An Emboli Detection System Based on Dual Tree Complex Wavelet Transform

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Abstract—**Automated decision systems for emboli detection is a crucial need since it is being done by visual determination of experts which causes excess time consumption and subjectivity. This work presents an emboli detection system using various dimensionality reduction algorithms on Doppler ultrasound signals recorded from both forward and reverse flow of blood transformed via Fast Fourier Transform (FFT), Discrete Wavelet Transform (DWT), and Dual Tree Complex Wavelet Transform (DTCWT). The combined forward and reverse DTCWT based features produced the highest performance when fed to SVMs classifier. As to compare dimensionality reduction algorithms, although PCA and LDA gave comparable accuracies, LDA has accomplished these accuracies only with two components due to its less than the number of classes' orthogonal projective directions limitation. SVMs yielded higher classification accuracies than *k*-NN with all considered dimensionality reduction methods since SVMs classifier is more robust to noise and irrelevant features. With the ability to localize well both in time and frequency, wavelet transform based extracted features gave higher overall classification accuracies than FFT with the more stable classifier SVMs. Additionally, DTCWT accuracies are higher with SVMs than those of DWT since it also has the ability of being shift-invariant.**

Keywords—**Discrete Complex Wavelet; Embolic Signals; Dimensionality Reduction; Support Vector Machines.**

I. INTRODUCTION

The transcranial Doppler ultrasound is a commonly used method to detect asymptomatic embolic signals (ES) in the cerebral circulation [1]. In certain conditions, such as carotid artery stenosis, cardiac valvular disease and atrial fibrillation, asymptomatic ESs are used for the identification of active embolic sources in stroke-prone individuals and the selection of high-risk patients for appropriate treatment.

Traditionally, for detecting ESs, individual spectral recordings are analyzed visually by experts. This type of detection is time consuming and subject to observer's experience. As a consequence of these drawbacks, an automated system is required for a reliable and clinically useful emboli detection technique.

A Doppler ultrasound signal detected by the transcranial Doppler ultrasound system can contain two types of high intensity signals other than the ESs. These signals can be named as the Doppler speckles (signals caused by red blood cell aggregates), and the artifacts (signals caused by tissue movement, probe tapping, speaking, and any other environmental effects).

ESs are resulted because of the reflection of transmitted Doppler ultrasound signals from embolic particles which are bigger than red blood cells. Therefore ESs have some distinctive characteristics when compared to Doppler speckles (DS) and artifacts. ESs appear as increasing and then decreasing in intensity for a short duration, usually less than 300 ms and their bandwidth is usually much less than that of DSs (Therefore, ESs can be considered as narrow-band signals relative to DSs).

The output of a Doppler ultrasound system has two components which are called as in-phase and quadrature-phase components. The information concerning blood flow direction is encoded in the phase relationship between these two components and by using various methods forward and reverse blood flow signals are obtained. Unlike the artifacts, which are bidirectional, ESs and DSs are approximately unidirectional (there can be small leakages in the opposite direction).

Generally the aim is to distinguish ESs from artifacts and DSs using Doppler ultrasound. Subsequently an automated system is tried to be built up with feature extraction from these signals using various methods followed with classification. After a selected feature extraction technique, PCA can be used to reduce the dimensionality of the extracted features that were used in an automated emboli detection system [2].

If we go deep into the feature extraction, the Doppler ultrasound signal can be considered as a narrow-band signal when an embolus appears; therefore frequency analysis based methods are frequently used as feature extraction steps in ES detection systems [3]. In [4] a spectrogram analysis based detection method is proposed. Along with these techniques, fast Fourier transform (FFT) is also commonly used in feature extraction. However, continuous wavelet transform (CWT) based methods perform better than fast Fourier transform (FFT) in describing ESs [5]. In the discrete wavelet transform (DWT) case which is a fast implementation of CWT, an automated system which uses DWT to derive several parameters for detecting ESs was

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proposed in [6]. In this study Doppler ultrasound signals were decomposed into an optimum number of frequency bands and then these bands were reconstructed. From these reconstructed bands several parameters were obtained and used in detection algorithm.

