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Assessment of Dual Tree Complex Wavelet Transform to improve SNR in collaboration with Neuro-Fuzzy System for Heart Sound Identification

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Abstract

Here we propose a novel de-noising method to improve the outcome of heart sound (HS)-based heart condition identification. We applied Dual Tree Complex Wavelet Transform (DTCWT) in collaboration with Adaptive Neuro Fuzzy Inference System (ANFIS) classifier. The method consisted of three steps. First, preprocess to eliminate 50 Hz noise. Second, application of DTCWT to de-noise and reconstruct time-domain HS signal. Third, evaluation of ANFIS on total 2735 HS recordings from an international dataset (PhysioNet Challenge 2016). The signal-to-noise ratio (SNR) with DTCWT was significantly improved ($p < 0.001$) as compared to original HS recordings. Quantitatively, there was a 11% increase in SNR after DTCWT, representing a significant improvement in de-noising HS. In addition, the ANFIS, using six time-domain features, resulted in 55-86% precision, 51-98% recall, 53-86% f-score, and 54-86% MAcc in comparison to other attempts on the same dataset. Therefore, DTCWT is a successful technique in de-noising information such as HS recordings. The adaptive property of ANFIS exhibited capability in classifying HS recordings.

Keywords Heart Sound Classification. Dual Tree Complex Wavelet Transform. Adaptive Neuro Fuzzy Inference System. De-noising signals.

Introduction

Healthy cardiac valves (CV) play essential roles in our overall health [1]. Functional conditions of CV can be examined by the sounds of CV opening and closing in heart beats. The heart sounds (HS) measured by phonocardiograph (PCG) are consisted of 4 different sounds, S1, S2, S3 and S4 [1, 3]. Various CV diseases can be detected from the heart sounds, mostly during S1 and S2 but the accuracy of such diagnosis is largely depending on experience and expertise of a cardiologist [2, 3]. However, PCG is a complicated non-stationary signal in nonlinear low frequency, which can be easily interfered by surrounding signal sources [3, 4].

Since S1-S2 section is the vital portion of HS in diagnosis for CV diseases from PCG, human errors in the diagnosis may cause life hazard [3]. To aid cardiologist in distinguishing healthy Normal Heart Sounds (NrHS) from Pathological Heart Conditions (HC) various signal processing and artificial intelligence algorithm have been applied to S1 and S2 [2]. To date, there have been 1,347 studies for algorithms for automatic analysis and classification of HS [2]. The earliest attempt was in 1963 by Gerbarg et al. who applied merely signal processing analysis on 1000 HS recordings [1]. Since then, hundreds of attempts have been reported that applied the more advanced information technology, such as the artificial neural networks (ANN) classifiers and mathematical transforms including Fourier transform (FT) and wavelet transform (WT). Most of previously applied signaling processes had a three steps of construction: a de-noising process, the extraction of signal “features” to discern HC from NrHS, and application of a “classifier” such as ANN or Deep Learning (DL) (i.e. Machine learning) [5]. The signal features are usually extracted either from time domain, wavelet domain, frequency domain, or morphological operations [6–9]. Many types of ANN and DL techniques have been applied on different datasets with a range of accuracy [10–13]. To facilitate the research to develop an efficient and reliable computer algorithm supporting the diagnosis of heart diseases, international databases have been established containing large PCG data sets of HC and NrHS. PhysioNet Challenge 2016 is an example, which was Massachusetts Institute of Technology (MIT) in the Unites States [14].

The Physio-Net Challenge 2016 dataset, as a single data source, has allowed quantitative comparisons in between different signal processing techniques and associated algorithm [4, 15–28]. A number of different techniques and algorithm have been tested using Physio-Net Challenge 2016 data set, including AdaBoost Classifier, Gram Polynomials and probabilistic Neural Networks, and Convolutional Neural Network (CNN), tensor technique, Ensemble feature-based Feed-Forward Neural Networks (FNN), Drop Connected Neural Networks (DCNN), LogitBoost, Random Forest, and Cost-Sensitive Classifier [4, 15, 16, 26–28]. The outcome indicated a range of classification accuracies from 75% to 92% from the dataset. We generated Table 4, in the discussion section, to list some of the remarkable and relevant efforts.

