Examining Wavelet Transform Performance on ETG Signal to Eliminate Noise

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Abstract - The aim of this study was to investigate the performance of wavelet transform on ETG signal to eliminate noise. This research is aimed at improving the method of recognizing inner emotions. The proposed new method is an automated method for classifying emotions using signals (EDA). Temporal analysis of the acquired frequency that provides a space of characteristics, based on which different emotions can be identified. For this purpose, the complex wavelet function (C-Morlet) is applied to the recorded EDA signals. The data set used in this study is a set of multifaceted recordings of social and communication behaviors as well as EDA records. The data set is interpreted to extract a time sequence corresponding to the three main emotions "happiness", "boredom" and "acceptance". The simulation results show that the level 3 violet sym4 conversion removes noise from the ETG signal well and increases the signal to noise. The results of the simulation using this method are more efficient than other methods and reduce more noise.

Keywords: *Inner emotion detection, Wavelet transform, Noise removal, ETG signal*

Introduction

Feelings and emotions have a significant role in human communication and are expressed with emotional words, tone of voice, facial expressions and posture (Safari, 2014). The ability to recognize emotions can have an effective role in building machines with emotional characteristics close to humans (Arghiani, 2016). As facial expressions have a significant role in human communication. Studies show that in these communications, the speech conveys only 7% and the phonetic part 83% of the message, and 55% of a human's emotional message is conveyed by facial expressions. The existing approaches to identifying emotions for classification of their types can be divided into three main categories: knowledge-based techniques, statistical methods, and hybrid approaches (Chollet, 2017). One way to measure emotion is to use mood swings like changes in a person's voice and face. The use of these methods has problems like hiding the feeling by the person and individual differences in the occurrence of the situation and makes it difficult to measure the feeling. Thus, using physiological reactions like the changes in heart signal, brain signal and body temperature can help measure emotions (Hassani et al., 2017). Accordingly, the scholars have worked on the development of intelligent systems with the ability to detect emotions for a variety of auxiliary programs like assistive devices, which consider all components of the Electro Dermal Activity signal (Moharreri et al., 2019). In a study entitled "Auxiliary displacement estimation based on comparative learning for non-resident evaluation of EEG signal motion image based on brain-computer interface BCI," Raza et al. (2019) stated that the proposed cognitive learning algorithm based on group learning algorithm significantly increases BCI performance in MI classifications. In a study entitled "Emotional Analysis of Movie Review Using: Microsoft Text Analysis and Google Cloud Natural Language API" Chowdary et al. (2019) stated that it is Microsoft Cognitive Services and Google Cloud Natural Language that enable them to create scores and classify them based on movie reviews. Pitsilis et al. (2018) examined the subject of detecting offensive language in tweets using in-depth training. In a study entitled "Emotion Analysis on Twitter: A text mining approach to the Syrian refugee crisis," Öztürk et al. (2018) stated that the purpose of this study is to examine public perceptions and feelings about the refugee crisis, which has affected millions of people and conducted on social media around the world. In a study entitled "Network analysis of textual emotions," Luo et al. (2018) suggested combining LDA and GRU-CNN text indices with Latent Dirichlet Allocation (LDA) and Convolution Neural Network (CNN). The simulation results showed that this method could effectively enhance the accuracy of text emotion classification.

González et al. (2017) conducted a study on the analysis of emotions using inclusive education. This is a study involving the EURF-UPV team in four works from the second half of this year. Our approach is based on using convolutional and recurrent neural networks (back propagation) and a combination of general and specific keywords with polarity dictionaries. They participated in all proposed processes for English and Arabic using a system with minor modifications. Majumder et al. (2017) conducted a study on the subject of document modeling based on deep learning to identify characters from the text. Shin et al. (2017) developed an emotion recognition interface using a complex ECG / ECG biography system for interactive contents. Baja and Pajuri (2015) recognized human emotions using features based on multiple wavelet-transforms of EEG signals. Zamanian and Farsi (2015) enhanced the accuracy of emotion recognition using EEG signals with innovation in combining feature extraction. According to their results, considering the characteristics of time domains and frequency of EEG signals and using multi-class SVM algorithm, optimized by the genetic evolutionary algorithm, provides better performance. In a study entitled "Improving the clustering algorithm for emotion analysis in Persian texts," Hashemzadeh et al. (2017) stated that the purpose of this study is to analyze the emotion within the texts. The results showed that the proposed method was significantly better than previous methods. Recently, few studies have focused on recognizing external emotions like facial expressions, tone of voice, and speed. External emotions are very recognizable, but can be artificially manipulated, which reduces complexity. To overcome these problems, the study recognizes the inner feelings and examines the performance of the wavelet transform on ETG signal to eliminate noise.

