

## Robustness to Noise Test for the Machine Learning Model of Neurology Problems

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### ABSTRACT

Cerebral Vasospasm (CV) is a narrowing of the blood vessels in the human brain. Transcranial Doppler (TCD) is a noninvasive device and can be used as for diagnosis various brain diseases and CV detection. TCD signals can be contaminated with noise from sources power line and electrodes before using these signals in signal processing steps. The goal of this study is to evaluate the CV detection model accuracy against the noise. Time-frequency feature extraction was used as a technique to enhance the detection accuracy and efficiency. In the previous studies, we extracted CV and normal classifier model by using the combination of 12-time frequency features, but the results generated a moderate accuracy when examined in real-time [put a reference]. In this study, we test the robustness to noise of proposed model; experiments were applied in real-time on the recorded TCD signal from the right and left middle cerebral artery (MCA) region of the brain of 160 subjects. The experimental results give us 87.5% sensitivity for CV. This percentage starts to decrease at 30% of signal to noise ratio (SNR), and 89% specificity for normal and this percentage starts to decrease at 60% of SNR.

**KEY WORDS:** Neurology, Signal Processing, Machine Learning, Feature Extraction.

### INTRODUCTION

Transcranial Doppler (TCD) is generally used to diagnose cerebral hemodynamics, stenosis, trauma, aneurysm and hemorrhage [1]. To measure the measurement of the brain blood flow rate requires an advanced imaging processing techniques. The Doppler concepts in the medical field depended on transmitting frequency to the brain and observing the difference between the transmitted and reflected frequencies. The Doppler shift  $\Delta f$  is given by the equation (+): [put a reference]

$$\Delta f = 2 \frac{v}{c} F \cos \theta \quad (1)$$

where  $F$  is the transmitted frequency,  $v$  is the velocity of blood,  $\theta$  is the beam-vessel angle and  $c$  is the speed of sound in tissue. TCD can detect the decrease or increase in blood flow rate or resistivity variation. The second choice is the magnetic

resonance or angiography techniques, but those techniques are very expensive, and they require the continuous attendance of expert's physicians.

In the literature, TCD signals were classified by Ozturk et al. by using neuro-fuzzy classifier of the non-stationary chaotic invariant TCD signal [2]. Uguz proposed the Rocchio-based hidden Markov model (HMM) and fuzzy discrete hidden Markov model (FDHMM) for enhancing the classifications of TCD signals [3,4]. Guler et al. applied the fast Fourier transform (FFT) and adaptive autoregressive-moving average (A-ARMA) for spectral image analysis of TCD signal. A-ARMA produced the best spectral resolution [5]. Serhatlioglu et al. used the neural network as a classifier of FFT transcranial signals [6].

As seen in many studies, Fourier transform is used widely, but it is a technique that cannot display all time and frequency information details which means that it has a significant problem to detect many diseases due to poor of spectral resolution and the different noise power especially in non-stationary signals. So, we will try in the future to use the wavelets as a feature extraction method due to because it gives optimal time-frequency resolution in all ranges of frequencies. The major advantage of the wavelet transform is that the window size can be varied for low and high frequencies and high one. For this benefit, the wavelet transform is applied in image processing [7,8], signal processing [9,10] and biomedicine [11].

In this work, TCD signals recorded from the right and left middle cerebral arteries (RMCA, LMCA) of 16 patients were sent by auxiliary cable to a personal computer (PC) by using a 16-bit sound card. The machine learning model method was applied to the recorded signals in order to classify the CV. The results were compared with the physician's decision for verification of the proposed work and then testing the extracted model is tested at with different noise power. Internal or external noise to the signal will cause appearance of a new or extra frequency which can influence the estimation detection of neurology problems.

The following section presents the structure of the methods and techniques for TCD signal processing for medical diagnosis the cerebral vasospasm (CV). In the Results and Discussion section, we display the results of CV detection with

taking into consideration the effect of noise on the dataset and the performance of the different SNR. Finally, the Conclusion section summarizes our studies and proposes future research directions.

## RESEARCH METHODOLOGIES

### A. TCD Signal Collection

An audio database has 160 wave files of 3-10 seconds in duration with ~~sampled~~ a sampling rate of 44.3kHz. All of them were transferred from TCD to the ~~PC personal computer~~ by an auxiliary audio cable. Two steps are applied on the dataset to detect the CV subjects. The first is the feature extraction and then the classifier. All the results are compared with the decision of vascular neurologist.

#### B.1 Feature Extraction

This step is used in machine learning and audio signal processing to compress the redundancy that is found in the dataset [12], where the outputs datasets are small in size and help to ~~enhance~~ ~~increase~~ the performance of the classifier. We used the two domains, time and frequency, features. The time domain features are zero cross rate, energy, and energy entropy. The frequency features ~~that~~ used are Mel-frequency cepstral coefficients (MFCC), chroma coefficients, spectral centroid, spread, entropy, spectral roll-off, spectral flux and harmonic ratio. We displayed the effect of each of these 12 features on the CV detection in the results section. These features were fed to different classifiers.

