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An emboli detection system based on Dual Tree Complex Wavelet Transform and ensemble learning

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ABSTRACT

The traditional visual and acoustic embolic signal detection methods based on the expert analysis of individual spectral recordings and Doppler shift sounds are the gold standards. However, these types of detection methods are high-cost, subjective, and can only be applied by experts. In order to overcome these drawbacks, computer based automated embolic detection systems which employ spectral properties of emboli, speckle, and artifact using Fourier and Wavelet Transforms have been proposed. In this study, we propose a fast, accurate, and robust automated emboli detection system based on the Dual Tree Complex Wavelet Transform (DTCWT). Employing the DTCWT, which does not suffer from the lack of shift invariance property of ordinary Discrete Wavelet Transform (DWT), increases the robustness of the coefficients extracted from the Doppler ultrasound signals. In this study, a Doppler ultrasound dataset including 100 samples from each embolic, Doppler speckle, and artifact signal is used. Each sample obtained from forward and reverse blood flow directions is represented by 1024 points. In our method, we first extract the forward and reverse blood flow coefficients separately using DTCWT from the samples. Then dimensionality reduction is applied to each set of coefficients and both of the reduced set of coefficients are fed to classifiers individually. Subsequently, in the view that the forward and reverse blood flow coefficients carry different characteristics, the individual predictors of these classifiers are combined using ensemble stacking method. We compare the obtained results with Fast Fourier Transform and DWT based emboli detection systems, and show that the features extracted using DTCWT give the highest accuracy and emboli detection rate. It is also observed that combining forward and reverse coefficients using stacking ensemble method improves the emboli and artifact detection rates, and overall accuracy.

1. Introduction

The transcranial Doppler ultrasound, which enables monitoring the middle cerebral artery, 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 ES are used for the identification of active embolic sources in stroke-prone individuals and the selection of high-risk patients for appropriate treatment [2]. Therefore, for these patients, accurate detection of asymptomatic ES has a significant clinical importance.

Traditionally, for detecting ES, visual detection by using individual spectral recordings and acoustic detection by hearing the Doppler shift sound by human experts are the gold standards. These types of detection techniques are time consuming (recordings of the patients may last for 1 h or more) 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 contains two more signal types other than the ES. These signals are the Doppler speckle (DS) (signals caused by red blood cell aggregates) and the artifacts (signals caused by tissue movement, probe tapping, speaking, and any other

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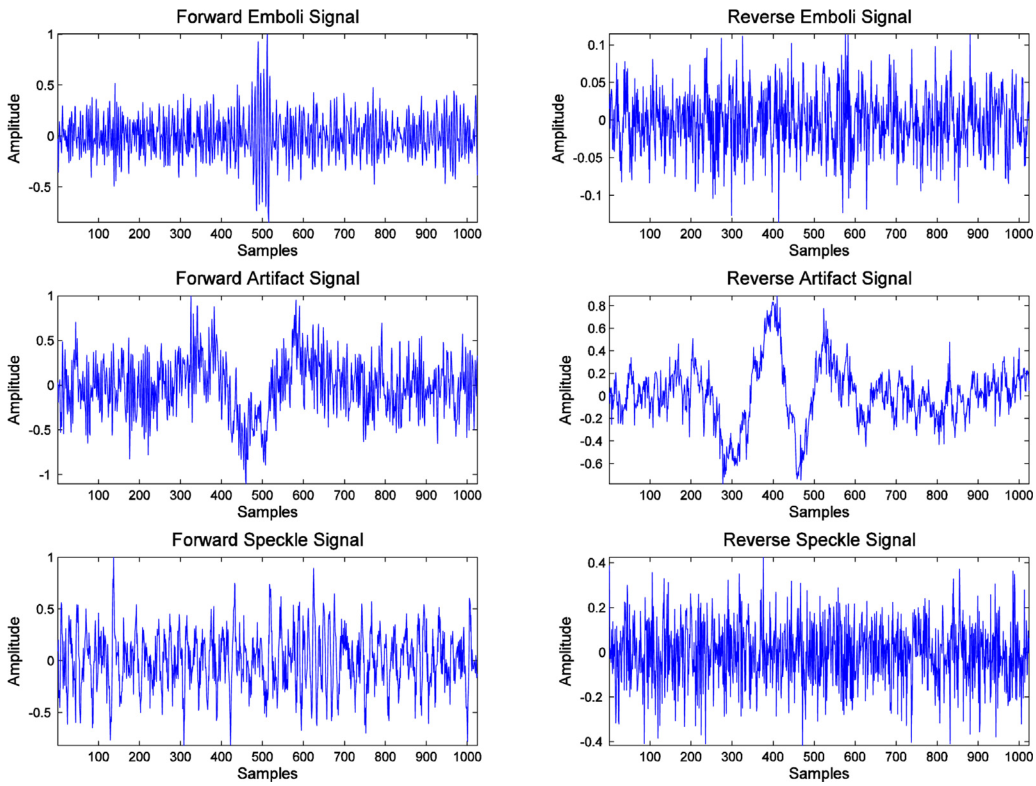

Fig. 1. Time domain representation of an ES, an artifact and a DS.

environmental effects). ES are the results of the reflection of transmitted Doppler ultrasound signals from emboli which are bigger than red blood cells. Therefore, ES have some distinctive characteristics when compared to DS and artifacts. ES appear as increasing and then decreasing in intensity for a short duration, usually less than 300 ms and their bandwidth is usually much narrower than that of DS. Therefore, ES can be considered as narrow-band signals relative to DS [3].

