AUTOMATIC SEGMENTATION OF HEART SIGNALS

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Mechanical and electrical heart signals received on the chest wall bear valuable information about the underlying cardiovascular processes. To extract this information we describe an automatic algorithm that detects distinct segmentation points in low-frequency heart signals. The algorithm uses signal processing and pattern recognition techniques to identify multi-scale extrema points having high repeatability and low variability, without using any prior knowledge on the signal's morphology. We demonstrate the algorithm's ability to accurately detect points with known physiological meaning in electrocardiogram and carotid pulse signals recorded from multiple subjects, and propose a quantitative measure for evaluating the segmentation quality. We suggest that this algorithm can be used for automatic extraction of physiological features that represent cardiovascular functionality.

1 Introduction

The mechanical processes within the cardiovascular system produce low-frequency vibratory and acoustic signals that carry valuable physiological information [1]. In a previous work we demonstrated the technological and medical feasibility of using automatic analysis algorithms to extract quantitative information from vibro-acoustic heart signals such as the carotid pulse, apexcardiogram and phonocardiogram [2].

A fundamental component of any automatic heart signal analysis framework is a segmentation algorithm, which partitions the signal into segments representing distinct components or events in the cardiac cycle. Typically, heart signals have intrinsic physiological variability as a result of the complex interactions between the cardiovascular system, the pulmonary system and the central nervous system. Consequently, the morphology of each signal cycle is slightly different, making the segmentation task non-trivial.

Previous work on segmentation of vibro-acoustic heart signals used a heuristic approach, which utilizes prior knowledge of the expected morphology of the signal and the relations between various signals [2]. Another approach used probabilistic modelling by a hidden Markov model [3], which also requires the main components of the signal to be predefined.

In this paper, we suggest to exploit the statistical properties of the periodic heart signals in order to infer the temporal location of meaningful segmentation points. Our proposed segmentation algorithm is described in the next section, followed by preliminary results obtained by applying it to various heart signals. Finally, we discuss the benefits of the algorithm and potential directions for further research.

2 Methods

Multiple heart signals, including carotid pulse (CP), apexcardiogram (ACG), phonocardiogram (PCG), electrocardiogram (EKG) and echo-Doppler audio signals were simultaneously recorded from both healthy volunteers and cardiac patients by a digital data acquisition system described in [2]. The acquired signals were pre-processed by band-pass filtering in order to remove low-frequency baseline wandering and high-frequency ambient noise. The automatic segmentation algorithm was then applied on the signals. The algorithm gets a periodic signal and finds distinct points in each cycle, which are highly-repeatable and have low-temporal and amplitude variability.

The main steps of the segmentation algorithm are as follows (Figure 1):

(1) The signal is first partitioned into cardiac cycles according to the peaks of the QRS complex in the simultaneously-recorded EKG.

(2) An iterative phase-shift averaging technique is applied to compute an average signal cycle. A signal cycle which best fits the average signal is selected as a reference signal.

(3) A multi-scale extrema detection procedure is applied to each signal cycle and its first derivative. A scale-space image is built using Gaussian convolution, and extrema points are localized by tracking them from high to low scale [4].

(4) The highest-scale extrema points detected in each cycle are registered against the reference signal using constrained dynamic time-warping procedure [5].

(5) The best points are chosen by considering the repeatability, temporal variability, amplitude variability and maximal scale.

In order to examine the segmentation quality, the morphological similarity between the created segments in all signal cycles is estimated. This is done by aligning and scaling the segments of all cycles relative to the reference cycle, and measuring the standard deviation of the amplitude at each time point. It is expected that as the segmentation is more accurate, the segments will be more similar and the average standard deviation will decrease.

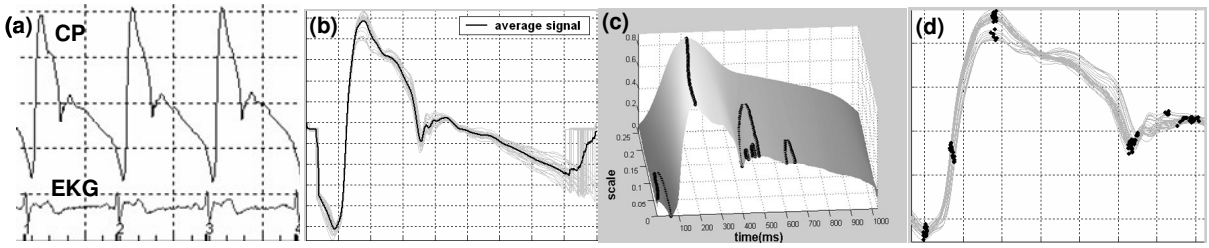

Figure 1: Main steps of the segmentation algorithm. Cycle partitioning by EKG (a), selection of a reference cycle (b), multi-scale extrema detection (c) and multi-cycle extrema points registration (d).