In this study, we tested a new technique to de-noise the HS using the Dual Tree Complex Wavelet Transform (DTCWT) using the Physio-Net Challenge 2016 data set. The DTCWT was

modified from discrete wavelet transform (DWT) to overcome the drawbacks during sampling procedure, leading to inadequate noise elimination primarily due to failure in the anti-aliasing and shifting invariance properties [29].

Our findings from 2,735 HS signals indicated that the signal-to-noise ratio (SNR) was improved by DTCWT. A set of time-domain HS signal features was extracted and analyzed using the Adaptive Neuro Fuzzy Inference System (ANFIS). Our study may suggest the efficiency and reliability of DTCWT in processing HS data, followed by the accurate diagnosis as compared to other studies on PhysioNet 2016.

Materials and methods

The PhysioNet Challenge is an international dataset of HS signals, acquired from multiple sites around the world including non-clinical and clinical health organizations, professional and nonprofessional supervision, and various medical recording instruments. It is consisted of five classes categorized as A, B, C, D, and E, containing NrHS and HC signals [14]. There is a total of 3,153 HS in the dataset, with *unevenly* distributed HC severity among classes [5]. In addition, each class was constructed to contain some emergency *external noise* such as uncontrolled environment voices [5, 14].

In this research, we downloaded the HS recordings from all the five classes in the dataset. These HS recordings were divided into training and test sets using the 80-20% split protocol, as widely applied in ANN. We combined the class C data with class D due to their low numbers of HS signals to allow 80-20% ANN split protocol. To meet the objectives of this paper, we discarded obvious distorted HS recordings that contained unusual external sounds using our experience as biomedical engineers, so we had 2735 out of 3,153 HS recordings, approximately 87% of the entire dataset, as illustrated in Table 1. As the HS signal is periodic where S1 and S2 are repetitive, we assigned 5 seconds HS duration to cover the S1 and S2 and sampled the signals at 2,000 Hz, as per the specifications of the PhysioNet.

Table1 Dataset Distribution

Class	SETS	# Subjects	Abnormal HC	Normal HS
A	<i>Training</i>	313	218	95
	<i>Test</i>	78	54	24
B	<i>Training</i>	356	72	284
	<i>Test</i>	88	18	70
C+D	<i>Training</i>	50	28	22
	<i>Test</i>	12	7	5
E	<i>Training</i>	1472	121	1351
	<i>Test</i>	366	28	338
A, B, C, D, E	<i>Training</i>	2191	439	1752
	<i>Test</i>	544	107	437
Total HS Signals		2735		

Figure 1 shows the block diagram of the proposed method. It differs from our previous work [4] in which we investigated a new de-noising technique (DTCWT) and employed ANFIS

using time domain features instead of spectral domain. To best of our knowledge, the DTCWT, which is a tool that permits quantitative SNR analysis, has not been explored for HS recordings in PhysioNet Challenge 2016.

FIG. 1 The Block diagram of the proposed HS recordings de-noising and classifier

Pre-processing of HS Signal

Each HS signal was pre-processed by applying a Notch filter to eliminate the primary 50-60 Hz noise. Then, a Butterworth filter was applied using two cutoff frequencies; $FC1=0.025$ and $FC2=0.4$ [30, 31]. Figure 1 shows examples of on an HC after applying previous steps.

