Coronary Artery Disease Identification Using Acoustic Features Based on QDA

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Abstract: Optimizing risk assessment may reduce use of advanced diagnostic testing in patients with symptoms suggestive of stable coronary artery disease (CAD). Detection of diastolic murmurs from post-stenotic coronary turbulence with an acoustic sensor placed on the chest wall can serve as an easy, safe, and low-cost supplement to assist in the diagnosis of CAD. Coronary artery disease (CAD) accounts for approximately 30% of the deaths in the European Union. The detection of diastolic murmurs from post-stenosis coronary turbulence reported already proposed for safe, cost-effective, and easy non-invasive evaluation of patients with suspected CAD. In the existing system, the system shown that heart sound contain weak murmurs caused by turbulent flow in the coronary arteries, and that those murmurs are indicators of CAD. In this project the system proposed a method for noninvasive detection of CAD with a commercially available electronic stethoscope. Three different approaches were used for analyses of the frequency distribution of the diastole periods: parametric spectral modeling, instantaneous frequency and the power in third octave frequency bands. using the quadrature discreminant analysis identifying the CAD.

I.INTRODUCTION

Coronary artery disease [1] is one of the foremost causes of morbidity and mortality in industrialized nations. Frequently, acute myocardial infarction or unexpected death is the first clinical circumstance of coronary artery disease. Calcification in the intima of coronary arteries results from atherosclerosis and innovative coronary artery disease. Postmortem studies have shown a correlation between extensive calcification of coronary arteries and the severity of coronary stenoses, as well as the frequency of acute myocardial infarction, even though the occurrence of the latter is strongly related to the lipid content of the atherosclerotic plaque. Segments of arteries with large calcifications had a greater number of atherosclerotic plaques than those segments with fewer calcifications. Survival has been shown to be lower in patients with recognized coronary artery disease and calcifications. Other studies have suggested that patients with calcifications in coronary arteries and who undergo thoracotomy have a high incidence of complications. Early understanding and changes in several risk factors are unvarnished elements for reducing mortality or morbidity, or both, in coronary artery disease. However, the early diagnosis and prevention of atherosclerotic coronary artery disease are rendered difficult by the low performance of noninvasive methods for detecting the disease, mainly in young asymptomatic patients. In these patients, early intervention and changes in the risk factors have great value.

II.LITERATURE SURVEY

1. *Noise and the detection of coronary artery disease with an electronic stethoscope:*

Advantages:

- The pole extracted from the 250-1000 Hz frequency band was very sensitive to noise.

Disadvantages:

- In contrast to the remaining noise sources abdominal noise is not controllable.

2. Heart Sound Segmentation of Pediatric Auscultations Using Wavelet Analysis:

Advantages:

- The proposed method provides a robust heart rate estimate prior segmentation based on singular value decomposition.

Disadvantages:

- The existence of low energy events that were not detected.

3. Detection of coronary artery disease with an electronic stethoscope:

Advantages:

- The advantages are low cost and that the test result is directly related to cardiac functionality.

Disadvantages:

- The disadvantage is low accuracy, sensitivity is 68% and specificity is 77%.

4. Empirical Mode Decomposition For EEG Signal Analysis:

Advantages:

- Features obtained from IMF can be applied to classifier to show effectiveness of EMD process.

Disadvantages:

- The subjects are asked to relax in this task means they are not performing any mental task.

III.PROPOSED SYSTEM:

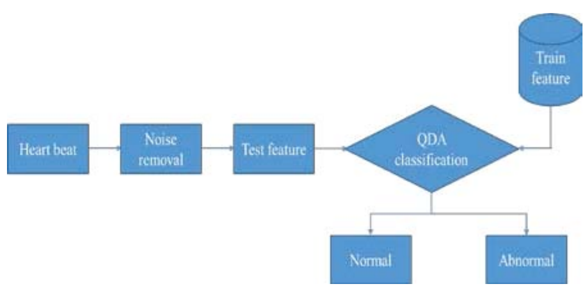

Fig 1: Block Diagram of CAD identification using acoustic features based on QDA

3.1ADVANTAGES:

- The well noise removal signal is take for feature extraction.
- The sufficient feature is get, so the classification accuracy is improved.
- The different types of feature extraction get the better result.