Methods

The new method proposed is an automated method for emotion classification using EDA signals to improve the internal emotion recognition method. In acquired frequency temporal analysis, which provides a property space based on which various emotions can be identified, the complex wavelet function (C-Morlet) is applied on the recorded EDA signals. The dataset is a multifaceted recording of social and communication behaviors as well as an EDA record interpreted to extract the time sequence corresponding to the three main emotions of "happiness", "boredom" and "acceptance". As we are developing an emotion classification method based on time frequency analysis of EDA signals, the main features of continuous wavelet transform assuming a complex wavelet transform are presented for the first time in this study. Then the steps of preprocessing and extracting the wavelet-based feature are then discussed. Ultimately, the characteristics of the support vector machine (SVM) are applied using the classifier method, and experiments were done on EDA signals to classify emotions using SVM, where the function of emotion classification improves significantly over time compared to other methods.

There is a data redundancy frequency in the time domain, so the domain that cannot have this redundancy is the wavelet domain. The signals used were from TIMIT database and the proposed algorithm is simulated based on these signals.

SVM classifier separate $y_i \in \{-1, +1\}$ ، $x_i \in R^d$ ، $D = \{x_i, y_i\}_{i=1}^{N}$ by plotting an optimal hyper-plane ⟨w, x⟩ + b = 0 between classes so that the margin between them is maximized. H1 and H2 are backup planes, and the optimal hyper-plane separates this margin, so that it is at the same distance from each hyper-plane that shows the margin between H1 and H2 is $2/\|W\|$.

In linearly separable classes, the classifier is obtained by maximizing $2/\|W\|$ margin, equivalent to a minimum of 2/w with the convex quadratic (QP) process constraint expressed as follows.

Equation (1)

$$min\frac{1}{2}\|w\|^2 \quad s.t. \quad y_i(\langle w, x_i\rangle + b) \geq 1$$

In this equation, w and b are the parameters of the hyper-plane… are the symbols of the product of internal multiplication. However, various classes are rarely separated by the hyper-plane as their instances overlap in the property space.

In such cases, the slack variable $\xi_i \geq 0(slack)$ and the penalty parameter $C \geq 0$ (penalty) with the optimization step to obtain the best possible decision boundary are defined as follows:

Equation (2)

$$min\frac{1}{2}\|w\|^2 + C\left(\sum_{i=1}^{N}\xi_i\right) \quad s.t. \quad y_i(\langle w, x_i\rangle + b) \geq 1 - \xi_i$$

Various kernel functions are commonly used to deal with nonlinearly separable data. Thus, the original x_i data is defined on another attribute space via the mapping function φ (.) and uses the kernel function $k(x_i, x_j) = \langle\varphi(x_i), \varphi(x_j)\rangle$. Specified kernel position specifies that the candidate kernel is actually an internal kernel.

If k $k(x_i, x_j)$ is a symmetric continuous kernel defined in the range $t_1 \leq t \leq t_2$, the kernel can be divided into series $\sum_{n=1}^{\infty} \lambda_n \varphi_n(x_i) \varphi_n(x_j)$ where $0 \quad \lambda_n$ is the eigenvalues and φ_n functions are extended to eigenvectors. To maximize the planes margins, H1 and H2 are separated until they reach the backup vectors on which the solution depends. The Lagrangian double equation is defined as follows to solve this optimization problem.