##### B.1.1 Zero Crossing Rate and Harmonic Ratio

ZCR is used as a feature in the narrowband signals. It occurred when the sample changes the algebraic sign [13]. The average rate can be used as a feature in the classifier input. On the other hand, ~~concerning~~ the harmonic ratio, we can assume the TCD signals as quasi-periodic to calculate the fundamental period by applying the algorithm ~~explained~~ in [14]. ~~By~~ comparing the signal with its shifting.

##### B.1.2 Energy and Energy Entropy

They are used for feature extraction in the audio signal analysis. The energy entropy is measured ~~my~~ by dividing each wave file into frames and each frame to segments then ~~normalized~~ ~~normalizing~~ by the energy of the frame [15]. It can reflect the sudden energy transition.

##### B.1.1.3 Mel-Frequency Cepstral Coefficients and Chroma

MFCC is defined as the short time speech spectrum; it can be measured by taking the log to the power spectrum of nonlinear Mel frequency and then applying the linear cosine transform [16]. MFCC ~~are~~ used in speech analysis and in the application of human speech prediction [17,18]. It also measures the signal cepstral; ~~w~~ ~~e~~ ~~c~~ ~~a~~ ~~l~~ ~~c~~ ~~u~~ ~~l~~ ~~a~~ ~~t~~ ~~e~~ ~~d~~ ~~t~~ ~~h~~ ~~e~~ ~~f~~ ~~i~~ ~~r~~ ~~s~~ ~~1~~ ~~3~~ ~~c~~ ~~o~~ ~~e~~ ~~f~~ ~~f~~ ~~i~~ ~~c~~ ~~i~~ ~~e~~ ~~n~~ ~~t~~ ~~s~~ ~~f~~ ~~o~~ ~~r~~ ~~C~~ ~~V~~ ~~d~~ ~~e~~ ~~t~~ ~~e~~ ~~c~~ ~~t~~ ~~i~~ ~~o~~ ~~n~~ ~~ا~~ ~~ج~~ ~~م~~ ~~ل~~ ~~ة~~ ~~ع~~ ~~ر~~ ~~ب~~ ~~ي~~ ~~ة~~. On the other hand,

Chroma is the displaying of spectral energy as Wakefield. It can be measured by transforming the Discrete Fourier transform (DFT) coefficients into bins. It is widely used to predict the music that is produced from piano [19].

#### B.1.4 Spectral Centroid, Spread, and Entropy

They are used for music ~~[20]~~ and speech discrimination [20]. The spectral centroid represents the mass center of the spectrum, and the spectral spread is calculated by the second moment of the spectral centroid. With regards to spectral entropy, it can be obtained using the same technique like the energy entropy. But, in this technique, the frame spectrum is divided to sub-bands and is then normalized by the energy of spectrum frame.

#### B.1.5 Spectral Roll-off and Flux

Spectral roll-off is used to distinguish between the voiced and unvoiced signal [21]. It can be ~~measured~~ ~~obtained~~ by calculating the frequency ~~that~~ under 85% of the concentrated spectrum magnitude. With regard to the spectrum flux, it monitored the deviation between two successive frames.

#### B.1.6 Classifiers

First, for standardizing the feature values, we apply feature scaling and mean normalization as a preprocessing step. We applied various classifying methods like a decision tree, K-nearest neighbors (KNN), support vector machine (SVM), and logistic regression. We found that ~~bagged decision tree~~ ~~بي~~ ~~مش~~ ~~م~~ ~~و~~ ~~ج~~ ~~و~~ ~~د~~ ~~ة~~ ~~ف~~ ~~ي~~ ~~ال~~ ~~ط~~ ~~ر~~ ~~ق~~ ~~ال~~ ~~م~~ ~~ذ~~ ~~ك~~ ~~و~~ ~~ر~~ ~~ة~~ ~~ال~~ ~~س~~ ~~ط~~ ~~ر~~ ~~ال~~ ~~ل~~ ~~ي~~ ~~ق~~ ~~ب~~ ~~ل~~ ~~ها~~ and KNN gives highest detection percentage.

## RESULTS AND DISCUSSION

Firstly, we should test the efficiency and evaluate the success of the proposed algorithm that is based on 12 features. The 12 features were added and the results are calculated in terms of sensitivity, specificity, and accuracy using the decision tree classifier. The main purpose in this article is to test the influence of noise on the tested dataset. The experimental results of 160 wave files with the bagged decision tree classifier are 87.5% for sensitivity and 89.77% for specificity, ~~but all these results from the previous studies [22] and without adding any type of noise to signal amplitude~~ ~~ص~~ ~~ل~~ ~~ح~~ ~~ا~~ ~~ه~~ ~~ا~~ ~~ش~~ ~~و~~ ~~ف~~ ~~ق~~ ~~ص~~ ~~د~~ ~~ك~~ ~~ا~~ ~~ي~~ ~~ه~~ ~~؟~~ ~~؟~~ ~~؟~~

In the TCD device, Power M-mode program is built-in TCD. It can simulate the velocity of blood in RMCA, LMCA, and Basial artery (BA) with ~~calculating~~ its power, the number of samples, mean, DIAS (Desmoteplase (chemical compound) in Acute Stroke) and PI (pulsatility index) is calculated by peak systolic velocity-end diastolic velocity)/time averaged velocity). This can be shown in Figure 1. After that, the recorded wave file is taken from TCD to Matlab to confirm signal processing on wave file and then to detect the patient in normal case or CV. ~~where~~ Figure 2 shows the signal before training and

testing by machine learning. Later in, it would be desirable to predict CV before it happens.

