full binary tree.

Let $\ell=1, \dots, L$ denote the level in the tree, with $\ell = 1$ being the root and $\ell = L$ being the lowest level, where each sample x_j is a single leaf. Also, let V^ℓ denote the space of functions constant on all folders (subtrees) at level ℓ , and let 1_X denote a constant function on X with the value 1. Then $V^1 = \text{Span}_{\mathbb{R}}\{1_X\}$, $V^L = V$ and by construction

$$V^1 \subset \dots \subset V^\ell \subset V^{\ell+1} \subset \dots \subset V^L$$

Now, let W^ℓ ($1 \leq \ell < L$) be the orthogonal complement of V^ℓ in $V^{\ell+1}$. Then, the space of all functions V can be decomposed as

$$V = V^L = \left[\bigoplus_{\ell=1}^{L-1} W^\ell \right] \oplus V^1$$

Here we focus on the case of constructing the complete full binary trees and the corresponding orthonormal bases. Let c_j^ℓ denote the j -th point at level ℓ of the tree, where $c_j^\ell = x_j$, and let P_ℓ and p_ℓ denote a set and a vector containing point indices, respectively. Also, let $\omega(\cdot; \cdot)$ be a distance measure in \mathbb{R}^n , and let W^ℓ be a distance vector associated with the ℓ -th level of the tree, where $w_{i,j}^\ell = w(c_i^\ell, c_j^\ell)$. The distance function describes the first order interaction between data-points, and therefore it should be chosen so as to capture some notion of similarity between them, which would be meaningful to the application at hand. A complete full binary tree can be constructed from the data according to its algorithm which is defined in section 3.2.2. An example for such a tree is shown in Figure. 2.

In the case of a complete full binary tree, the Haar-like basis constructed from the tree is essentially the standard Haar basis which we denote $\{\varphi_j\}_{j=1}^N$. The adaptivity of the transform is obtained by the fact that this basis is used to represent a permuted version of the signal f , which is more efficiently represented by the Haar basis than f itself. The permutation is derived from the tree, and is dependent on the data X . Let p denote a vector of length N , which contains the indices of the points x_j , in the order determined by the lowest level of the fully constructed tree. For example, for the tree in Fig. 1, $p = [1; 3; 4; 8; 2; 5; 6; 7]^T$. Also let f^p be the signal f permuted according to the vector p . The wavelet coefficients can be calculated by the inner products $\langle f^p, \varphi_j \rangle$. We hereafter term the scheme described above as tree-based Haar wavelet transform, and we show next that it can be extended to operate with general wavelet filters.

3.2.2. Generalized Tree Construction and Wavelet Transform

In this case the process of building the tree is little different from its previous section. In every level ℓ of the tree, we first construct a distance vector W^ℓ using the mean points c_j^ℓ and the distance ω . The algorithm for construction of full binary tree is as follows

Given the points $\{x_j\}_{j=1}^N$ and the distance function ω .

- Set $c_j^\ell = x_j$ as the tree leaves
- Perform the following steps for $\ell = L, \dots, 2$
 1. Construct a distance vector W^ℓ , where $\omega_i^\ell = \omega(c_i^\ell)$
 2. Set $P_\ell = \emptyset$
 3. Group the points in level ℓ in pairs by repeating $N/2^{1+L-\ell}$ times
 - Choose a random point $c_{j_0}^\ell$, $j_0 \notin P_\ell$ and update $P_\ell = P_\ell \cup \{j_0\}$
 - Pair $c_{j_0}^\ell$ with the point $c_{j_1}^\ell$
 - Update $P_\ell = P_\ell \cup \{j_1\}$.
 4. Place in a vector p_ℓ , the reordered point indices of P_ℓ
 5. Construct the coarse level $\ell-1$ from the finer level ℓ by replacing each pair c_i^ℓ and c_j^ℓ with the mean point $1/\sqrt{2}[c_i^\ell + c_j^\ell]$

The above algorithm yields the tree node points c_j^ℓ and the vectors p_ℓ containing the points order in each tree level as its output.