IV.MODULES

Fig1 shows the block diagram of basic modules is

- Dataset collection

- Preprocessing
- Noise removal
- QDA classification

4.1 MODULE DESCRIPTION
4.1.1 DATASET COLLECTION:

Bedside recordings were made from the 4th intercostal space at the left sternal border on the chest of patients using an electronic stethoscope. This stethoscope has a flat frequency response from 20-1000 Hz and a spectrum analysis shows that the noise floor is at least 15-20 dB lower than the power of the diastole sound up to 1000 Hz. Each recording is 8 seconds long corresponding to the capacity of the stethoscope. Patients were asked to breathe normally during the heart sound acquisition and between one and six recordings were collected from each subject. To avoid overrepresentation of some subjects a maximum of four recordings were selected per individual.

4.1.2 PREPROCESSING:

In the current study we used the method of dividing diastole periods into 50% overlapping sub-segments of short duration (100 ms) and discarding sub-segments with high variance to reduce the influence of friction spikes and other types of noise such as respiration noise. Each feature is then calculated as the median of the values in the remaining sub-segments from all heart beats. Due to the short sub-segment duration the CAD murmur can be assumed to be stationary in each sub-segment. The threshold of acceptable variance was set as α times the median of the variance in the sub-segments. Since the optimal variance threshold is likely to vary among the spectral bands, α was determined for each band. Since the coronary blood flow is highest in diastole and peaks in the early diastole, the features were extracted from sub segments within analysis windows during diastole.

4.1.3 NOISE REMOVAL:

The noise tolerance α, the start of the analysis window and the duration of the analysis window is adjusted individually for cross validation folds and for the different frequency bands. Across all frequency bands and cross validation sets the optimal starting point of the analyzing period is zero samples after the endpoint of the second heart sound. The most commonly selected duration of the analysis window is 400 ms, which is the case in 54% of the cross validation folds and frequency bands. In the 250-1000 Hz frequency band an allowed variance of 4 times the median variance is the most optimal threshold for identification of noise sub-segments.

4.2 SIGNAL COMPLEXITY FEATURES:

Turbulent flow, causing the CAD murmurs, is of a chaotic nature and may thus alter the complexity of the heart sounds. Semmlow et al. applied the Grasberger algorithm for estimation of the correlation dimension and found that the correlation integral in CAD subjects saturated at low dimensions compared to non-CAD in subjects, indicating the presence of a low-dimensional chaotic attractor. However, this is in contrast to findings by Schmidt et al. who found no indications of nonlinear or chaotic characteristics in carotid murmurs, concluding that cardiovascular murmurs could be described as a linear stochastic process. To test if CAD changes signal complexity, the following measures were evaluated: sample entropy (SE), simplicity (Simp), spectral entropy (SPE), and some simple complexity (SC) measures were examined as follows.

a) Sample Entropy:

SE is the negative logarithm of the conditional probability that a point which repeats itself within a tolerance of in an m dimensional phase space will repeat itself in an m + 1 dimensional phase space.

$$\mathrm{SE}\left(m, \tau, , \in\right) = -\log\left(\frac{C\left(m+1, \tau, , \in\right)}{C\left(m, \tau, , \in\right)}\right).$$

C(m, τ,∈) is the number of repeating points in the m dimensional phase space. Repeating was defined as points closer in a Euclidean sense than to the examined point. The allowed tolerance was 0.2 times the standard deviation of the signal. The phase space was reconstructed of a vector of m signal points,
Sampled from the signal at intervals τ :

$$X_i = \left[x\left(t_i\right), x\left(t_{i+\tau}\right), \ldots . x\left(t_{i+(m-1)\tau}\right)\right]^T .$$

SE was calculated using $m = 2$ and for embedding delays
$\tau = 1, 2, 4, 6, 8, 10$ or 12 (Samples).
b) Simplicity:

The simplicity measure is the inverse of phase space complexity, where complexity is defined as the dimension of the underlying dynamic system [29]. This was measured by overestimating the embedding dimension, calculating the correlation matrix and estimating the eigenvalues λj from the correlation matrix. If the dimension of the underlying dynamic system is lower than the embedding dimension redundancy will occur, resulting in rank deficiency in the correlation matrix, therefore some eigenvalues will be dominant and others will approach zero. Opposite if the signal is random, all rows of the correlation matrix will be independent and the eigenvalues will spread out. The similarity of the eigenvalues was quantified using the entropy of the normalized eigenvalues [29]

$$H = -\sum_{k=1}^{m} \hat{\lambda}^j \log\left(\hat{\lambda}^j\right)$$

Here ˆλj are the eigenvalues normalized to their sum. A logarithmic base of 2 is used for estimating the number of average states of the dynamic system

$$\Omega = 2^H .$$

The simplicity was the inverse of Ω. Simplicity was calculated with embedding dimensions from 2, 4, 8, and 20 to ensure an overestimated embedding dimension and with $\tau = 1, 2, 4, 6, 8, 10$, or 12.

c) Spectral Entropy:

If cardiovascular murmurs are a linear stochastic process, all statistical information is kept in their power spectral densities (psd). The signal complexity can then be described by the SPE calculated from the normalized psd, which is normalized to a total area under the curve of 1, thereby matching a probability function:

$$\mathrm{SPE} = -\sum_{f} \mathrm{psd}\,(f) \log(\mathrm{psd}(f))$$

Here f is frequency. d) Simple Complexity Measures: Some simple measures of signal complexity such as the number of zero crossings and the number of turning points were calculated together with the Hjort parameters [30] “Mobility” and “Complexity:

$$\mathrm{Mobility} = \frac{\sigma'}{\sigma} \quad \mathrm{Complexity} = \frac{\sigma''/\sigma'}{\sigma'/\sigma}$$

Here σ is the standard deviation and σ' and σ'' are the standard deviations of the first and second derivatives of the signal.

e) Statistical moments as features (smo): variance, skewness, and kurtosis were used as features for detection of cad by akay et al. [31] and were therefore estimated in the five frequency bands.

D. Classification and Statistics

K-fold cross validation ($K = 10$) is used to avoid overfitting. Cross validation is used for adjustment of the feature estimation settings, the selection and test of single features and the training and validation of the multivariate classifier. The same set of cross validation folds is used throughout the whole study. Cross validation is stratified to ensure an equal ratio between CAD and non-CAD in both training and test set. The cross validation is done at subject level ensuring that all recordings from the same subject were in the same subset. The performance of the individual features in both the training and test set is validated by the area under the receiving operator characteristic, AUC. The AUC is validated at recording levels. t-Statistics were applied to test if the AUC were significantly ($\alpha = 0.05$) different from 0.5. Since multiple recordings were used from each subject the standard error is estimated from the variation across the ten folds [32]. To reduce the risk of type 1 error, the Holm–Bonferroni method is used for iterative adjustment of the α value.

4.3 QDA CLASSIFICATION:

A multivariate classifier based on a Quadratic discriminant analysis (QDA) is used to construct a single CAD-score from several features. The features for the QDA were selected from the feature type which produced the best AUC across the five frequency bands. The number of features is reduced by selection of the 3 best features from each of the frequency bands. Next, the best subset is found by an exhaustive search among the remaining features, as the subset with the highest AUC in a sub K- fold cross validation (K=10) in the training sets.

Quadratic Discriminant Analysis does not make the simplifying assumption that each class shares the same covariance matrix. This results in a quadratic classifier in xx:

$$\delta_k(\mathbf{x}) = -\frac{1}{2}(\mathbf{x}-\mu_{\mathbf{k}})^\top \Sigma_k^{-1}(\mathbf{x}-\mu_{\mathbf{k}}) - \frac{1}{2}\log(|\Sigma_k|) + \log(\pi_k)$$

The following plot shows the quadratic classification boundaries that result when a sample data set of two bi-variate Gaussian variables is modelled using quadratic discriminant analysis:

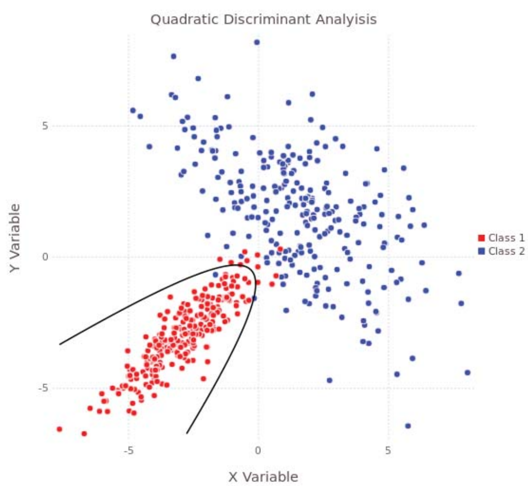

Fig 2:QDA Classification

V. SIMULATION RESULTS:

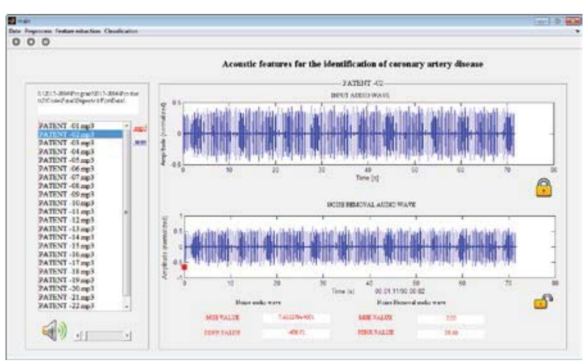

Fig 3:Input heart beat signal

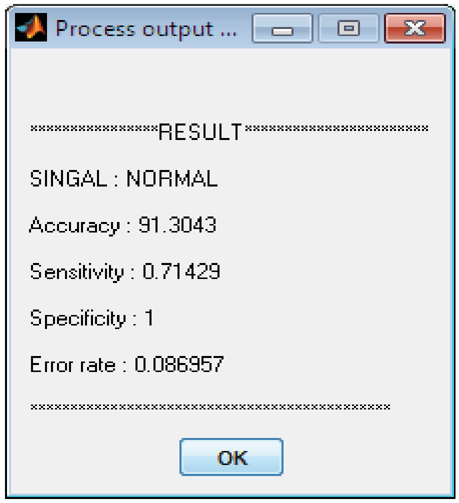

Fig 4: value based results

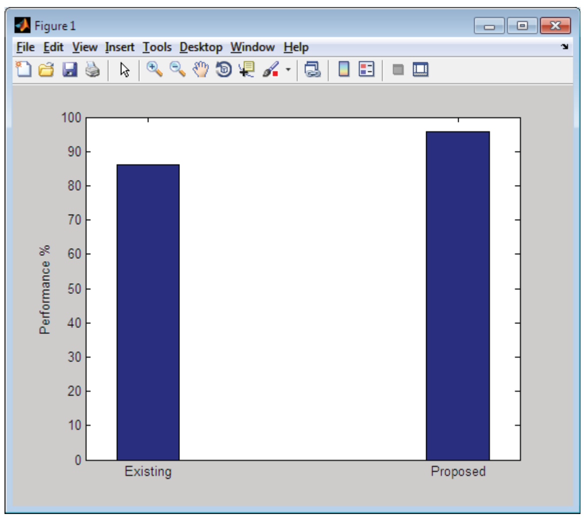

Fig 5: comparison between EMD and QDA analysia method based on accuracy.

V.CONCLUSION

The current study identified new features, describing changes in the low frequency part of the signal, for the diagnosis of CAD patients. Known features from the higher frequencies performed poorly in the recordings from the electronic stethoscope, which is probably due to noise from various sources, such as motion artifact which is a specific problem for the hand-held electronic stethoscope. By combining features from different frequency bands using a QDA, The diagnostic performance of the widely used ECG exercise tests, but if the noise problems would be solved the features from high and low frequency bands might supplement each other well and there by improve the performance of the stethoscope based CAD-score.

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