3 Results

The segmentation algorithm was tested on several types of heart signals, collected from 13 different subjects (9 healthy volunteers and 4 cardiac patients). The average number of cardiac cycles in each recording was 50. The ability of the algorithm to detect points that have known physiological meaning is demonstrated in Figure 2a and 2b. In the carotid pulse (CP) signal, points indicating the beginning of ejection, peak of ejection and the dicrotic notch were clearly identified. In the EKG signal, the algorithm was able to identify the Q and S points, as well as the T-wave and the P-wave. As summarized in Table 1, these events were detected in most of the subjects, and, when detected, were highly repeatable, appearing in most of the signal cycles. The algorithm was also successfully used on other heart signals such as the apexcardiogram, phonocardiogram amplitude envelope and blood flow profiles derived from echo-Doppler.

The quality evaluation of the segmentation points showed a significant decrease in the variability of the inferred segments, after temporal alignment and amplitude scaling. A representative example is given in Figure 2c, where the average standard deviation of 31 CP cycles segmented by 4 points decreased by factor of 0.45.

Table 1: Event detection in carotid pulse (CP) and EKG signals recorded from 13 subjects. CP events: ejection beginning (EJ), ejection peak (P), dicrotic notch (DN). EKG events: Q and S points, T-wave (peak and end points), P-wave (peak point). Detection ratio is the portion of subjects in which the event was identified. Repeatability ratio is the average portion of detection in all signal cycles of these subjects.

Signal	**CP**			**EKG**				
Event	*EJ*	*P*	*DN*	*Q*	*S*	*T-peak*	*T-end*	*P-peak*
Detection ratio	0.92	1.00	0.92	0.85	0.92	1.00	0.85	1.00
Repeatability ratio	0.90	0.89	0.86	0.88	0.96	0.94	0.91	0.89

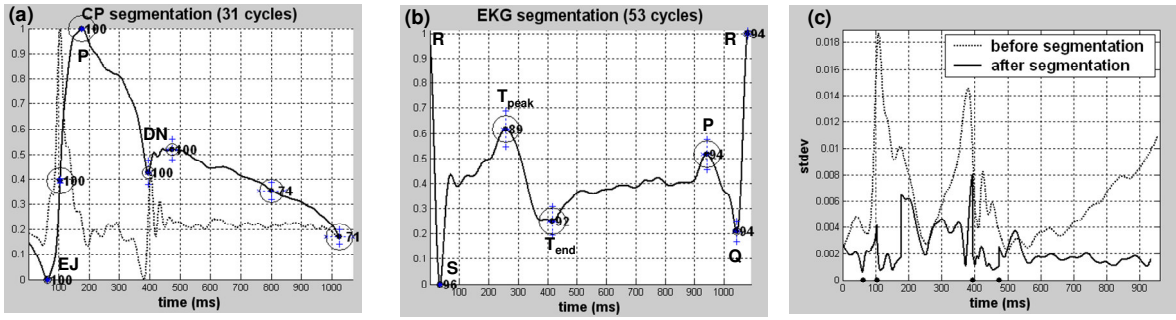

Figure 2: Segmentation points detected in a carotid pulse signal and its first derivative (a) and in an EKG signal (b). The horizontal and vertical error bars indicate temporal and amplitude variability. The empty circles indicate scale and the numbers indicate repeatability percent. (c) Amplitude standard deviation of 31 CP cycles before and after alignment and scaling by 4 segmentation points.

4 Discussion

Segmentation is an essential part of any biomedical signal processing framework. Reliable segmentation enables to decompose the signal into sub-components that might be genrerated by different processes, and to extract temporal and morphological features that characterize these processes. The algorithm proposed in this work is general enough to be applied to a large variety of periodic low-frequency biomedical signals. Since it depends only on the statistical properties of the signals, it is more robust and more accurate than a heuristic approach, especially for signals that are contaminated by noise and artifacts. However, prior knowledge can be incorporated as a second processing stage, in order to assign a physiological meaning to each of the automatically-detected points. In order to further establish these preliminary results we intend to use simulated signals, constructed according to a physiological model, to quanitfy the performance and the limitations of the proposed segmentation algorithm. In addition, we plan to evaluate the algorithm on heart signals with large physiological variability, recorded during stress tests, and to assess its applicability for autoamtic extraction of physiological features that can be used to monitor the cardiovascular functionality continuously and non-invasively.

5 Conclusions

We have described an algorithm for detecting and evaluating segmentaion points in periodic low-frequency heart signal. The algorithm was able to detect points with known physiological meaning in a variety of heart signal, and is potentially useful for reliable extraction of physiological features.

References

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