Dual Tree Complex Wavelet Transform

The DWT, developed to aid signal analysis, suffers filtering difficulties during sampling procedure, leading to inadequate noise elimination due to failure in the anti-aliasing and shifting invariance properties [29]. To overcome such limitations, DTCWT was developed to enhance noise abolition by DWT [31]. The DTCWT includes several sequential steps during the decomposition and reconstruction process. As these two processes are applied to the real and imaginary constituents of the signal so it is denoted as *Dual Tree*. Each tree is a one-dimensional DWT presentation consisted of the real and imaginary parts, which is referred as *Complex Wavelet Transform*. As shown in Figure 2, each tree can be considered as a Filter-Bank (FB) tree containing low pass filter (h_0 or g_0) and high pass filter (h_1 and g_1). During the decompose process, the low and high pass filters divide signals into *Approximate Coefficients* (cA) and *Detail Coefficients* (cD). The size of cA and cD are successively decreased by factor of 2 at each decomposition level. The factor of 2 was selected because it is the optimum DTCWT performance as indicated in ref [29]. During the reconstruction process, a reverse procedure is applied to rebuild the signal successively with progressive de-noising, leading to optimal reconstruction with the minimum anti-aliasing and shift invariance impacts [29].

Particularly, the DTCWT satisfies the well-known condition of Hilbert Analytic, which is illustrated in top of Figure 1 (denoted in dashed box), indicating that the scaling complex function and the wavelet complex function collaborate to generate Hilbert pair. Equation 1 shows its mathematical presentation as previously described [29, 31, 32].

$$\psi_c(t) = \psi_r(t) + j\psi_i(t) \quad (1)$$

Where $\psi_r(t)$ is real (even), $j\psi_i(t)$ is imaginary (odd), and $\psi_c(t)$ is the DTCWT signal (analytic). The best performing DTCWT design can be achieved [31, 33] when internal structure of FBs satisfies the following three requirements:

1. Perfect reconstruction (PR) to make the reconstructed signal $\hat{X}(t)$ identical to the original (input) signal.
2. Successful application of half sample shift of low pass filters (h_0 and g_0).
3. The shifting procedure extended to one sample in the first divergence in the dual tree with respect to g_0 and g_1 , respectively.

FIG. 2 One Dimensional DTCWT for analysis FB (decompose) and synthesis FB (reconstruct). $X(t)$ represents the input signal. $cA1$, $cA2$, $cA3$ and $cA4$ denote the *Approximate Coefficients* at level 1, level 2, level3, and level 4, respectively, while $cD1$, $cD2$, $cD3$, and $cD4$ denote the *Detail Coefficients* at level 1, level 2, level3, and level 4, respectively. $\hat{X}(t)$ is the reconstructed output signal [2].

Therefore, DTCWT solves drawbacks in DWT by permitting q-shift and anti-aliasing during analysis and synthesis processes, according to Hilbert pair. This suggests that DTCWT may lead to better de-noising performance. Subsequently, the SNR of HS signals is expected to improve, consequently allowing more precise time-domain feature extraction.

SNR Calculations

HS signals frequently contain many types of ambient noises, such as electronic circuit noise and interface between electrodes and skin [5]. It is often that a type "A" noise is blocked by another noise in type "B" that makes it challenging to precisely assign types of the embedded noises in the HS signals [34, 35]. Therefore, it is recommended for the SNR to be calculated depending on the value of accumulative residual noises, and we calculated the SNR of HS using equation (2):

$$\text{SNR} = \text{mean}(\text{Noisy_HS}^2) / \text{mean}(\text{Residual_Noise}^2) \quad (2)$$

Where,

$$\text{Residual_Noise} = \text{Noisy_HS} - \text{Denoised_HS} \cdot$$

It was converted to decibels (dB) by using equation (3).

$$\text{SNR}_{\text{dB}} = 10 * \log_{10}(\text{SNR}) \quad (3)$$

Then, the SNR percentage difference (SNR%) after DTCWT was calculated by equation (4):

$$\text{SNR \%} = \frac{\text{Mean SNR after DTCWT} - \text{Mean SNR before DTCWT}}{\text{Mean SNR before DTCWT}} \quad (4)$$

Feature Extractions

From HS signals after DTCW, we extracted a set of seven features, including Entropy, Skewness, Kurtosis, Standard Deviation (STDev), Minimum (min), Maximum (max), and Mean as listed in top-right of Figure 1. These features were calculated in the training NrHS and HC signals after applying the DTCWT. Then, statistical significance between HC and NrHS measurements of the extracted features was assessed. The results indicated that all the features had yielded significant difference between NrHS and HC ($p < 0.05$), excepting for the mean.

