35th Annual International Conference of the IEEE EMBS
Osaka, Japan, 3 - 7 July, 2013

A New Seismocardiography Segmentation Algorithm for Diastolic Timed Vibrations

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***Abstract* — An algorithm based on the combination of electrocardiography (ECG) and seismocardiogranphy (SCG) is used to detect the start and the end of diastole in diastolic timed vibrations (DTV). The proposed algorithm uses the ECG-R wave as the reference point and detects the aortic valve closure (AC) and mitral valve closure (MC) points of the SCG signal. This algorithm enables DTV to operate very efficiently in comparison with previous ECG based algorithm. Prediction rate of 95 and 88 percent was achieved for detection of SCG-MC and SCG-AC respectively.**

Keywords: diastolic timed vibration, seismocardiography

I. INTRODUCTION

Diastolic timed vibration (DTV) is a methodology of applying low frequency mechanical vibration to the chest of a myocardial infarct patient during diastole of the heart cycle. The goal of this procedure is to improve the coronary blood flow by dissolving and/or breaking the thrombus [1]. In recent years, studies have been conducted to find the optimum frequency range, location to vibrate, and pattern of vibrations for best clinical results [2, 3].

The most important design aspect of DTV is detection of the diastolic period. Vibration must be avoided during systole where it could interfere with the contractile apparatus of the heart muscle. On the other hand, clinical trials have indicated that vibrations, timed exclusively to the diastole of the cardiac cycle, can advantageously facilitate heart muscle relaxation, improving the strength of heart contractions [1].

ECG has been used in the past for diastole estimation for DTV application [2, 5]. ECG based algorithms, for DTV applications, initiate vibration by detecting the middle or the end of the ECG-T wave and stops vibration by detection of the ECG-R wave. It is shown that such algorithms are not very efficient for both start and stop of the vibration [6]. This is due to the fact that the middle or the end of the ECG-T wave can fall in any region of ventricular ejection, IVRP, and ventricular filling. The first case is in the systolic period which is undesirable.

For the second case when the ECG-T wave falls in later stages of the ventricular filling period, the efficiency in terms of vibration duration decreases significantly. This can occur during ST-elevation which is a symptom of myocardial infarction. ECG-R wave can also fall in the IVCP which makes stopping the DTV undesirable as well.

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Research has shown that specific peaks of the SCG signal correspond to different stages of the cardiac cycle, including the start and the end of diastole [7]. Figure 1 shows the Wiggers diagram amended with the SCG signal. It also shows the cardiac intervals of diastole period consisting of isovolumetric relaxation period (IVRP) and ventricular filling and also the systole period consisting of isovlumeteric contraction period (IVCP) and ventricular ejection.

As it can be observed in Figure 1, mitral valve closure (MC) and aortic valve closure (AC) of the SCG signal correspond to the start of the IVCP and IVRP, respectively. Therefore, by real-time estimation of the SCG-MC and SCG-AC, the start and end of diastole can be estimated for DTV purposes. This paper proposes a methodology to implement this estimation based on a probabilistic algorithm as is explained in the next section.

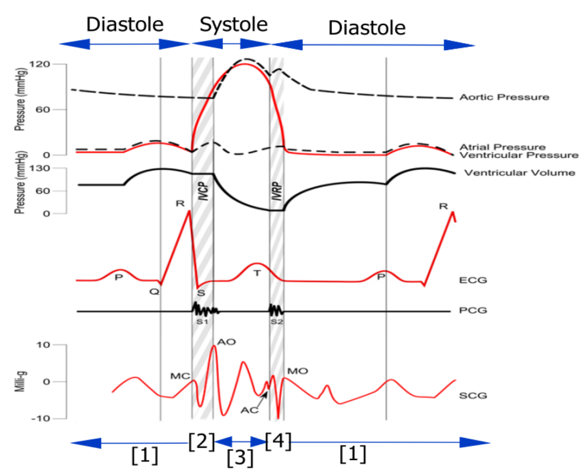

Figure 1 – Wiggers Diagram Amended with SCG and intervals of ON/OFF during vibration. [1] Ventricular Filling, [2] IVCP, [3] Ventricular Ejection [4] IVRP

II. METHODOLOGY

The SCG signal can be measured by placing an accelerometer on the sternum of a patient to measure the vibration of the heart. However, the induced vibration during DTV operation can completely distort the SCG signal. Hence, the detection of SCG-AC and SCG-MC are not possible when the vibration is applied.