The outputs of a Doppler ultrasound system employing quadrature detection are in-phase and quadrature-phase components. The information concerning blood flow direction is encoded in the phase relationship between these two components; forward and reverse blood flow signals are obtained by using various methods [4,5]. Unlike the artifacts, ES and DS are unidirectional.

Generally, the aim of automated emboli detection systems is to distinguish ES from artifacts and DS using Doppler ultrasound. For this purpose, an automated system is aimed to be built up by extracting features from these signals using various methods followed with classification. After the feature extraction step, any dimensionality reduction method such as principal component analysis (PCA) or linear discrimination analysis (LDA) can be applied to deal with the curse of dimensionality problem [6]. A preferred method is to obtain the spectra of audio recordings via complex discrete Fourier transform and use PCA to make it easy for a classifier such as support vector machines (SVM) to identify whether the signal contains ES or not [7].

Considering the narrow-band assumption, frequency analysis based methods are frequently used as feature extraction step in ES detection systems [8]. In [9] 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 FFT in describing ES [10]. Another approach is to use DWT to extract features from signals, for instance in [11], an automated system using DWT to derive several parameters for detecting ES was proposed. In [11], 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 Wavelet Transform (DTCWT), which is an improved version of ordinary DWT with limited redundancy, can also be used in the analysis of ES. The DTCWT was developed to overcome the lack of shift invariance property of ordinary DWT [12,13]. 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. In literature, the success of DTCWT in the analysis of non-stationary signals such as ES was proved in [14,15].

In our study, a Doppler ultrasound dataset consisting of 100 samples from each embolic, DS and artifact 1024-point signal pairs – forward and reverse direction – is used. Exemplary time-domain representations of ES, artifact and DS in both forward and reverse directions can be seen in Fig. 1. FFT, DWT and DTCWT are applied to these 300 signal pairs in order to extract features. Thereafter, the dimensionality (1024 in this case) of resulted coefficients is reduced with a dimensionality reduction method for removing signal components that do not carry useful information. Dimensionality reduction is a critical preprocessing step in machine learning problems especially when the dimensionality of the dataset is high when compared with the number of samples such as the Doppler ultrasound dataset dealt with in this paper [16]. The dimensionality reduction techniques can be categorized into two groups: (1) unsupervised techniques that do not utilize the class labels (PCA), and (2) supervised techniques (linear discriminant analysis – LDA) that incorporate the class labels into their frameworks [17]. Even though mainly the PCA is used in this work, the LDA is also used to visualize the samples according to their classes.

Ensuing the feature extraction and dimensionality reduction phases, the features acquired from forward flow direction of the blood are fed into k-NN and SVM. Additionally, in order to increase the classification accuracy, the information extracted from the features acquired from reverse flow direction of the blood is also used. However, these features are not combined in a conventional way. First, the features from forward and reverse directional signals are fed to classifiers separately since forward signals are suitable for three-class classification (embolic signal, speckle or artifact) whereas the reverse signals are for two-class classification (artifact or non-artifact). Then, the outputs of these two classifiers are combined using the stacking ensemble combination technique. The obtained individual and combined results are presented and compared for each feature extraction method in detail. The results indicate that the proposed emboli detection system is superior to related studies in terms of emboli detection rate (in [9,18,19] the emboli detection rates are 86.6%, 87% and 87.6%, respectively).

The remaining of the paper is organized as follows: Section 2 gives the description of the Doppler ultrasound dataset, presents the theory of signal processing methods used, and declares brief information about feature extraction and dimensionality reduction methods. Additionally, in Section 2 individual and combined emboli detection systems are explained. Section 3 provides the experimental results on the Doppler ultrasound dataset. Lastly, Section 4 is the discussions and conclusions.

2. Methods

2.1. Doppler ultrasound dataset description

Doppler ultrasound signals were recorded using a transcranial Doppler system (EME Pioneer TC4040 which is manufactured by Nicolet Biomedical, Madison, USA) with the sampling frequency of 7150 Hz and the data length of 1024 points. The recordings were taken from the ipsilateral middle cerebral artery of 35 patients with symptomatic carotid stenosis, who appealed in the Neuroscience Clinic of St George's Hospital, London, UK. The ages of the patients vary between 42 and 69 (59.5 ± 7.4). A Doppler ultrasound dataset including 100 embolic, 100 Doppler speckles, and 100 artifact signal pairs was constituted from the recordings. Tapping the probe, speech or coughing created the artifacts artificially during patient recordings and natural artifacts occurred during patient movement, speech, or coughing during routine patient recordings [11].