Equation (3)

$$\max_{a} \sum_{i=1}^{N} a_i - \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} y_i y_j a_i a_j k(x_i, x_j)$$

$$s.t.\ 0 \leq a_i \leq C, \sum_{i=1}^{N} a_i y_i = 0, \quad i = 1, \ldots, N$$

In this equation, $\{a_i\}$s are Lagrange coefficients, some of which are non-zero. These non-zero values correspond to the support vectors that define the parameters of the hyper-plane $w = \sum_{i=1}^{N} a_i y_i x_i$. Thus, the experimental sample label (y_z) is defined as follows.

Equation (4)

$$y_z = sgn\left(\sum_{i=1}^{N} a_i y_i k(x_i, z) + b \right)$$

EDA signals based on facial expressions are examined to evaluate the accuracy of the proposed feature extraction method on the function of emotion classification. EDA dataset is categorized according to the various emotions in the plane margins, including the feelings of “happiness”, “boredom” and “acceptance”. The function of emotion classification is enhanced when the proposed wavelet-based features are used with the SVM classifier.

In this study, the signals used are TIMIT database and the proposed algorithm is simulated based on these signals. In this study, the data needed to simulate the ETG signal was obtained from the MIT-BIH database.

Results

The proposed model is implemented as follows to evaluate the system in accordance with the title of research based on increasing the quality of ETG signal:

MIT-BIH database data has 84 30-minute electrocardiograms recorded in 42 hours out of 74 (data 102 and 202 were taken from one person). Eleven-bit signal resolution is in the range of ten millivolts. Firstly, the data is received from the following address, which includes two datasets: 100 and 200.

https://www.physionet.org/physiobank/database/mitdb

The 100 series data was randomly selected from 4000 pieces, and the 200 series data include rare and important arrhythmias that are not well represented by random selection. Each data consists of three files annotations and Header, Signals, Reference.

Table 1: Data formats in MIT-BIH database

Reference annotations	Signals	Header
100.atr	100.dat	100.hea
101.atr	101.dat	101.hea
102.atr	102.dat	102.hea
103.atr	103.dat	103.hea
104.atr	104.dat	104.hea
105.atr	105.dat	105.hea
106.atr	106.dat	106.hea
107.atr	107.dat	107.hea
108.atr	108.dat	108.hea
109.atr	109.dat	109.hea
111.atr	111.dat	111.hea
112.atr	112.dat	112.hea
113.atr	113.dat	113.hea
114.atr	114.dat	114.hea
115.atr	115.dat	115.hea
116.atr	116.dat	116.hea

The 100m.mat matrix is downloaded from the database and the sampling frequency is 360 Hz, so each beat may be between 441 and 234 samples to use the data in MATLAB. ETG signal after initial preprocessing and sampling can be seen in Figure (1):

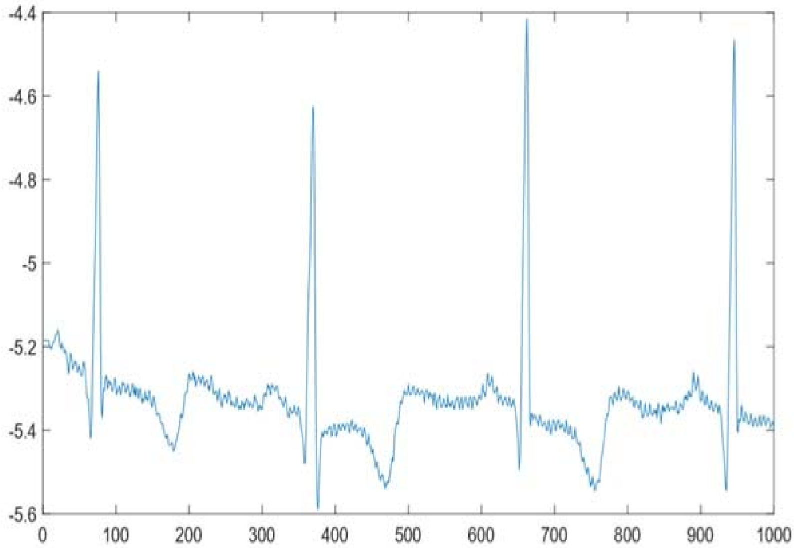

Figure 1: ETG signal

We added 50 Hz noise to the simulated ETG signal to simulate the ETG signal infected with this noise, so ETG noise signal can be seen as in Figure (2):