Our previous study shows that if the average of 15 interval of ECG-R to SCG-MC (R-MC) and ECG-R to SCG-AC (R-AC) cardiac cycles are calculated, the location of R-MC and R-AC of the upcoming cycles can be estimated with a maximum prediction error of 20 ms [6]. As it is illustrated in Figure 2, the proposed ECG/SCG based algorithm finds the location of SCG-MC and SCG-AC and calculates the

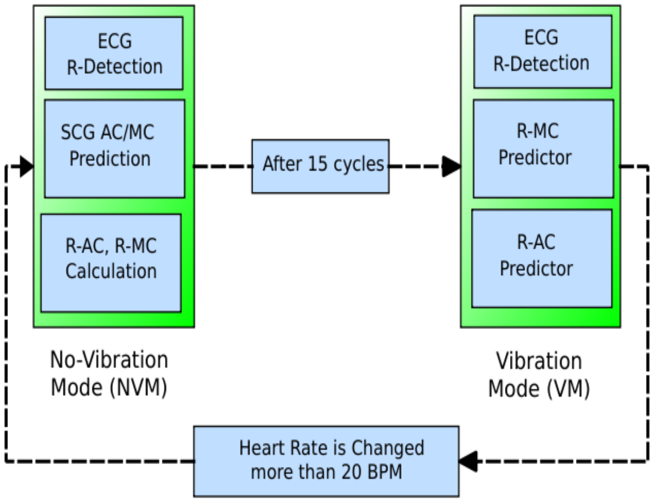

Figure 2 – Overview of the proposed DTV start and stop mechanism. The algorithms proposed in this paper are for the NVM part.

average of R-AC and R-MC in 15 consecutive cycles during non-vibration mode (NVM).

Afterwards, and during the DTV operation, the algorithm changes its state to a vibration mode (VM) and the location of SCG-MC and SCG-AC are estimated from the calculated R-MC and R-AC during NVM. During the VM, if the heart rate changes significantly, the algorithm mode will change to the NVM and will stop the DTV operation in order to recalibrate the location of SCG-MC and SCG-AC.

A. Modeling MC and AC during NVM

There is a significant SCG morphological variability between patients. For this reason, it is very hard to design a deterministic algorithm to extract SCG-MC and SCG-AC and hence, a probabilistic approach is proposed. The parameters of this model are trained in an offline manner. This model is used for detection of the location of SCG-MC and SCG-AC peaks during NVM.

An example of the ECG/SCG of one cardiac cycle is shown in Figures 3A. Our preliminary study shows that both SCG-MC and SCG-AC are very hard to detect because their features such as amplitude and timing with respect to the ECG-R wave are very similar to the adjacent extrema points. As a result, another strategy is proposed to extract multiple adjacent extrema points rather than a single one.

As it is shown in figure 3A, the SCG signal consists of eight extrema points, six of which have physiological significance: MC, IM, AO, MA, AC, and MA [7]. Points V_1 and V_2 do not have a physiological significance and are added for the purpose of explaining the algorithm. The first four extrema points, namely the MC, IM, AO, and MA are referred as the first profile, while the second four points, namely the, AC, V_1, V_2 and MO are refereed as the second profile (Figure 3A).

Interestingly it can also be observed that both the first and second profile consists of four consecutive extrema points. In the case of the first profile, the initial extrema point starts with MC as the local maximum while the second profile starts with AC as the local minimum.