2.2. Signal processing methods

The normal Doppler ultrasound blood flow signals are formed by the signals scattered from red blood aggregate and usually assumed as a random distribution [20]. However, the Doppler ultrasound signal produced by an embolus has more certain characteristics because of the following two reasons. Firstly, since an embolus can be assumed as a single scatterer, the velocity of an embolus is relatively stationary and this results a more located signal in the frequency spectrum. Secondly, in Doppler ultrasound the scattered power from a point scatterer is related to its sectional area [21]. The embolus has a much bigger volume than an ordinary red blood cell and this usually causes the ES to be more powerful than the signal of the normal blood flow. So, when the frequency characteristics of the ES are considered, they can be accepted as more located signals in frequency spectrum with high power compared to Doppler speckle and artifacts. Therefore, to make use of these characteristics of the blood flowing normally and with emboli for ES detection, frequency based features are extracted by using FFT, DWT, and DTCWT.

2.2.1. Fourier transform

In the separation process of the ES from the speckles and the artifacts, to reveal and enhance the narrow-band frequency characteristics of ES, Doppler ultrasound signals can be analyzed (decomposed) with classical Fourier transform, which is extensively used in many signal processing applications. It expands a time-domain signal onto orthogonal basis functions (sine and cosine waves) to reveal the frequency contents of the signal. But the classical Fourier transform cannot localize the frequency components in time and it assumes that the analyzed signal is stationary. However, due to the inherent time-varying characteristics of cardiovascular system, Doppler ultrasound signals are expected to have non-stationary character, independent of the time scale over which they are analyzed. In this study, the FFT, which is a fast algorithm to implement classical Fourier transform in real time, is used for extracting Fourier transform coefficients that used in detection algorithm.

2.2.2. Discrete Wavelet Transform

Doppler ultrasound signals obtained from blood flow have highly complex time-frequency characteristics (non-stationary characteristics). Therefore, any appropriate analysis method which deals with them should have adjustable time-frequency resolution. Wavelet transform [22,23] (WT) is known as a good tool for the analysis of non-stationary signals having transient behavior such as embolic signals. The WT can be thought as an extended version of the classic Fourier transform. Unlike Fourier transform, WT works on a multi-scale basis.

In WT, a signal can be represented in terms of simple building blocks, named as wavelets. These building blocks are actually a family of functions which are derived from a single generating function called the mother wavelet by translation (shifting) and dilation (scaling) operations. The WT can be categorized into continuous and discrete. Continuous wavelet transform (CWT) of a signal $s(t)$ is defined by

$$W_s(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} s(t)\psi\left(\frac{t-b}{a}\right) dt \tag{1}$$

where a is the scale, b is the translation, and $\psi_{a,b}$ is the mother wavelet. Scaling either dilates (expands) or compresses a signal. Large scales (low frequencies) expand the signal and provide global information about the signal, while small scales (high frequencies) compress the signal and provide the detailed information hidden in the signal.

In the CWT, the scale and translation parameters change continuously, and this results in a huge computation complexity and a vast amount of data. Therefore, in real-time applications, in order to reduce memory requirements and increase the computation speed of the analysis, Discrete Wavelet Transform (DWT), in which the scale and translation parameters are discretized, is commonly used.

In the DWT, a countable set of coefficients are obtained at the end of the transform and these coefficients correspond to the points on a two-dimensional grid of discrete points in the time-scale domain. The formula of the DWT can be defined as

$$W_s(m,n) = \frac{1}{\sqrt{a_0^m}} \int_{-\infty}^{+\infty} s(t)\psi\left(\frac{t-nb_0a_0^m}{a_0^m}\right) dt \tag{2}$$

where m and n are discrete scale and translation steps. When compared with CWT, a and b are replaced by a_0^m and $nb_0a_0^m$, respectively, where a_0 and b_0 are discrete scale and translation step sizes.