Next let $f = [f(x_1), \dots, f(x_N)]^T$, and let a_ℓ and d_ℓ denote the approximation and detail coefficient vectors, respectively, received for f at level ℓ , where $a_L = f$. Also, let P_ℓ denote a linear operator that reorders a vector according to the indices in p_ℓ . Then, applying the Haar transform derived from the tree to f can be carried out according to the decomposition algorithm which is as follows

Given the signal f , the vectors $\{p_\ell\}_{\ell=2}^L$, and the filters h' and g'

1. Set $a_L = f$
2. Perform the following steps for $\ell = L, \dots, 2$
 - Construct the operator P_ℓ , that reorders its input vector according to the indices in p_ℓ
 - Apply P_ℓ to a_ℓ and receive a_ℓ^p
 - Filter a_ℓ^p with h' and decimate the result by 2 to receive $a_{\ell-1}$.
 - Filter a_ℓ^p with g' and decimate the result by 2 to receive $d_{\ell-1}$.

This algorithm yields the approximate coefficient a_1 and detail coefficients $\{d_\ell\}_{\ell=1}^{L-1}$ as its output corresponding to signal f .

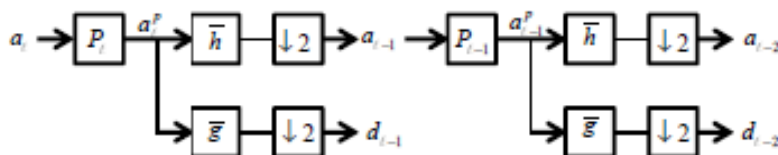


Figure 3. Two single level tree based decomposition steps

Figure. 3 describes two single-level decomposition steps carried out according to decomposition algorithm. We note that here the adaptivity of the transform is related to the permutations applied

to the coefficients a_ℓ in every level of the tree. In fact, without the operator P_t applied in each level, the decomposition scheme of decomposition algorithm reduces to that of the common 1D orthogonal wavelet transform. Also, since permutation of points is a unitary transform, the described transform remains unitary. The EEG signals can be considered as a superposition of different structures occurring on different time scales at different times. Selection of appropriate wavelet and the number of decomposition levels is very important in the analysis of signals using the WT.

3.3 Classifiers used for Classification

Directed Acyclic Graph Support Vector Machine(DAGSVM)

Support Vector Machines (SVMs) [1] are very popular and powerful in learning systems because of attending high dimensional data, providing good generalization properties, their ability to classify input patterns with minimized structural misclassification risk. In two ways we can have a multi-class SVM classifier; one is to directly consider all data in one optimization formulation, and the other is to decompose multi-class problem to several binary problems. The second solution is a better idea and has been considered more than the first approach [13-17] because binary classifiers are easier to implement and moreover some powerful algorithms such as Support Vector Machine (SVM) are inherently binary [18]. Two major decomposition implementations are: “one-against-all” and “one-against one”.

The one-against-all [1] method constructs n SVMs where n is the number of classes. The i -th SVM is trained to separate the i -th class from remaining classes. The one-against-one [14] (pairwise SVMs) instead, constructs $n(n-1)/2$ decision functions for all the combinations of class pairs. In determination of a decision function for a class pair, we use the training data for the corresponding two classes. Thus, in each training session, the number of the training data is reduced considerably compared to one-against-all support vector machines, which use all the training data. Experimental results in [19] indicate that the one-against-one is more suitable for practical use.

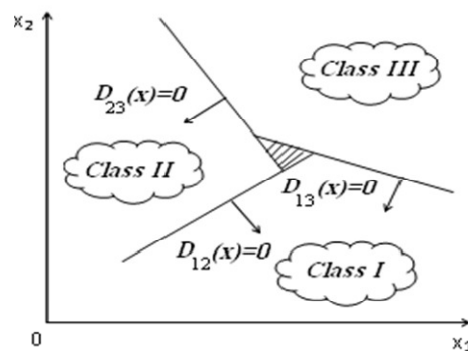


Figure 4. Unclassifiable regions formed by pairwise function.