Our objective is to extract all the combinations of the four extrema points close to each profile and to extract the desired one. In order to achieve this goal, a window of 250 ms for the first profile and a window of 200 ms for the second profile are defined with respect to the ECG-R wave (Figure 2B). The first profile window starts 50 ms before the peak of ECG-R wave while the second profile window starts 300 ms after the peak of ECG-R wave.

Within each window, all the combinations of four extrema points are extracted. In this document, the extrema points in each profile window are referred as the candidate points. For instance, extrema points X_1-X_{10} for the first profile and Y_1-Y_{10} for the second profile are the selected candidate points (Figure 2B).

Once the candidate points are selected, every combination of the four consecutive candidate points with similar sequential pattern of the desired profile (MC, IM, AO and MA for the first profile and AC, V_1, V_2 and MO for the second profile) are selected. These sequential patterns are referred as candidate records in this document. For instance, X_1, X_2, X_3, and X_4 is one candidate record with the same pattern as MC, IM, AO and MA. Figure 3C shows all the possible candidate records for each profile. As it can be observed, both profiles contain 10 candidate points and 4 candidate records.

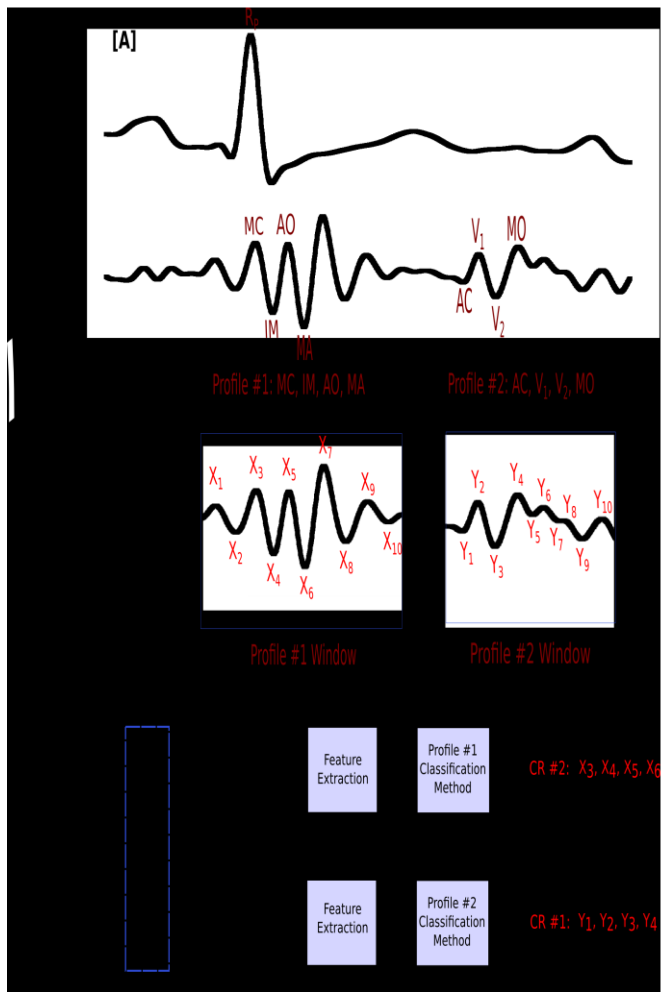

Figure 3 – Overview of the SCG Segmentation Algorithm in NVM, [A] ECG/SCG Signal, [B] Profile Window for Each Profile [C] Feature Extraction and Classification for Profile #1 and #2.

