Personalized Detection of Motion Artifacts for Telemonitoring Applications

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Personalized Detection of Motion Artifacts for Telemonitoring Applications

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Abstract. Among its main benefits, telemonitoring enables personalized management of chronic diseases by means of biomarkers extracted from signals. In these applications, a thorough quality assessment is required to ensure the reliability of the monitored parameters. Motion artifacts are a common problem in recordings with wearable devices. In this work, we propose a fully automated and personalized method to detect motion artifacts in multimodal recordings devoted to the monitoring of the Cardiac Time Intervals (CTIs). The detection of motion artifacts was carried out by using template matching with a personalized template. The method yielded a balanced accuracy of 86%. Moreover, it proved effective to decrease the variability of the estimated CTIs by at least 17%. Our preliminary results show that personalized detection of motion artifacts improves the robustness of the assessment CTIs and opens to the use in wearable systems.

Keywords. Telemonitoring, motion artifacts, Cardiac Time Intervals, template matching, personalized medicine, heart sounds

1. Introduction

The spread of wearable sensors has opened to novel possibilities in terms of monitoring the health status of chronic patients in a telemedicine framework. Telemonitoring has several well-known advantages: reduced burden, time and costs for the hospital, increased quality of life and empowerment for patients [1]. Telemonitoring is particularly effective in the management of chronic diseases because it enables a timely follow-up and the detection of the earliest physiological changes leading to an acute episode [1,2]. Moreover, telemonitoring allows for a personalized management of the disease, based on biomarkers extracted from signals [2]. The assessment of the signal quality is a critical point in telemonitoring. In fact, signals are typically recorded by inexperienced users who cannot be trusted to define whether the signal is good enough for processing or not. Nevertheless, good signals are key to ensure the reliability of extracted biomarkers.

In this work, we focus on the telemonitoring of patients affected by chronic heart

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failure to prevent acute episodes and related hospitalizations. It was found that variations in the Cardiac Time Intervals (CTI), extracted from simultaneous recordings of electrocardiogram (ECG) and heart sounds (phonocardiogram, PCG), are correlated with variations in the status of compensation of the patient [3,4]. In a previous study, we studied how the quality of the heart sounds recordings affects the CTIs' estimate [5]. In this study, we tackle the problem of motion artifacts, i.e., artifacts due to a reciprocal movement between the sensor and the skin. This is a common problem of wearable acquisitions, particularly in acoustics [6]. Identifying a motion artifact in the PCG signal is not naïve, because its frequency content may overlap with the one of heart sounds, leading to the artifact being misrecognized as a sound generated by the heart [6]. The goal of this study is to propose a personalized method to automatically detect motion artifacts in multimodal recordings of heart sounds and thoracic accelerations and analyze its effect on the estimated CTIs.

2. Materials and Methods

2.1. Recording system and experimental protocol

Multimodality was obtained by integrating two different devices, both designed and developed by our research group. Simultaneous ECG and PCG signals were recorded by a wearable array designed for the purpose. The flexible pad is designed to adapt to the left hemithorax of the patient and embeds 48 electret condenser microphones along with 3 electrodes. The distribution of the microphones was proved to enable inexperienced users to perform good-quality recordings without the help of clinical nor technical staff. More details about the device can be found in [7]. Accelerations were recorded by means of a miniaturized system based on a 3D magneto-inertial sensor. Data processing is handled on-board by a highly capable floating-point microcontroller. The inertial system was located on top of the array, on the sternal area, as shown in Figure 1. The two systems are asynchronous. The alignment between the two recordings was performed by considering that, when filtered in the bandwidth of heart sound (20Hz to 100Hz), PCG and accelerometer signals convey similar information. Therefore, a cross-correlation based alignment could be performed [8]. All signals were resampled to 1 kHz.