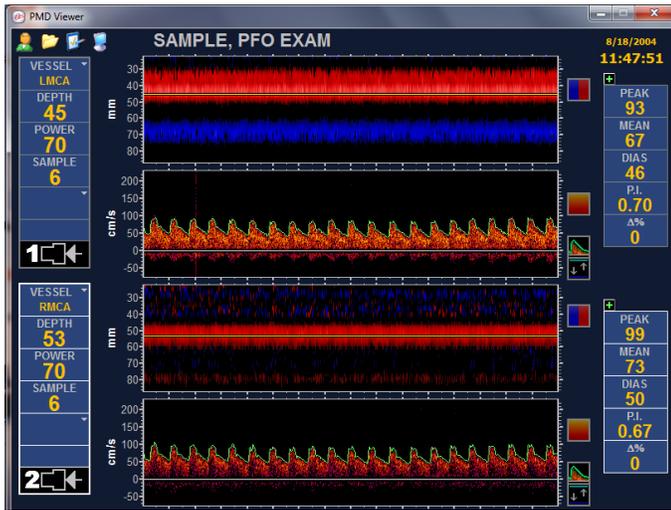


Figure 1. TCD Signal Monitoring.

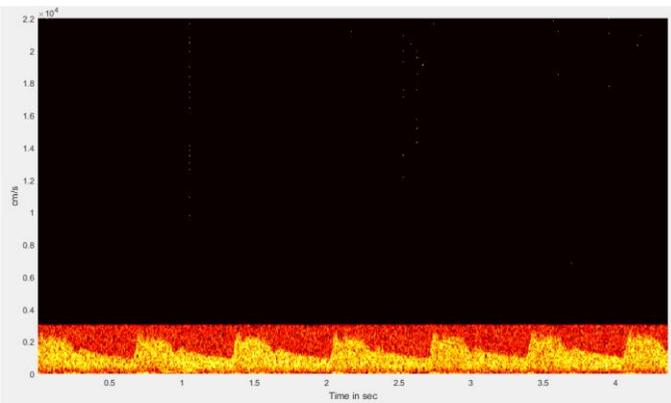


Figure 2. Simulated TCD Signal Before Applying Machine Learning Step.

As seen, there are slight differences between the TCD signal and the signal that reached the Matlab. So, it is important to study the robustness to noise on the dataset with different noise power. Figure 3 shows the evaluation of the proposed model to noise robustness, by adding the Additive White Gaussian noise (AWGN) to the dataset, where the x axis is the signal to noise ratio (SNR) percentage and y axis are the sensitivity and specificity percentage. The experiments show that the CV detection model is robustness to noise until 30dB SNR and but in the normal detection until 60dB SNR. These This AWGN can come yield from the TCD cable, power line or TCD probes.

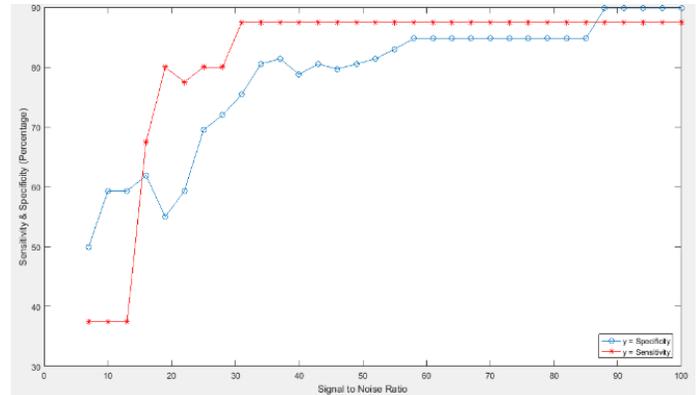


Figure 3. SNR Percentage with Sensitivity and Specificity Percentage. Put unit dB in x-axis

### CONCLUSION

This research aimed to test CV detection model against the noise by using 12 features with ensemble bagged decision tree. When the developed algorithm is tested, the classification efficiency performance is achieves 87.5% sensitivity and 89% specificity.

But, by applying difference noise power ratio, it gives us a different results at 60 dB SNR for sensitivity and 30 dB SNR for specificity. In a future work, we can use the wavelet features as an additional feature with the proposed model as an assistant diagnostic tool for brain problems evaluation and decreasing the physician's attendance in the neurology clinics and on other hand denoising or eliminating noise using infinite impulse response filter (IIR).

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