Dual tree complex discrete wavelet transform (DTCWT), which is an improved version of ordinary DWT with limited redundancy, can also be used in the analysis of ESs. The DTCWT was developed to overcome the lack of shift invariance property of ordinary DWT [7]. This property of DTCWT can be very important when the wavelet coefficients are used as features in machine learning algorithms to detect emboli, because the emboli information is encoded in the phase relationship of the in-phase and quadrature-phase components and any phase-distortion during the analysis steps can reduce the discriminative power of wavelet features. The success of DTCWT in the analysis of non-stationary signals such as ESs was proved before in [8].

In this study, a Doppler ultrasound dataset consisting of 100 samples from all embolic, DS and artifact 1024-point signal pairs – forward and reverse direction – is used. FFT, DWT and DTCWT are applied to these 300 signal pairs and the dimensionality (1024 in this case) of resulted coefficients is reduced with various dimensionality reduction methods for removing signal components which do not carry useful information.

As a result of these processes, the dimensionality reduced features are obtained and they are fed into two classifiers *k*-NN and SVMs. The obtained results are presented and compared for each transform in detail.

II. MATERIALS AND METHODS

A. Emboli Dataset Description

For this study a Doppler ultrasound dataset consisting of 100 embolic, 100 DS, and 100 artifact signal pairs was created. The Doppler ultrasound signals were recorded using a transcranial Doppler system (EME Pioneer TC4040 which is manufactured by Nicolet Biomedical, Madison, USA). The sampling frequency was 7150 Hz and the data length was 1024 points. The recordings were made from the ipsilateral middle cerebral artery of patients with symptomatic carotid stenosis. The artifacts were created artificially during patient recordings by tapping the probe, speech or coughing and obtained from natural artifacts occurring during patient movement, speech, or coughing during routine patient recordings [6].

B. Overall Emboli Detection System

The collected Doppler ultrasound signals are transformed with FFT, DWT, and DTCWT methods to obtain transform coefficients. The obtained datasets consists of 1024 features (transform coefficients) and 300 samples. In order to overcome the curse of dimensionality problem, before feeding to classifiers, the dimension of the datasets are reduced by applying linear dimensionality reduction techniques. Finally, the obtained reduced dimensionality feature sets are fed to SVMs with linear kernel and *k*-NN classifiers.

i. Feature Extraction

In FFT feature extraction part, Fourier transform coefficients are found and the absolute values of the coefficients are used as features. For DWT and DTCWT feature extraction parts, both forward and reverse Doppler ultrasound signals are decomposed to 5 scales. In DWT, the filter coefficients given in [9] and for DTCWT the filter coefficients given in [7] were used. After these processes the absolute value of DWT and DTCWT coefficients are used as features for dimensionality reduction steps. For an ES, the extracted FFT (only one side), DWT, and DTCWT features for both forward and reverse channels can be seen in Figure 1; as expected only in forward direction emboli occurs. As it can be seen, in FFT features emboli shows itself as a narrowband signal pattern. In DWT and DTCWT features emboli patterns can be seen in second and third scales.

ii. Dimensionality Reduction

In this paper, we use PCA as an unsupervised technique and LDA as a supervised technique to reduce the dimensionality of the emboli dataset. For the application of PCA, the dimensionality of each dataset is reduced by preserving the 90% of the data variance. As known, LDA has the limitation of less than number of classes' orthogonal projective directions due to the rank deficiency of the between-class scatter matrix [10]. Therefore, as the emboli dataset includes three classes, we reduced the dimension of the datasets to two with LDA.