A problem with both on-against-all and pair wise support vector machines is unclassifiable regions . Figure 4 shows the unclassifiable problem for three classes. To resolve this problem, Vapnik proposed to use continuous decision functions. Namely, we classify a datum into the class with maximum value of the decision functions. Inoue and Abe proposed fuzzy support vector machines, in which membership functions are defined using the decision functions. Another popular solution is DAG SVM that uses a decision tree in the testing stage. Training of a DAG is the same as conventional pair wise SVMs. Classification by DAGs is faster than by conventional

pairwise SVMs or pairwise fuzzy SVMs. The decision tree for three class DAGSVM is shown in Figure 5.

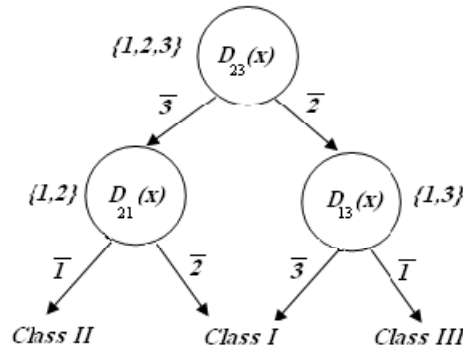


Figure 5. DAG Classification

The generalization regions become as shown in Figure 6. Unclassifiable regions are resolved, but clearly the generalization regions depend on the tree formation.

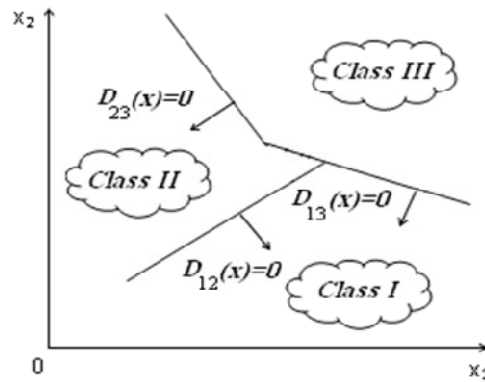


Figure 6. Generalization region by DAG classification

4.Results and Discussion

In our work, we employed a tree based wavelet transform for extracting wavelet coefficients from the dataset in order to extract transient features. The wavelet base features possess good characteristics such as robustness in the characterization of the epileptic patterns and low computational burden. Wavelet based features were computed for both normal and epileptic EEG signals and are fed as inputs to the three classifiers such as PNN, RBFNN and DAGSVM. Figure 7 compares between-class-distance and within-class-distance for the three classes of datasets based on the tree based wavelet features. From the figure, it was observed that the within-class-distance was minimum and the between-class-distance was maximum. So the extracted features are well suited for discriminating various classes. Figure 8 shows EEG Signal Patterns based on the wavelet features. For the classification of EEG signals we have used a DAG SVM. Among the available 100 EEG data sets, 50 data sets are used for training and the remaining data sets are used for testing the performance of the neural network and SVM classifiers. Computational cost and the classification time for the proposed DAGSVM classifier depend on the number of support vectors required for the design of the classifier and the kernel employed. Increase in number of support vectors lead to increase in computational requirements. It is shown that our wavelet based

features possesses good characteristics such as robustness in the characterization of the epileptic patterns and low computational burden. The Classification and misclassification results of various EEG datasets represented by the features are given in Table 2. The performance in the rate of classification of the two classifiers such as PNN, RBFNN and DAG SVM have been and which is shown in Table 3. The Multi-class DAGSVM using wavelet based features gives superior performance that is 97% in terms of classification rate.