In practice, the DWT can be implemented by using multi-resolution analysis (MRA) approach [24,25], which is computationally more efficient. In MRA, the dyadic DWT employs two set of functions named as scaling functions and wavelet functions, which are associated with the low-pass filters and high-pass filters (a pair of quadrature mirror filters) respectively. To decompose a time-domain signal into different frequency bands, these high-pass and low-pass filters must be applied to that signal and the resultant signal of each filter must be down-sampled by a factor of two. At the end of these processes, the time-domain signal is split into two components, and each of these two components has half-size of the original signal length. One of these components contains the low-frequency (coarse) information and the other one contains high-frequency (detail) information. If these computations are performed for one level of decomposition, for the first level, the decomposition is expressed mathematically as follows

$$D_1[k] = y_{high}[k] = \sum x[n]h[2k-n] \tag{3}$$

$$A_1[k] = y_{low}[k] = \sum x[n]g[2k-n] \tag{4}$$

where $h[n]$ and $g[n]$ are the high-pass and low-pass filters, $y_{high}[k]$ and $y_{low}[k]$ are the resultant coefficients of high-pass and low-pass filters, respectively. High-pass and low-pass coefficients are also named as detail ($D_1[k]$) and approximation ($A_1[k]$) coefficients of the first level. This procedure, which can be applied with a binary tree, is usually performed for the second level of analyses using the coarse part of the first level as a new input to the second one, and this process can be repeated up to a certain number of levels for further decomposition (ultimately until a single sample is left). The structure of the DWT can be seen in Fig. 2a. At the end of all levels, the dyadic DWT consists of the set of detail coefficients generated at each level of the transform, together with the approximation coefficients generated at the last level of the transform.

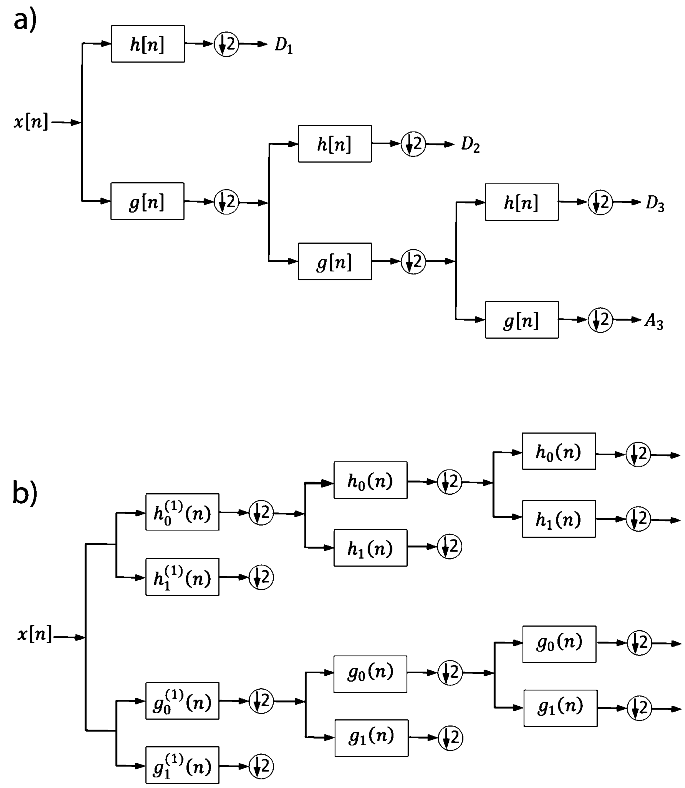

Fig. 2. (a) A 3 level binary tree implementation, only the analysis part, of the DWT. D_1, D_2 and D_3 are the detail coefficients and A_3 is the approximation coefficients. (b) Structure of the analysis part of the DTCWT for 3 levels. $h_0^{(1)}(n)$ is the low-pass filter of real tree and $g_0^{(1)}(n)$ is the low-pass filter of imaginary tree in the first band. $h_0(n)$ and $h_1(n)$ are the low-pass and high-pass filters of the real tree for following bands. $g_0(n)$ and $g_1(n)$ are the low-pass and high-pass filters of the imaginary tree for following bands.

2.2.3. Dual Tree Complex Wavelet Transform

In literature, the DWT has been widely used in various medical application areas such as denoising, feature extraction, etc. [26–28]. Despite of all its useful time-frequency resolution and fast computation advantages, the DWT has some very important drawbacks such as alising, lack of directionality, and shift variance [12]. In processing ES, due to the transient time behavior of ES, shift variance problem of the DWT arising from the use of down-sampling operator becomes crucial. As a consequence of this shift variance limitation, which means that any small shift in the input sequence greatly distorts the wavelet coefficients and changes their energy in each sub-band, the DWT based features that are fed into a machine learning algorithm to detect emboli, are badly affected. Therefore, in order to obtain more robust wavelet based features, the DTCWT having near shift-invariant property is more appropriate than the ordinary DWT.

DTCWT [12,13], which utilizes two real DWTs operating in parallel on an input signal, is a recent enhancement to the ordinary dyadic DWT and it is approximately shift-invariant. In DTCWT, the first DWT stands for the real part of the transform while the second DWT stands for the imaginary part. The analysis part of the DTCWT for 3 levels can be seen in Fig. 2b.

In order to attain perfect shift-invariance property in the DTCWT, the second tree's (imaginary tree) wavelet function ($\psi'(t)$) must be the Hilbert transformed version of the first DWT's wavelet function ($\psi(t)$) as shown below,

$$\psi'(t) = H[\psi(t)] \tag{5}$$

where $H[\,]$ stands for the Hilbert transform and this relation is named as Hilbert transform pair condition.