Besides, as emboli blood flow is observed in two directions (forward and reverse); our dataset can be treated as a multi-view (two-view) dataset. The term "multi-view" is used to refer multiple sets of features about the same underlying phenomenon. Hence, other than the single view dimension reduction methods (PCA and LDA), we also perform Canonical Correlation Analysis (CCA) [11] method to reduce the dimensions of the forward and reverse views. CCA is a feature fusion method which aims to explore the linear relationships between two different but related views (multidimensional variables).

It is known that the sample covariance matrices used in the formulation of CCA are sensitive to outliers and noisy samples [11]. To solve the sensitivity and also the singular matrix problems, we regularize CCA by applying PCA as a preprocessing step.

III. EXPERIMENTAL RESULTS

The overall SVMs and *k*-NN accuracies and detection rates of emboli, artifact, and speckle classes are presented in Table 1, respectively. The training sets are generated by randomly choosing half of each class samples (50 from each), and use the other half as the test set. The train-test splits are repeated 20 times for statistical significance and average accuracies along with class detection rates are reported. As seen in Table 1, the highest overall accuracies are obtained with DTCWT features for all dimensionality reduction techniques. Overall accuracy is obtained by feeding the components of forward and reverse views as input to the classifier together. The stand-alone accuracies of forward and reverse signals are also higher with DTCWT features.

Besides, it must be noted that both DWT and DTCWT performed higher accuracies than FFT. Another point to be emphasized is the success of DTCWT in the detection of emboli signals. The SVMs classifier accomplished higher accuracies with the components of PCA and LDA single view dimension reduction methods than those of CCA.

As seen in Table 1, although *k*-NN ($k = 3$) is a non-linear local classifier, it performed worse than linear kernel SVMs which shows the superiority of SVMs on *k*-NN in detection of emboli signals. Although FFT features gave higher accuracies than DWT and DTCWT with *k*-NN classifier for PCA and PCA+CCA dimensionality reduction methods, it is also observed that DWT and DTCWT are more successful at detecting the emboli samples. Furthermore, DTCWT is again superior on FFT with LDA features.

The projections of the FFT and DTCWT feature sets on the LDA components of the forward view are shown in Figure 2. It is seen that for both feature sets the artifact samples are well discriminated from the other two classes. It is also observed that while with FFT features some emboli samples are intermixed with artifact samples, with DTCWT features the emboli and artifact samples are better discriminated. The other remarkable point is that DTCWT features have better discriminated the emboli and speckle samples than those of FFT.

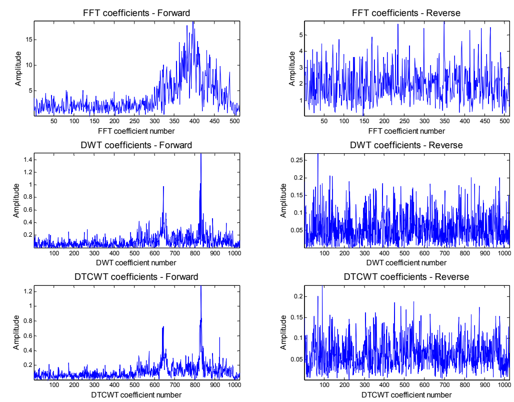

Fig. 1 Extracted features from an embolic signal with FFT, DWT and DTCWT

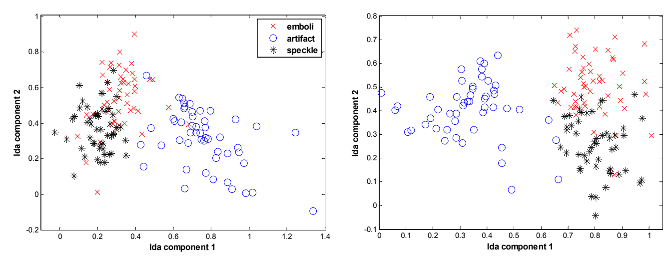

Fig. 2 Projections on the LDA components extracted from (left) FFT and (right) DTCWT data of forward view

Table 1 Overall accuracies (%) and detection rates (%) of each class with SVMs and *k*-NN

