Detection of Coronary Artery Disease with an Electronic Stethoscope

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Abstract

A noninvasive method for detection of coronary artery disease (CAD) with an electronic stethoscope is proposed. Heart sounds recorded in clinical settings are often contaminated with background noise and noise caused by friction between the skin and the stethoscope. A method was developed to reduce the influence of the noise artifacts. The diastolic parts of the heart sounds were divided into multiple sub-segments, where noisy sub-segments were indentified as sub-segments with a low degree of stationarity or with a high energy level. The sub-segments not identified as noisy were analyzed with an Autoregressive (AR) model, where the pole-magnitude of the 1st pole was used as a discriminating parameter. A test on 50 subjects showed that removal of the noisy sub-segments before analyses improved the diagnostic performance of the AR-model considerably, thereby reducing the influence of noise related to the use of a handhold stethoscope.

1. Introduction

Coronary artery disease is the top single cause of death in the western world. The process of diagnosing CAD is comprehensive and expensive. In spite of well established diagnostic methods as coronary angiography and exercise tests, diagnostic challenges still remain. Common for the diagnostic tests available today is that they are costly and time consuming. The current study proposes a noninvasive method for detection of CAD with an electronic stethoscope. An electronic stethoscope is inexpensive, fast and easy to use, thus having the potential of becoming a tool for assessment of patients with risk of CAD in the early diagnostic phase. A more precise assessment may allow a more efficient referral and thereby reduce the number of demanding examinations.

Previous studies have shown that heart sounds may contain weak murmurs caused by turbulence in poststenotic blood flow in the coronary arteries and that this turbulence related sound is a indicator of CAD [1]. The murmurs are rarely audible, but algorithms to automatically detect the murmurs through signal analysis have been proposed [1-6]. The acoustic component related to poststenotic turbulence has been found to be associated with increased energy in the 300-800 Hz frequency band [3]. Since coronary flow peaks during diastole the murmur intensity is also highest in the diastolic period.

Prior methods developed for the detection of CAD used custom made sensitive and fragile recording equipment, which is not compatible with a clinical environment.

The main dificulty related to the analysis of heart sounds recorded with handheld stethoscopes in clinical settings is that they often are contaminated with background noise and noise caused by friction between the stethoscope and the skin, see figure 1a. Several frequency analyzing methods like Fast Fourier transform (FFT), wavelet analyze, and parametric models as AR-models has pervious been applied to indentify the turbulence related signal component.

The focus of the current study is to develop a method for use in clinical settings and the data used in the current study is recorded in the clinic, with a commercially available electronic stethoscope.

2. Methods

2.1. Data collection

Bedside recordings were made from the left 4th intercostal space on the chest of 50 patients using a commercially available electronic stethoscope (3M Littmann E4000). Each recording was 8 seconds long corresponding to the capacity of the stethoscope and transferred to a portable PC. The audio files were converted to 8 kHz WAV files through 3M Littmann Sound analysis software before analysis in MatLab. The patients were referred for coronary angiography at the Cardiology Department at Aalborg Hospital. The

coronary angiography images from the patients were analyzed with Quantitative coronary angiography, giving the precise dimensions of the stenosis. Previous studies showed that stenosis with at least 30% diameter reduction is detectable through audio analysis and subjects with at least one stenosis of at least 30% diameter reduction were defined as diseased subjects in the current study.

2.2. Preprocessing

The diastolic periods were indentified through manual analyses of the heart sounds. In total 373 diastoles were indentified. The diastolic segments were band pass filtered with a low cut-off frequency at 240 Hz and a high cut-off frequency at 1500 Hz. The diastolic segments were divided into non-overlapping sub-segments of 50 ms duration.

2.3. Stationarity analysis

The degree of non-stationarity of each sub-segment was measured as the variation of the instantaneous variance (IVar), which was estimated by filtering the squared amplitude of the signal with a moving average filter. To eliminate amplitude differences the sub-segment were normalized by their standard deviations before the IVar was calculated.

$$IVar(n) = \frac{1}{M}\sum_{m=0}^{M-1}\left|\frac{x_{sub}(n+m)^2}{\sigma_{X_{sub}}}\right| \quad n = 1, 2, \ldots . N - M$$

where x_{Sub} is a diastolic sub segment, M is the length of the moving average filter, which is 5 ms, N is the length of the diastolic sub-segment and $\sigma_{X_{sub}}$ is the standard deviation of the sub-segment. The degree of non-stationarity was then calculated as the variance of IVar. If the variance of IVar for a given sub-segment exceeded a defined threshold α, then the sub-segment was defined as noisy and was removed, see figure 1. The optimal value of α was estimated in the results section.