The six features showing significant improvements, including Entropy, Skewness, Kurtosis, STDev, Max, and Min, were normalized between 0 and 1 prior to be applied for the ANFIS using the equation (5) adopted from a previous study [4]:

$$\vec{F}_{j,\text{normalized}} = (\vec{F}_j - F_{j,\text{min}}) / (F_{j,\text{max}} - F_{j,\text{min}}) \quad (5)$$

Where, F_j and $F_{j,\text{normalized}}$ are the original and normalized j -th feature, respectively; $F_{j,\text{min}}$ and $F_{j,\text{max}}$ are the minimum and the maximum of the j -th feature values calculated for all 2,735 samples, respectively. In other words, the j -th feature ($j=1$ to 6) for n samples ($n=1$ to 2735) was normalized

between 0 and 1 values. Thus, the classification process, described in the following section, should not be affected by different magnitudes of HS signal.

Adaptive Neuro Fuzzy Inference System (ANFIS)

The ANFIS is a machine-learning (ML)-based classifier algorithm that have been used for a variety of engineering problems in biomedical fields. It is a rule-based method originally developed by Jang [36]. The ANFIS has the ability of ANN ML that exploits fuzzy inference system to deduce decisions by a fuzzy logic method that takes in the account the membership degree of input-output variables [36]. The ANFIS architecture has two fuzzy if-then rules based on the Sugeno model. It has two set of input rules, which are applied to generate one output. The connection between the two input rules and the Sugeno fuzzy output is reconstructed in five layers of nodes, two layers are adaptive with flexibility, while the other three are fixed.

We applied ANFIS to each class of the HS dataset. Figure 3 shows an example of the ANFIS outputs on the test set in class A. The blue color indicates HC signals, while red color indicates NrHS signals. The ANFIS output was set to either 1 if pathology is predicted, or 2 if pathology is not predicted. Finally, the ANFIS performance was analyzed by the PRECISION and RECALL statistical metrics using Equations 6, 7, and 8, as in the following:

$$\text{Precision} = \text{TP} / (\text{TP} + \text{FP}) \quad (6)$$

$$\text{RECALL} = \text{TP} / (\text{TP} + \text{FN}) \quad (7)$$

$$\text{F-score} = 2 * \text{precision} * \text{RECALL} / [\text{precision} + \text{RECALL}] \quad (8)$$

Where:

TP: true positive represents the HC-pathological samples detected correctly

FP: false positive represents the NrHS-normal samples detected as abnormal

TN: true negative represents the NrHS-normal samples detected correctly

FN: false negative represents the HC samples detected as NrHS

Additionally, the modified accuracy (MAcc) was calculated, which is the average of precision and recall rates (i.e. (precision+ recall)/2).

FIG. 3 ANFIS testing results for class A.

Results

For each HS signal (Normal or abnormal), the SNR was calculated twice before and after applying DTCWT. Table 2 shows the Average (AVG) and Standard Deviation (STDev) of SNR measurements on each class in the data set. It also shows the SNR percentage difference calculated from the equation 4 and statistical difference by z-test between SNR measurements. The AVG and STDev values indicates that SNR was increased after applying DTCWT with statistical significance (p-value <0.001).

Table2 The SNR measurements before and after DTCWT for all HS recordings in the dataset

Dataset (Before and after DTCWT)		Average SNR [dB]	SNR Standard Deviation [dB]	SNR Percentage Difference [dB]	Statistical Significance P-value
Class A	Before	7.1	2.4	+ 0.11	< 0.001
	After	7.9	2.4		
Class B	Before	0.7	0.6	+ 13.96	< 0.001
	After	10.8	3.5		
Class C+D	Before	5.6	3.7	+ 0.58	< 0.001
	After	8.9	4.0		
Class E	Before	5.6	3.0	+ 0.65	< 0.001
	After	9.3	4.8		

In the second experiment, we calculated the time-domain features for each HS signal after DTCWT. Then the ANFIS classifier was trained and applied to each test set. The rate of recall, precision, and F-score was reported on each class in the dataset. The MAcc, which is often used in recent literature, was also reported. Table 3 shows that the average precision, recall, F-score, and MAcc were 0.68, 0.81, 0.74, 75%, respectively. Whilst, Figure 4 shows the box-plot of SNR measurements on HS recordings for the five classes in dataset (Table 1), indicating the increment in SNR after

applying DTCWT. Finally, we compared our findings with several previous findings with wavelet transform and other approaches applied on PhysioNet challenge 2016 (Table 4).