In [29,30], it is stated that if the low-pass filter of second tree ($g_0(n)$) is equal to the half sample delayed version of the low-pass filter of first tree ($h_0(n)$), then the wavelet functions of DTCWT satisfy Hilbert transform pair condition and this condition can be shown as below in time domain.

$$g_0(n) \approx h_0(n-0.5) \Rightarrow \psi_g(t) \approx H[\psi_h(t)] \tag{6}$$

In frequency domain, this can be interpreted as

$$G_0(w) = e^{-j0.5w}H_0(w) \text{ for } |w| < \pi \tag{7}$$

FIR filters can never satisfy half sample delay condition and hence the resulting wavelet function pairs can never be perfectly analytic. Therefore, it is necessary to make an approximation [29]. To overcome this condition, instead of using a half sample delay system, in the first stage different filters from the following stages can be employed. For the first stage any orthonormal perfect reconstruction filter pair which satisfies the following equation can be used

$$g_0^{(1)}(n) = h_0^{(1)}(n-1) \tag{8}$$

where $h_0^{(1)}(n)$ is the low-pass filter of real tree and $g_0^{(1)}(n)$ is the low-pass filter of imaginary tree in the first band. If these conditions can be satisfied, then an approximately analytic DTCWT at every stage excluding the first can be obtained. For the inverse DTCWT case, to invert the transform the real tree and the imaginary tree should be inverted separately and then the outputs should be summed.

2.3. Feature extraction and dimensionality reduction methods

2.3.1. Feature extraction

Features are extracted from the forward and reverse directional signals in three different ways. First one is the FFT. The absolute values of the FFT coefficients are found and used as features. Secondly, forward and reverse directional Doppler ultrasound signals are decomposed into 5 scales in DWT and DTCWT feature extraction phase. In DWT, the filter coefficients given in [31] and for DTCWT the filter coefficients given in [13] are used. As the FFT, also both for the DWT and the DTCWT absolute values of coefficients are given to the dimensionality reduction algorithm. Usually, embolic signal exists only in the forward direction [11]. In FFT features emboli shows itself as a narrow-band signal pattern [8]. In DWT and DTCWT features emboli patterns are seen in second and third scales [11].

2.3.2. Dimensionality reduction

Large input dimensionalities make a classification model more complex and more samples should be fed to the classifiers to deal with the curse of dimensionality problem [32]. Dimensionality reduction is a stage of machine learning to avoid high dimensionality - small sample size problem which is very common especially in the field of biomedical applications [33]. Therefore, in order to reduce the dimension of the feature set obtained by FFT, DWT, and DTCWT, PCA, which is an unsupervised dimensionality reduction technique, is used with different proportions of variance [34] since not all eigenvalues contribute to the variance substantially [35]. Dimensionality of the forward directional signal dataset is reduced by preserving the 90% of the data variance. Similarly 90% of the data variance is kept for the ensemble method initially, then 95% and 99% of the data variance are used to observe the change in accuracy of the classifiers.

Additionally, for visualization and comparison of feature extraction methods, LDA is employed as a supervised dimensionality reduction technique. 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 [36]. Therefore, as the emboli dataset includes three classes, the dimension of the datasets is reduced to two by using LDA.

2.4. Overall structure of the 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 the features to the classifiers, the dimension of the datasets are reduced by applying linear dimensionality reduction techniques. Also the number of samples in the training set (90 or 150 samples) and the proportion of variance values of the dimensionality reduction method is changed to view if there is a significant difference in accuracy when the number of training instances or the proportion of variance varies. Finally, the obtained reduced dimensionality feature sets are fed to SVM with linear kernel and k-NN classifiers. We should note that we also tried SVM with polynomial and radial basis function kernels in our experiments but obtained similar classification error rates in comparison to linear kernel. Therefore, we use SVM with linear kernel since it is a simpler model with less variance and given comparable empirical error, a simple model is expected to generalize better than a complex model [36]. The classification process consists of two phases: using forward directional signals separately and the ensemble of forward–reverse directional signals as the inputs.

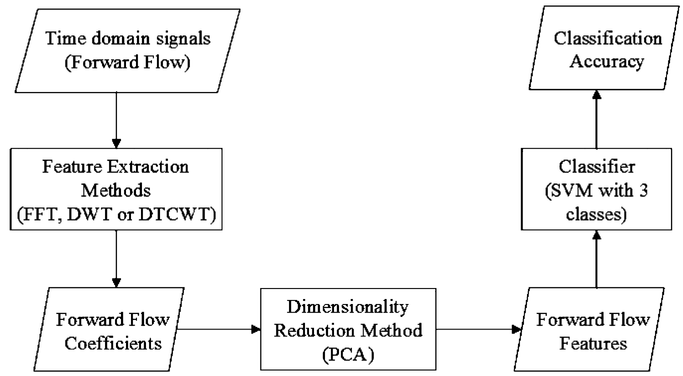

Fig. 3. Proposed individual emboli detection system.