2.4. Variance analysis

The sub-segments with high energy were indentified as sub-segments with a variance higher than an adaptive threshold. The threshold was calculated for each recording as the median of the variance of all sub-segments in the recording multiplied with a threshold coefficient.

$$Thres = \beta \times median(\sigma^2_{X_{sub}})$$

where β is the threshold coefficient and $\sigma^2_{X_{sub}}$ is the variance of the sub-segments. The optimal value of β was estimated in the results section.

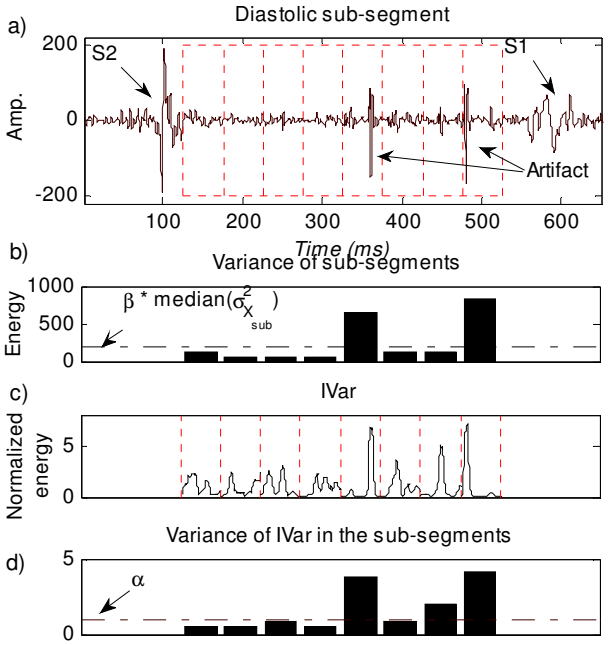

Figure 1. a) A diastolic sub-segment with artifacts is divided into sub-segments which are illustrated by the dotted lines. b) The variance is calculated from each sub-segment and a threshold is applied to indentify sub-segments with high variance. c) The instantaneous variance of the sub-segment. d) The variance of the instantaneous variance of the sub-segments.

2.5. Autoregressive model

The AR-model is a widely used modeling method in biomedical signal analyses. The presumption of the AR model is that each sample of the signal is an expression of a linear combination of the previous samples plus noise [7].

$$y(n) = -\sum_{p=1}^{m} a_p\, y(n-p) + e(n)$$

where $y(n)$ is the signal to be modeled, a_p are the model coefficients, m is the model order and $e(n)$ is the noise which is independent from the previous samples. In the current application the coefficients of the AR model were adjusted with the Burg method to maximize the models capacity to model the signal. Previous studies showed that a model order of 10 is sufficient to represent the signal [2] and, therefore, a model order of 10 was

chosen. The absolute pole magnitude of the 1st pole (PM1) was chosen as the discriminating parameter since it was the strongest discriminator in a preliminary analysis. A robust PM1 parameter was calculated as the median of the PM1 values from all the remaining sub-segments.

2.6. Performance measurement

The performance of the different filters was measured by measuring the separation between the PM1 values from subjects with at least one stenosis and subject without a stenosis. The degree of separation was measured by the F-ratio which is the between-groups mean square variance divided by within-groups mean square variance.

$$F = \frac{\text{Between Groups Mean Square Variance}}{\text{Within Groups Mean Square Variance}}$$

The F-ratio was used to find the optimal values of α and β by measuring the separation capability of PM1 for a range of α and β values. The values of α and β which generated the highest F-ratio was chosen. The two filter methods were tested both in combination and individually and compared to an implementation where no sub-segments were removed before the AR-model was applied. In addition, the results were compared with the performance of the method described in [3] where a 128 ms window in the middle of the diastolic segments was used for analysis.

3. Results

3.1. Optimal threshold values

The F-Ratio's obtained with different values of α and β are plotted in figure 2a and 2b. The F-Ratio increases with decreasing threshold α, thereby showing that a lower degree of non-stationarity in the sub-segments increases the separation capability of the PM1 parameter. However with an α-value of 0.5 only in average 22% of the sub-segments were left. Removal of all sub-segments with a higher degree of non-stationarity and furthered lowering of the threshold was not possible without the risk of removing all sub-segments in some recordings. When applying the variance analysis the maximum F-ratio was obtained at a value of the coefficient β of 0.7, see figure 2 b. When the stationarity and variance filter were applied in combination, meaning that both non-stationary and high-amplitude sub-segments where removed, was the maximum F-ratio obtained with α =0.7 and β =0.7.