Table 3 ANFIS Performance on dataset

Data set	Precision	Recall	F-Score	MAcc [%]
Class A	0.73	0.98	0.84	85.5
Class C+D	0.86	0.87	0.86	86.0
Class B	0.55	0.89	0.68	72.0
Class E	0.56	0.51	0.53	53.5
Average (A,B,C,D,E)	0.68	0.81	0.74	74.5

FIG. 4 SNR measurements on all HS recordings on all classes before and after utilizing DTCWT

Discussion

The results in Table 2 and Figure 4 demonstrate an improvement in the average SNR values after applying DTCWT in all classes with statistical significance ($p < 0.001$), indicating the *capability of DTCWT in de-noise HS recordings in PhysioNet 2016*. Additionally, these results reveal inequality in the percentage of SNR improvement among the five different classes in the dataset. This may suggest that there were incoherent noise conditions during HS recordings likely due to various instruments, diverse recording conditions, and/or the potential human interferences. Therefore, the results, on one hand, represent numerical proofs that the different classes contain unequal noise conditions making some HS recordings impracticable or incorrect HS recordings. On the other hand, it shows that *DTCWT can perform differently for different types and levels of embedded noises*.

Furthermore, Table 2 shows that class A has the lowest SNR percentage difference with no change in STDev after DTCWT, whereas classes B and E exhibit the largest SNR difference along with large change in STDev after DTCWT. It suggests that class A exhibits the lowest level of

embedded noises in the signal in comparison with the other classes. Similarly, the combined C+D, despite the smallest class sizes, resulted in a nearly equal STDev, suggesting the possible preservation of HS signal while elimination of noise through DTCWT. In contrast, the STDev was increased a number of decibels folds for classes B and E, likely indicating a possible weakening of HS signals. These findings are consistent with some studies suggesting that classes B and E contain the poorest quality of HS recordings [14, 21]. Kay E. et al. [16] argued that Class E should be excluded from PhysioNet Challenge 2016 as it contains clinically not practical HS recordings, which was also claimed by Gjoreski et al [5].

Whilst, analyzing the ANFIS classifying performances in Table 3 shows that ANFIS outputs on classes B and E appeared to be unsatisfactory in terms of accuracy. The ANFIS classifier is a machine code that can be trained to provide an optimal performance, so it is unlikely to be the reason. Therefore, the shortage in performance can be attributed to the quality of HS recordings, likely suggesting that classes B and E contained impractical HS signals, as claimed by references [10, 16, 25, 26]. The potential solutions for this issue could be either to increase the number of input features to ANFIS classifier as in references [19, 21, 28, 37], or to segment S1 and S2 portions from the five seconds HS recordings as in references [17, 18, 20, 28].

Nonetheless, our ANFIS performed the mathematical calculations to achieve 73-86% precision, 87-98% recall, 84-86% f-score, and approximately 86% MAcc (Table 3). This was achieved on all HS signals in classes A, C, and D, which presumably contained the correct S1-S2 segments, suggesting the *adaptive property ANFIS with only six time-domain features performs well in classifying biosignals* such as HS recordings. Our outcome is different from the previous finding by us [4] in many aspects. First, here we tested DTCWT for de-noise HS signals instead of Fourier bispectrum. Second, we employed time domain instead of frequency domain features as inputs to ANFIS. Third, we employed the kurtosis and skewness as inputs to ANFIS. Since we applied the new method in Figure 1 on 2735 instead of 1738 signals, we consider our outcomes in this paper to be more reliable. Therefore, combining the results in this paper along with our previous study [4] rationalized saying that the *adaptive property in ANFIS with either time-domain or frequency-domain features performs well in classifying biosignals* such as HS recordings.