2.4.1. Individual emboli detection system

The features extracted from the forward directional signals (according to the blood flow) are used to make predictions to estimate emboli, artifact or speckle. For the individual emboli detection system, primarily the features obtained from forward directional signals are used. Considering that a signal can be identified as emboli, artifact or speckle from the forward directional signals, the next stage is a three-class classification with the preferred classifiers. The flow chart of the proposed individual method can be seen in Fig. 3.

2.4.2. Ensemble of forward and reverse directional signals

Using different representations of the same input or object can end up with an explicit identification [36]. Consequently, features extracted from the reverse directional signals, which can estimate if there is an artifact or not, are also used for prediction. Then these predictions are combined to come up with our final ensemble model. In this way, we utilize the information contained in both forward and reverse flow directional signals to discriminate the emboli signals from artifacts and speckles.

In our ensemble emboli detection system, firstly only the features from the forward directional signals, which can set off a three class problem to discriminate ES, DS and artifacts, are fed into SVM. Secondly, a two class classification problem to identify if a signal is artifact or not using the features from the reverse directional signals is solved with SVM. As a result of these processes, two sets of probability estimates are obtained: the first set has the information extracted from the forward directional signals and the second has the reverse. Lastly, these two sets are merged into a final dataset consisting of probability estimates of the individual forward and reverse SVM models. This dataset is used to build a final model, which is a three class problem to classify ES, DS and artifacts. In this model, the three resultant probability estimate values of forward model and two probability estimate values of reverse model are combined into a row vector and constituted a dataset with five features. Later, this dataset consisting of five element row vectors is fed to the final SVM. The flow chart of the proposed ensemble method is illustrated in Fig. 4.

3. Results

Features extracted by FFT, DWT, and DTCWT using the forward directional signals are fed to SVM and k-NN classifiers with training sets including 150 and 90 samples and different PCA variance proportions. First, the half of the forward direction samples (50 samples) from each class is selected randomly for the training set and the left samples are used for the test set. The train-test splits are repeated 10 times for statistical significance and the average accuracies along with class detection rates are reported. For k-NN

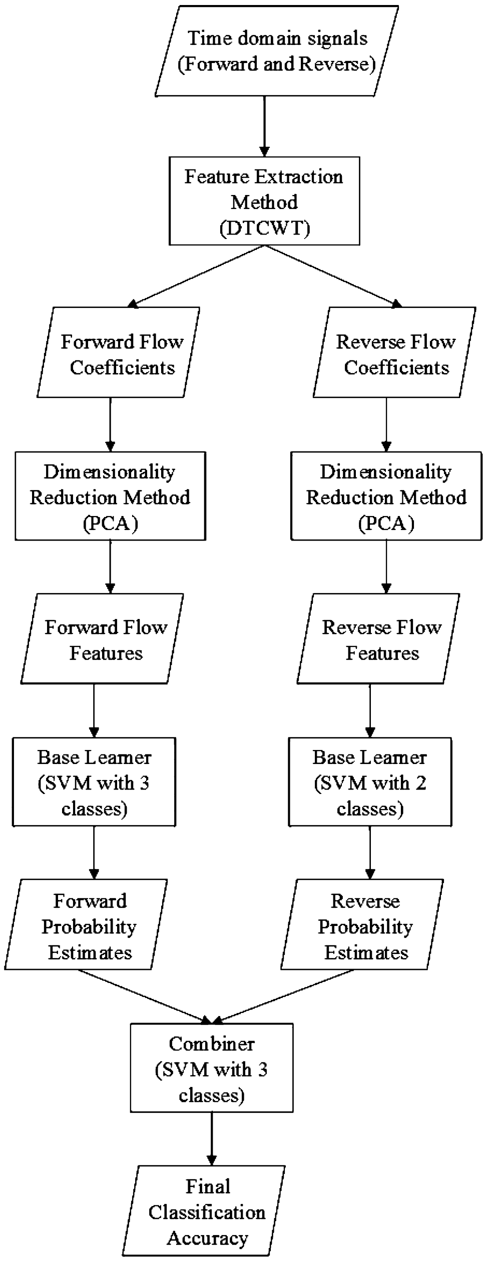

Fig. 4. Proposed ensemble emboli detection system.

classifier, Euclidean distance metric and k parameter of 3 are used. For SVM application, LIBSVM [37] package is used with a linear kernel along with cost value (c) parameter of one.

The overall SVM and k-NN general accuracy and detection rates of emboli, artifact, and speckle classes with half of the samples selected as the training instances after dimensionality reduction with PCA alongside 90% of variance kept of are presented in Table 1.