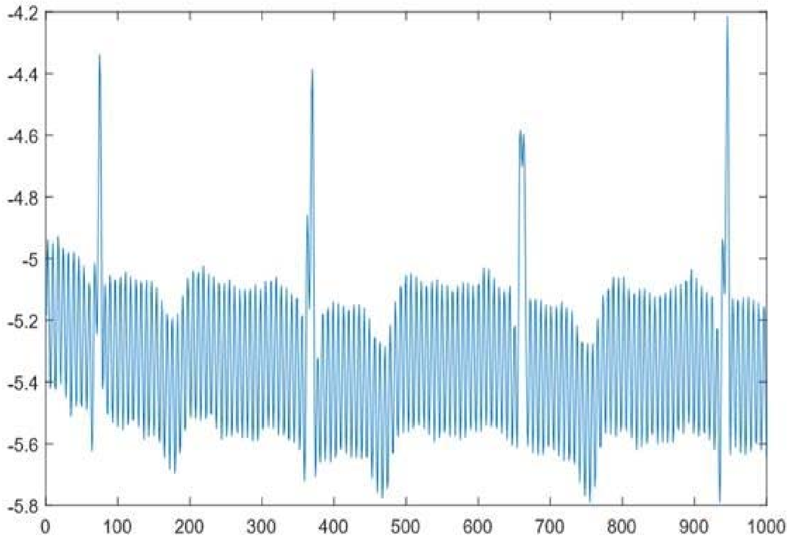

Figure 2: ETG signal infected with 50 Hz noise

A common problem in recording cardiac signals is noise and even body and eye movements that cause errors in signal recording or its analysis. Noise or artifacts can limit the use of ETG signals and it is necessary to remove the effect in this section where it is deleted. In this section, wavelet transform is used to eliminate or reduce ETG signal noise.

The wavelet function used on ECG signal considered for this study is as below.

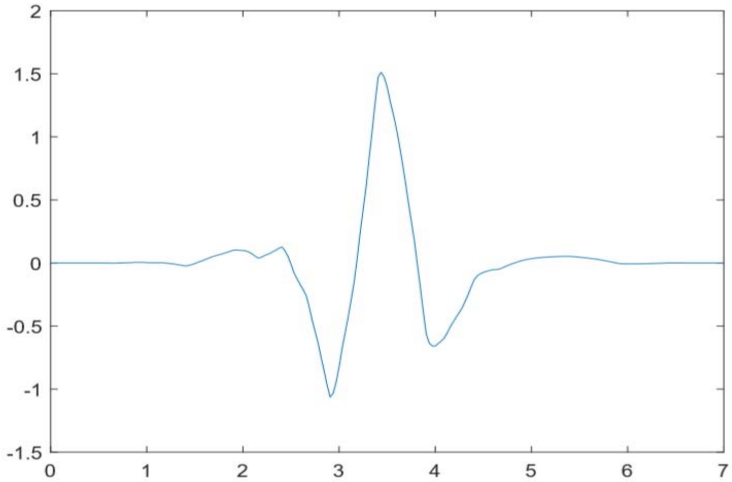

Figure 3: Wavelet function applied to the ECG signal

ETG signal after applying the wavelet transform (introduced above) at several levels can be seen as follows:

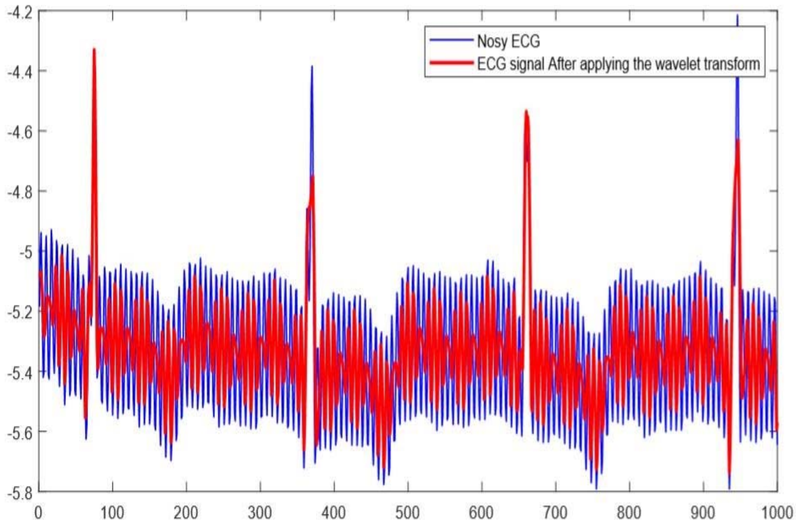

Figure 4: ETG signal before and after applying surface wavelet transform

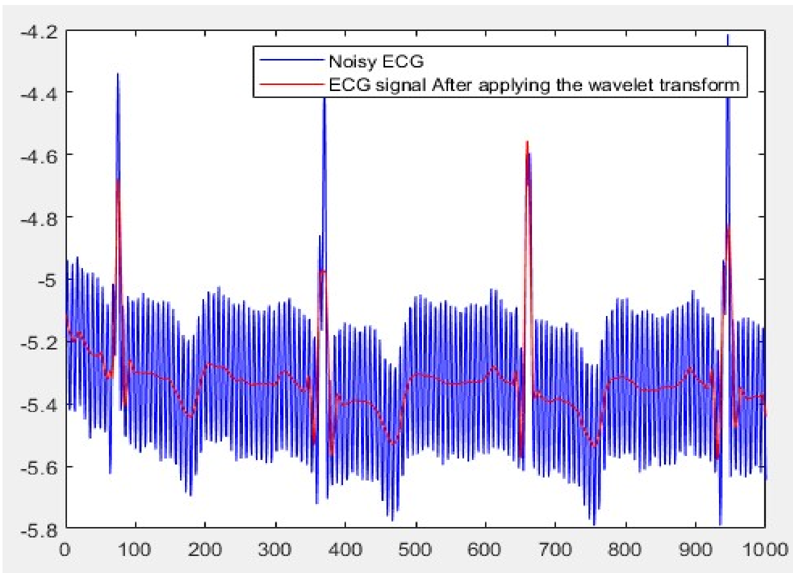

Figure 5: ETG signal before and after applying surface wavelet transform

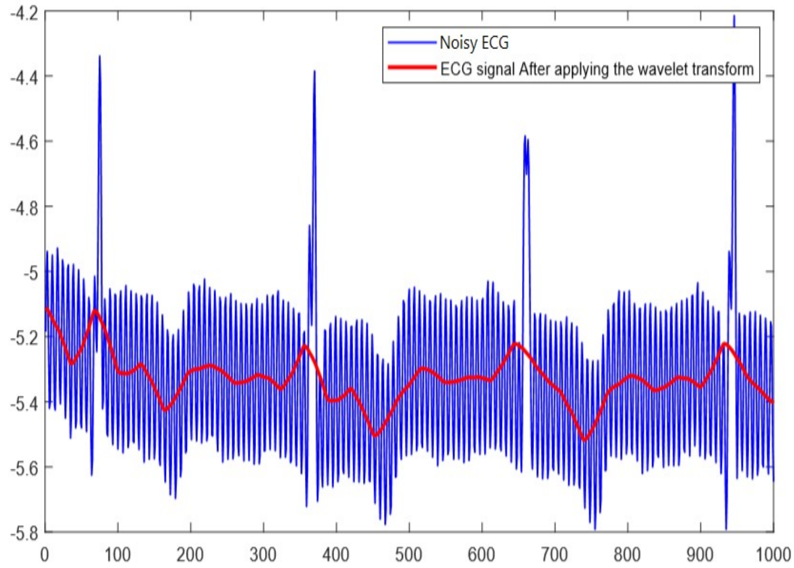

Figure 6: ETG signal before and after applying surface wavelet transform

Given the results observed after the simulation visible in Figures 4, 5 and 6, level-3 wavelet transform to other levels removes the noise from the ETG signal while preserving the signal properties and the desired wavelet is intended. In this case, the signal to noise will be equal to 14.4642.