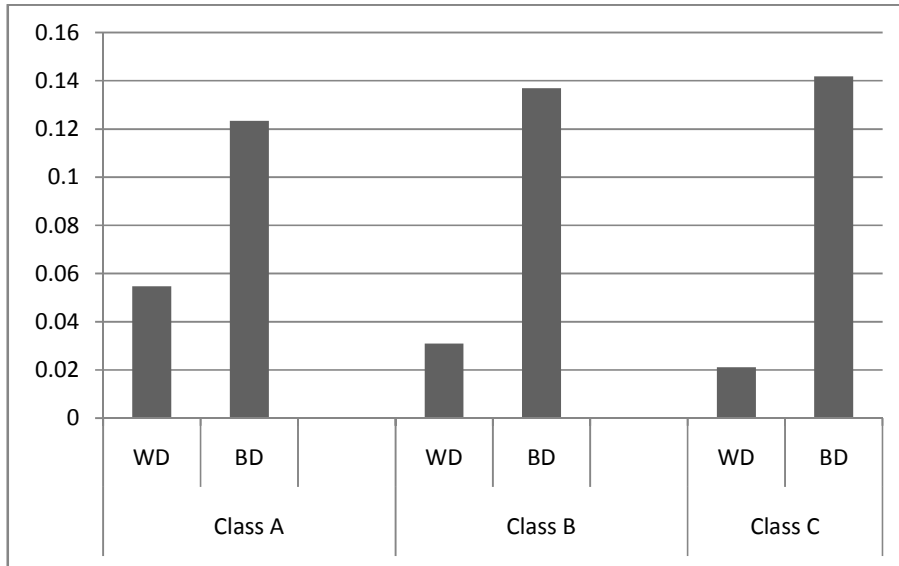


Figure 7. Comparison of between-class-distance and within-class-distance for various hierarchical classes based on the features

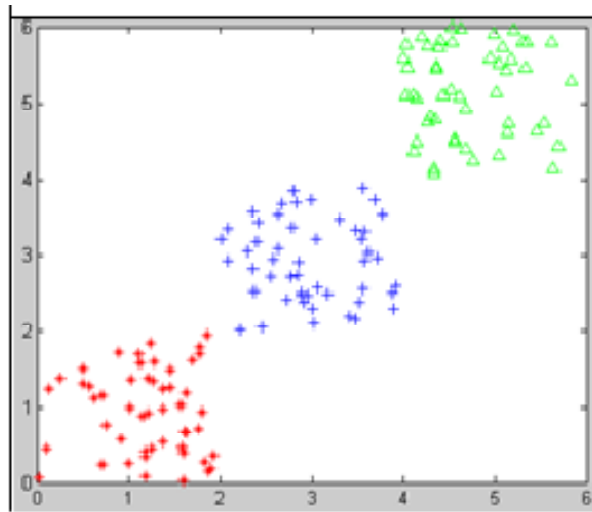


Figure 8. EEG Signal Patterns based on the wavelet features

Table 2. Classification and Misclassification Results of Various SVMs

Dataset	Size	Output Results	
		Correctly classified	Mis-classified
{A,B,C}	150	146	5
{A,B}	100	97	3
{A,C}	100	50	2

Table 3. Comparison of classifiers such as PNN, RBFNN and DAGSVM

Classifier	PNN	RBFNN	DAGSVM
Overall Classification Accuracy	94%	93%	97%

5. Conclusion

The Multi-class DAG SVM has shown great performance since it measures the predictability of the current amplitude values of a physiological signal based on its previous amplitude values. A robust and computationally low-intensive wavelet based features have been used for the proposed EEG classification system. Besides this, the PNN provided encouraging results, which could have originated from the architecture of the PNN. The performance of the other neural network was not as high as the DAGSVM. The results of the present paper demonstrated that the DAGSVM with the tree based wavelet features can well preserve the most discriminant information of EEG signals and improve the performance. In current work, focus was put on normal, seizure-free intervals and during seizure intervals. In the next stage of research, the results from this preliminary study will be expanded to include a more complete range of datasets.

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