As seen in Table 1, the highest general accuracy with the highest detection rates of emboli, artifact, and speckle classes is obtained with DTCWT features for both SVM and k-NN classifiers. Additionally, higher accuracies are obtained with DWT than FFT. As to compare the classifiers, SVM performed much better than k-NN since SVM is more robust to both noise and irrelevant features.

Subsequently, to observe the change in accuracy with the variation in the number of the training instances, the training set size is decreased. For this purpose, 30 samples from each class are used to constitute the training set, and the others are used for test phase.

Table 1
General accuracy (%) and detection rates (%) of each class obtained with SVMs and k-NN using 150 and 90 training samples.

Feature extraction	DTCWT		DWT		FFT	
Classifier	k-NN	SVM	k-NN	SVM	k-NN	SVM
150 Training samples						
General accuracy	0.7573	**0.9247**	0.6973	**0.8920**	0.7120	**0.8053**
Emboli detection rate	0.9040	0.8820	0.8900	0.8040	0.8080	0.7120
Artifact detection rate	0.9380	0.9480	0.9380	0.9280	0.8940	0.9040
Speckle detection rate	0.4300	0.9440	0.2640	0.9440	0.4340	0.8000
90 Training samples						
General accuracy	0.7671	**0.8986**	0.6976	**0.8776**	0.7310	**0.8033**
Emboli detection rate	0.9329	0.8586	0.9343	0.8314	0.8100	0.7214
Artifact detection rate	0.9029	0.9186	0.9043	0.9014	0.8914	0.8900
Speckle detection rate	0.4657	0.9186	0.2543	0.9000	0.4914	0.7986

Bold values indicate the highest accuracies for each feature extraction method.

The reason to decrease the number of training samples is to observe the behaviors of the feature extraction methods, classifiers, and ensemble model with small training sample size. In other words, we aim to examine if our method still learns a generalizable model with less number of training samples or overfits to the noisy samples and outliers. Once again the data splitting for the training and test sets is repeated for 10 times. The results attained by the small size training set are also shown in Table 1. Parallel to the results with 150 training samples, the highest accuracies are produced by the DTCWT features fed to SVM classifiers.

Thereafter gathering the results with forward directional signals, additionally reverse directional signals are used to build up the ensemble model. For the proposed ensemble model, SVM is used as the classifier since it yielded higher accuracies and 90 training samples are used since the accuracy is not significantly affected from the decrease in the number of the training samples. The information acquired from the reverse directional signals cannot be used to classify the signal as emboli, artifact or speckle but only as artifact or not. Even so it is still important to take this information into account. Accordingly, first the forward and reverse directional signals are fed to the SVM classifiers individually and the resultant probability estimates are combined and fed to another SVM classifier as an input. In other words, with this technique called the stacked generalization, the outputs of the classifiers (SVMs) used with the individual forward and reverse directional signals are fed to a combiner learner, which is also SVM. The results obtained with the forward directional signals individually and the ensemble of forward and reverse directional signals (combined signals) is given in Table 2 for comparison. As shown, using stacking to combine the forward and reverse directional signal estimates increases the accuracy approximately 1.5% by using all the feature extraction methods. This ratio might seem low but such low accuracy differences are vital in biomedical decision support systems. Yet, the highest accuracy is again reached by DTCWT features. Likewise the emboli and artifact detection are also better discriminated and the speckle detection rate is nearly the same. The DTCWT features are once more superior to the DWT and the FFT.

Last but not least, the SVM classification using DTCWT features is done again with repeating the PCA dimensionality reduction with different proportion of variance. Even though all eigenvalues might be greater than 0, not all of them contribute to the variance substantially. Hence usually different percentages of the eigenvalues are selected after sorting them in descending order. Selected percentage will be smaller if the dimensions are more correlated.

In our case, 90%, 95% and 99% of the variance are selected to inspect whether there is a significant difference in the general accuracy and emboli, artifact and speckle detection rates. 90%, 95% and 99% of the variance does not change the classification rates much (91.38%, 90.90% and 92.38%, respectively) as shown in Table 3. Once more the combined system yields better results. Although increas-

Table 2
General accuracy (%) and detection rates (%) of each class with SVMs using the forward directional signal individually and the combined signals.

Feature extraction	DTCWT		DWT		FFT	
Model type	Forward	Combined	Forward	Combined	Forward	Combined
General accuracy	0.8986	**0.9138**	0.8776	**0.8814**	0.8033	**0.8281**
Emboli detection rate	0.8586	0.8814	0.8314	0.8500	0.7214	0.7414
Artifact detection rate	0.9186	0.9429	0.9014	0.9229	0.8900	0.9371
Speckle detection rate	0.9186	0.9171	0.9000	0.8714	0.7986	0.8057

Bold values indicate the highest accuracies for each feature extraction method.

Table 3
General accuracy (%) and detection rates (%) of each class with SVMs using the DTCWT features forward directional signal individually and the combined signals with different proportion of PCA variance.