Conclusion

The purpose of the study was to examine the performance of wavelet transform on ETG signal to eliminate noise. The simulation results show that Level-3 sym4 wavelet transform well removes noise from ETG signal and increases signal-to-noise ratio. Various noise interactions are seen in unfiltered ETG signals. In this study, digital filters were proposed instead of using filters that use hardware to remove noise.

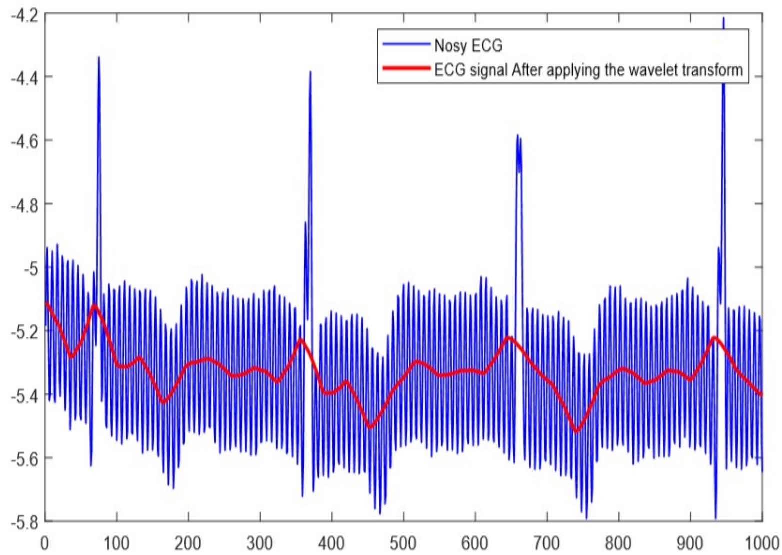

Figure 7: ETG signal before and after applying the wavelet transform by the simulation software

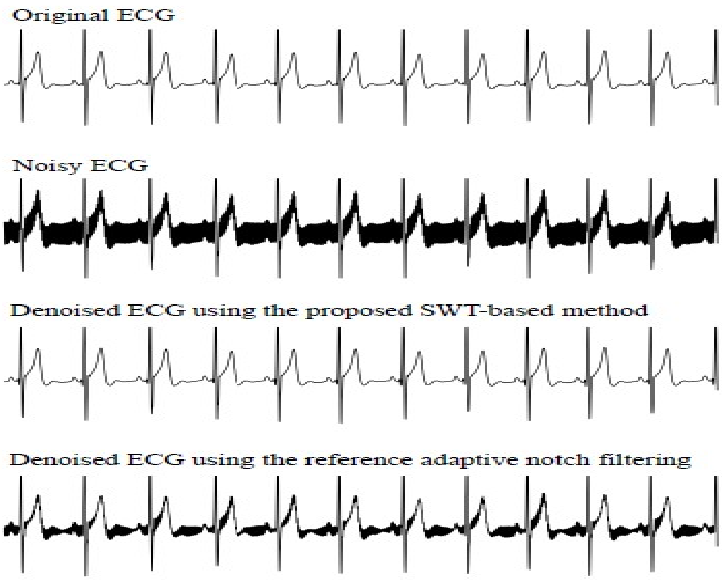

Figure 8: ETG signal before and after noise removal in (JuanR´odenas et al, 2018)

As is seen in Figures (7) and (8), the simulation results using this method are more efficient compared to JuanR´odenas et al. (2018) and reduce more noise. It is suggested that more digital filters such as Kalman filter on ETG signal can be examined to continue the research path.

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