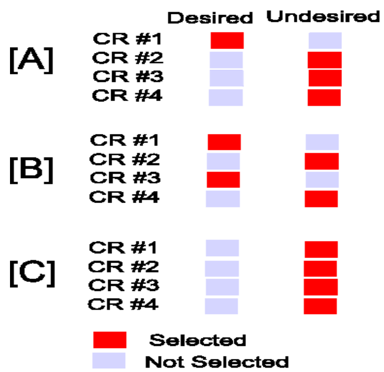

Figure 4 – Example of Different Combination of Classification Results for Four Candidate Records

The goal is thereafter to distinguish between the desired candidate record, for instance MC, IM, AO and MA of the first profile, among all other undesired extracted candidate records. Feature extraction and classification is applied to each candidate record separately. Heart rate (beat per minute), distance of ECG-R to SCG candidate points and the slope between the candidate points are used as the features for classification.

A binary classification method is applied to each candidate record to distinguish between the desired and undesired record. Figure 4 illustrates an example of the different combinations of the binary classification result for four candidate records. In Figure 4A, only one desired candidate is selected, Figure 4B two candidate records are selected; finally in Figure 4C no candidate record is selected. In a scenario such as Figure 4B, the desired class with a higher probability is selected whereas in Figure 4C the undesired class with lower probability is selected.

B. Data Acquisition and Annotation

There are two separate datasets used in this research, one was recorded at Simon Fraser University from athletes and healthy young adults (under the age of 30) and the other one recorded at the Burnaby General Hospital on patients with ischemic heart diseases and also elderly participants. The experiment included total of 62 subjects aged between 18 and 90 years old with the average of 39±20 years. Ages of thirty one of these subjects was greater than 60 years from which 10 had ischemic heart disease [6].

The dataset was annotated by two trained individuals. Every signal cycle was observed by both annotators and the results verified by a third individual for inconsistencies. The software was developed in Matlab to facilitate the manual annotation by proposing MC and AC points.

III. RESULTS AND DISCUSSION

In order to train the classification models for the first and second candidate record profiles, 70 percent of the cardiac cycles were used for training. A 10-fold cross-validation was used for training purposes and the class prediction rate was obtained from the remaining 30 percent of the data.

As it was mentioned in the modeling section, heart rate, location of ECG-R to the candidate points and the slope between the candidate points were used as the input features for classification. Only simple classification methods were considered: logistic regression, linear discriminant analysis (LDA) and quadratic discriminant analysis (QDA). QDA assumes a different covariance matrix for the two classes (desired vs. undesired candidate record) in comparison with LDA that assumes all classes have the same covariance matrix.

In this research, only selected candidate records with no local extrema points(s) between the candidate points were used for training and testing. This accounts for 65% of all the cases. The results are summarized in Table 1 and results suggest that the assumption of QDA is more valid.

Table 1. Prediction rate for the desired candidate record of the each profile.

	Prediction Rate	
Classification Methods	Profile #1	Profile #2
Logistic Regression	87%	78%
LDA	89%	80%
QDA	95%	88%

IV. CONCLUSION

In this paper, an SCG based algorithm for DTV was proposed. The algorithm uses 15 cycles for detection of the MC and AC points of the SCG signal during non-vibration mode. The average duration of R-MC and R-AC is also calculated and used during the DTV operation for estimation of diastole (ECG-R to SCG-MC and SCG-AC).

A probabilistic approach was proposed for detection of MC and AC in non-vibration mode due to the fact that there is a lot of variability in the SCG signal and a deterministic type algorithm is not possible. After this period, vibration is applied and the MC and AC points are estimated using R-AC and R-MC obtained in non-vibration mode.

In order to investigate the potential of SCG segmentation algorithm, only signals with no local extrema points between the candidate points were considered. The algorithm needs to be refined to eliminate the local extrema points by applying a smoothing filter.

In order to increase the prediction accuracy, more features such as time series ARMA coefficients and/or frequency coefficients (fast FFT transform) should be examined. Furthermore, more involved non-linear classification methods such as support vector machine, neural networks, and random forest will be also tested.

ACKNOWLEDGMENT

We would like to thank Burnaby General Hospital authorities for providing us with patient population and also thank Brandon Ngai and Ali Vaseghi for their help and efforts in signal acquisitions.

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