		PCA			PCA+CCA			LDA		
		FFT	**DWT**	**DTCWT**	**FFT**	**DWT**	**DTCWT**	**FFT**	**DWT**	**DTCWT**
SVM	**Overall Accuracy**	0.83	0.91	**0.93**	0.77	0.79	**0.84**	0.82	0.87	**0.91**
	Forward Accuracy	0.80	0.90	**0.92**	0.77	0.80	**0.83**	0.81	0.87	**0.90**
	Reverse Accuracy	0.73	0.77	**0.78**	0.72	0.69	**0.73**	**0.72**	0.68	0.69
	Emboli Detection Rate	0.75	0.83	**0.87**	0.64	0.67	**0.73**	0.73	0.77	**0.87**
	Artifact Detection Rate	0.82	0.98	0.99	0.76	0.90	0.93	0.80	0.95	0.96
	Speckle Detection Rate	0.95	0.91	0.92	0.91	0.81	0.85	0.95	0.89	0.89
		PCA			PCA+CCA			LDA		
		FFT	**DWT**	**DTCWT**	**FFT**	**DWT**	**DTCWT**	**FFT**	**DWT**	**DTCWT**
***k*-NN**	**Overall Accuracy**	**0.71**	0.66	0.70	**0.70**	0.64	0.65	0.77	0.81	**0.83**
	Forward Accuracy	0.71	0.69	**0.77**	**0.67**	0.62	**0.67**	0.47	0.44	**0.51**
	Reverse Accuracy	**0.69**	0.62	0.66	**0.65**	0.62	**0.65**	0.53	0.53	0.53
	Emboli Detection Rate	0.92	**0.98**	**0.98**	0.85	0.93	**0.96**	0.66	0.73	**0.78**
	Artifact Detection Rate	0.94	0.92	0.95	0.92	0.86	0.88	0.94	0.91	0.93
	Speckle Detection Rate	0.28	0.07	0.16	0.33	0.12	0.12	0.71	0.79	0.78

IV. CONCLUSIONS

In this paper, we propose an emboli detection system, in which firstly the Doppler ultrasound signals that belong to both forward and reverse blood flow directions are transformed with DTCWT, then the dimensionality of the obtained feature sets are reduced with PCA and LDA as single view dimensionality reduction methods and CCA as a feature fusion method. The obtained reduced feature sets of both forward and reverse directional signals are fed to SVMs and *k*-NN classifiers individually and also as combined. We compare the success of DTCWT features with those of FFT and DWT by applying the same dimensionality reduction and classification procedures.

First of all, we must note that SVMs based detection methods are superior on *k*-NN based methods for all the dimensionality reduction methods due to the known generalization and sensitivity to noisy samples and irrelevant feature problems of *k*-NN classifier especially on high-dimensional datasets. Accordingly, due to less than the number of classes' orthogonal projective directions limitation of LDA, the dimensionality of the reduced feature space of LDA is comparably lower than those of PCA and CCA. However, since the class labels are incorporated into the dimensionality reduction scheme of LDA, when only the first two components are used, the highest classification accuracies and also emboli detection rates are obtained with LDA.

Secondly, comparing the results of feature extraction methods we see that the highest classification accuracy and emboli detection rate are obtained when the combined forward and reverse DTCWT based features are fed to SVMs as input. Therefore, we can conclude that in the emboli detection the reverse blood flow direction has also significant discriminative information. Besides, DWT has performed better than FFT with SVMs classifier. The projections of the FFT and DTCWT feature sets on the LDA components confirmed the better discriminative ability of DTCWT features. As a conclusion, wavelet transform based extracted features give higher overall classification and emboli detection accuracies than FFT based features in SVMs classifier due to their well localization property in both time and frequency. As known, the wavelet transform provides a time-scale representation of signals which have good frequency resolution at low frequencies, but also have good time resolution at high frequencies. Additionally, due to its shift-invariance property, DTCWT surpasses DWT in overall accuracy and embolic detection rate with SVMs.

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