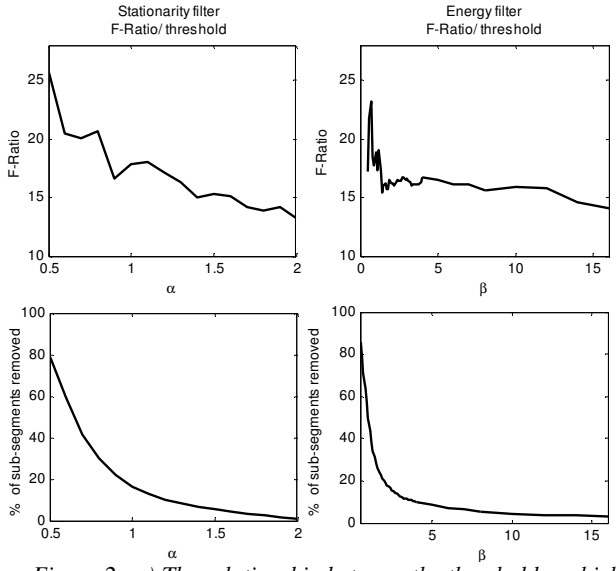

Figure 2. a) The relationship between the threshold α which is used to define non-stationary sub-segments, and the obtained F-Ratio. b) The relationship between the energy threshold coefficient and the obtained F-Ratio. c-d) The percentage of sub-segments which was removed when the threshold was applied.

3.2. Diagnostic performance

Tabel 1 shows the F-Ratios obtained by the different methods. The largest F-ratio was generated by removal of both the non-stationary sub-segments and the sub-segments with high energy. However the removal of either the non-stationery or the high energy sub-segments generates close to similar results with F-Ratio's at 25.6 and 23.6. The influence of removing the noisy sub-segments is clear since the F-ratio obtained without removing any sub-segments is only half the F-Ratio's obtained when noisy sub-segments are removed. Furthermore, the F-Ratio value obtained with the previously used method, where the entire mid-diastolic segment is analyzed as one segment, was considerable lower than the F-Ratios obtained by each of the multiple sub-segment methods.

Tabel.1 The F-ratio obtained by different methods.

Filtering methods	*F-Ratio*	*P-value*
Removal of both non-stationary and high energy sub-segments	26.9	4.97e-9
Removal of non-stationary sub-segments	25.6	9.90e-9
Removal of high energy sub-segments	23.2	3.68e-8
No removal of noisy sub-segments	12.6	2.77e-5
A 128 ms window is analyzed in the middle of the diastole.	6.1	0.0039

Figure 3 shows the receiver operating characteristic (ROC) curve of diagnostic performance with optimal

threshold settings using both the stationary filter and the high energy filter. The optimal classification yields a correct classification of 82%, with 86.2% sensitivity and 76.2% specificity.

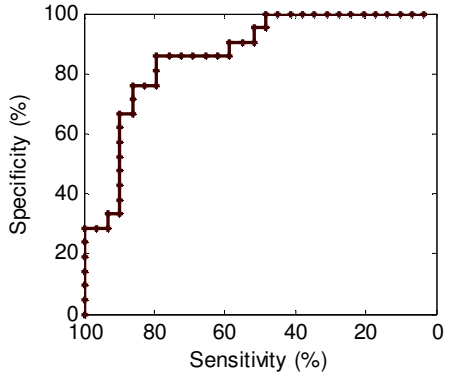

Figure 3. ROC curve showing the diagnostic performance, after excluding non stationary and high-energy sub-segments.

4. Discussion and conclusions

The results show that dividing the diastolic period into multiple sub-segments and the removal of the noisy sub-segments increases the capacity of parameter PM1 to separate diseased subject from non-diseased subjects. The noisy sub-segments can be indentified through analysis of either stationarity or variance level. Surprisingly, the maximum separation was obtained with very low values of the thresholds that define the degree of acceptable non-stationarity and the level of acceptable energy in the sub-segments. The implication of the low threshold values is that close to 80% of the sub-segments were defined as noisy and subsequently were removed before further analysis, see figure 2c and 2d. When 80% of the sub-segments are removed it is likely that the removed sub-segments not only include powerful friction spikes and dominating background noise, but also more damped noise such as other noise from flow in other parts of the cardiovascular system.

The specific values of the threshold are likely to be over fitted to the current dataset and will need adjustments in future applications.

Even if the thresholds values are over fitted to the current dataset does the correct classification rate at 82% implies that the proposed method using a hand-held electronic stethoscope is capable of indicating the presence of CAD. The threshold filter methods proposed in the current study provides a platform for future analysis of heart sounds recorded by a handhold electronic stethoscope.

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