	DTCWT					
	PCA 0.90		PCA 0.95		PCA 0.99	
Model type	Forward	Combined	Forward	Combined	Forward	Combined
General accuracy	0.8986	**0.9138**	0.8981	**0.9090**	0.9138	**0.9238**
Emboli detection rate	0.8586	0.8814	0.8914	0.9071	0.8700	0.8743
Artifact detection rate	0.9186	0.9429	0.9157	0.9414	0.9514	**0.9814**
Speckle detection rate	0.9186	0.9171	0.8871	0.8786	0.9200	0.9157

Bold values indicate the highest accuracies for each feature extraction method.

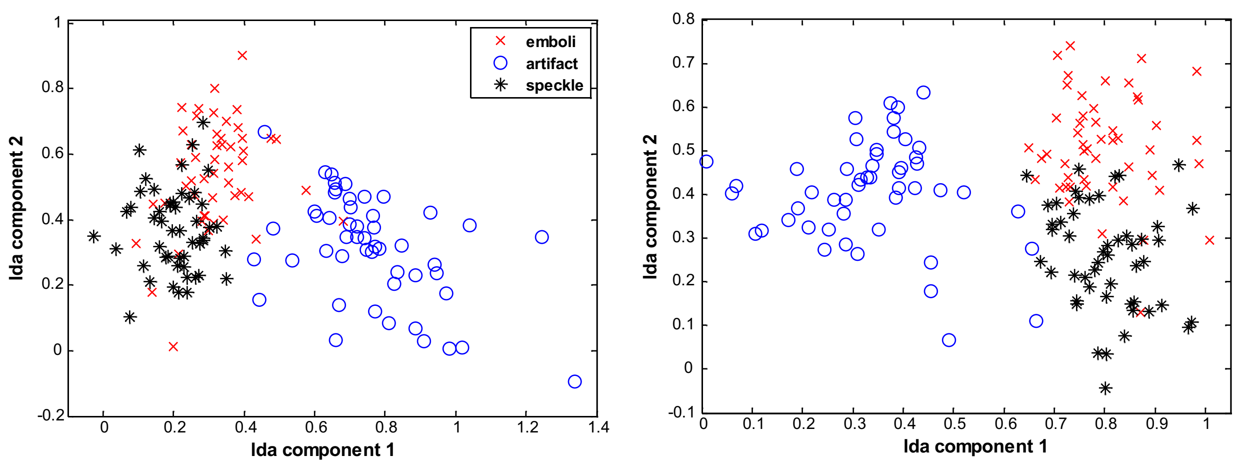

Fig. 5. Projections on the LDA components extracted from (left) FFT and (right) DTCWT data of forward flow view.

ing the proportion of the variance increases the general accuracy slightly and artifact detection rate significantly, it is better to use less proportion of the variance, because there is no gain in using PCA as the proportion of the variance increases.

As seen from the results, using DTCWT features increases the classification accuracy notably. To visualize this difference, the projections of the FFT and DTCWT feature sets on the LDA components of the forward view are shown in Fig. 5. The reason to choose LDA for this visualization is the usage of class labels in LDA. Artifact samples are well discriminated from the other two classes using both FFT and DTCWT features. Some emboli samples are intermixed with artifact samples with FFT features but not with DTCWT. Besides emboli and speckle samples are discriminated better by DTCWT features.

4. Discussion and conclusions

As visual analysis and detection of ES by experts are very time-consuming and also subjective to observer's experience, development of computer-based decision support systems that aim to discriminate ES from artifacts and noisy samples are very popular in the field of biomedical engineering. A robust ensemble emboli detection method is proposed in this paper. Employing the proposed method, a Doppler ultrasound dataset containing 100 samples of embolic, DS and artifact signal pairs in both forward and reverse directions are transformed using Dual Tree Complex Wavelet Transform (DTCWT). Then PCA is applied to both forward and reverse set of coefficients to reduce the dimensionality and the reduced sets of features are fed to classifiers separately. Finally the probability estimates of individual classifiers obtained from forward and reverse directional signals are combined using ensemble stacking method. The success of DTCWT features are compared with those of Fast Fourier Transform (FFT) and Discrete Wavelet Transform (DWT). First of all, we must note that SVM based detection methods achieves higher accuracy and emboli detection rate when compared to k-NN based methods due to the known generalization problem of k-NN classifier. Additionally, both DWT and DTCWT based extracted features give higher overall classification and emboli detection accuracies than the FFT based features due to the well localization property of wavelets in both time and frequency.

The results show that the DTCWT is superior to the DWT due to its shift-invariance property. Besides, combining the coefficients extracted from different directions of blood flow, namely forward and reverse, using ensemble stacking enhances the accuracy of the classifier. This shows that using the reverse directional signals as an additional data source increases the performance of the proposed emboli detection system since reverse blood signals also include significant and unique discriminative information. As a future direction, the proposed method can be implemented in real time to build an online emboli detection system.

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