When compared with previous attempts (Table 4) to apply various wavelet transform on PhysioNet Challenge 2016 dataset, we found the DTCWT is a feasible method to de-noise HS signals that has not been tested in literature before. Some of previous studies excluded doubtful HS signals in designing satisfactory HS decision support systems [4, 16, 20, 24, 31, 39]. However, there were other attempts which researchers included almost the entire 3,153 PhysioNet dataset so had to implement a high number of input features more than a hundred [25, 26, 37, 39]. All these attempts yielded a range of MAcc values from 75% to 86%, which comes close to results in this paper, but we evaluated the DTCWT and ANFIS classifier. Although our accuracy is lower than some of the previous outcome, it is within the range previous reports when impractical HS recordings were excluded, particularly

classes B and E as argued by references [10, 16, 24]. Finally, it is important to mention that this paper, in comparison to literature, *quantitatively presented the SNR percentage difference after applying de-noise*, prevailing that *DTCWT can perform differently for different types and levels of embedded noises* in PhysioNet 2016.

It is noteworthy that the performance of DTCWT and ANFIS may be affected by several parameters. One of which is the Butterworth Filter cut-off frequencies. However, we speculate that any marginal change in the cut-off frequency would only make marginal change in performance [30]. The other parameters likely affecting the performance are the cA and cD, the amplitude and detail coefficients in the DTCWT, respectively [29]. A follow-up prospective research of those two parameters may further improve the DTCWT reconstruction of HS signal, followed by an improvement of ANFIS performance. At the end, the number of decomposition and reconstruction levels in the DTCWT in Figure 2 also could have an impact.

Conclusion

In summary, this paper evaluated de-noising HS recordings by DTCWT, which has not been attempted. The results showed statistical significance in SNR improvement with substantial improvement, number of folds of [dB], in SNR percentage difference. The adaptive property of ANFIS classifier with 6-time domain features successfully resulted in an encouraging accuracy (74.5%) on 2735 samples. If non-clinically-accepted HS recordings were excluded as in reports [10, 16, 17, 20, 24, 38, 40], the proposed approach would result in 86% accuracy which come in range of accuracies in these reports, indicating the capability of DTCWT and ANFIS as a suggestive successful tool.

Declarations

Conflict of interest. The authors declare that they have no conflict of interest.

Table 4 Literature Samples on Physio-Net Challenge 2016 Using Wavelet Transform

Author	Methodology	# Features	Neural Network Classifier	# HS Samples	Accuracy MAcc%
C. Potes et al. [26]	Time and frequency-domain Features	124	CNN	3240	86%
Whitaker, B. M. et al. [20]	Sparse coding	20	SVM	2,153 *	86.5%
M. Tschannen et al. [24]	Wavelet deep convolutional neural network (CNN)	25	SVM	1277 *	81.2%
Goda et al. [37]	Wavelet envelope features	128	SVM	3000	81.2%
Langley et al. [38]	Wavelet Entropy	wavelet entropy	Classification algorithm	400 *	77%
Kay E. et al. [16]	Hidden semi-Markov model	50	fully-connected, two-hidden-layer neural network trained by error backpropagation	All dataset excluding Class E *	74.8%
Grzegorzcyk et al. [10]	Algorithm based on Hidden Markov Model.	48	Neural networks	3000	79 %
Nilanon et al. [25]	Spectrogram	Many time windows	SVM, CNN, and Logistic Regression (LR)	About 3000	68- 80 %
M. N. Homsy et al. [39]	Nested ensemble of algorithms	131	Random Forest, LogitBoost and a Cost-Sensitive Classifier	764 *	84.48%
This work	DTCWT	6	ANFIS	2735 dataset excluding Classes B , E	74.5% 86%

* Part of the 3153 HS recordings in the PhysioNet Challenge dataset were excluded.

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