Two-minute recordings were carried out on ten volunteers who denied any history of cardiopathy. Volunteers were asked to lay on an examination table in a supine position with a bare chest. The two devices were positioned by an investigator as described. The

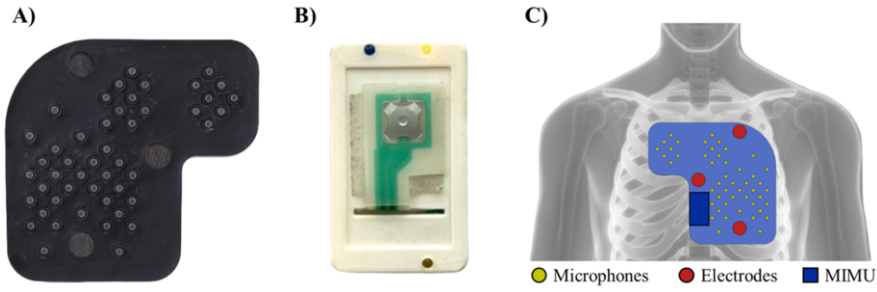

Figure 1. Recording system. A) Array to record ECG and PCG signals. B) Inertial sensor to record accelerometric signals (MIMU). C) Positioning of the devices on the thorax. Adapted from [7].

volunteers were instructed to perform five different tasks at given time instants, with the timing set by a video. Tasks included: coughing, head flex-extension, head right-left rotation, right arm protraction, pronouncing the sentence: "Can you bring me a glass of water, please?". The tasks were defined to simulate possible types of behavior that may occur during a short recording performed in a domicile setting without the supervision of clinical staff. The timing of the tasks is graphically represented in Figure 2.

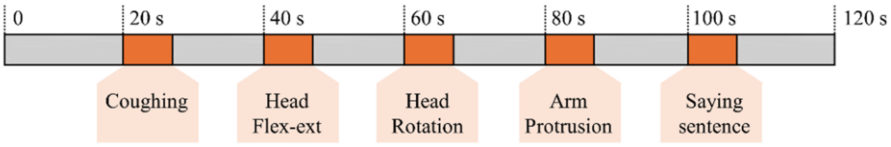

Figure 2. Experimental protocol. Heartbeats in the grey intervals are labelled as "clean". Heartbeats in the orange intervals are labelled as "artifact".

2.2. Motion artifacts detection and Cardiac Time Intervals estimation

Motion artifacts detection was performed on the accelerometer signals. The designed methodology grounds the detection on an envelope-based template matching approach. Contrarily to typical template matching algorithms, our method does not require any a priori assumption on the signal: a personalized template was estimated for each recording to make the detection sensitive to the characteristic of the cardiac cycle of the patient.

First, each axis was highpass filtered at 2 Hz to remove baseline wandering. The information from each axis was aggregated through the Euclidean norm. The envelope of the norm was extracted using the Hilbert transform. The envelope was segmented into heartbeats using the R-peaks, extracted from the ECG, as reference. The average heartbeat was used as a template. Two template matching approaches were tested:

1. *RMSE*. The RMSE between each heartbeat and the template was assessed. Heartbeats with an above-threshold RMSE were classified as "artifact".
2. *Correlation*. A sliding window of the length of the template was used and the Pearson correlation coefficient was computed point by point. For each heartbeat, the maximum correlation coefficient was used. Heartbeats with a below-threshold correlation were classified as "artifact".

In both cases, thresholds were defined specifically for each recording as a percentile of the distribution of respectively the RMSE and the correlation over the heartbeats belonging to the recording itself. In this sense, the detection is fully personalized. The percentile was tuned by constructing the ROC curves for all percentiles from 0 to 100 and selecting the point with the highest balanced accuracy.

The estimation of the CTIs relies on the ECG-PCG signals recorded using the multi-sensor array. The definition of the CTIs grounds on the estimate of the time of closure of the four cardiac valves from the first and second heart sounds (S1 and S2), with respect to the ventricular depolarization. Therefore, the intervals between the R-wave peak and respectively the mitral ($RS_{1,M}$) and triscupid ($RS_{1,T}$) component of S1, and the aortic ($RS_{2,A}$) and pulmonary ($RS_{2,P}$) component of S2 was considered. The R-wave peaks were identified in the ECG signal using Pan-Tompkin's algorithm. The mitral and tricuspid components in S1 and the aortic and pulmonary components in S2 were identified using our previously published envelope-based method [9].

2.3. Evaluation of the performances

The goal of the motion artifact detection phase is classifying the heartbeats of each recording as "clean" vs "artifact". The ROC curves were constructed for the entire sample population to optimize the percentile to be used for thresholding respectively the RMSE and the correlation values. The sensitivity, specificity and balanced accuracy at the selected operating point were used to evaluate the performances of the motion artifact detection phase. Balanced accuracy was preferred because of the imbalance of the dataset. The time of closure of the four cardiac valves was computed before and after the removal of heartbeats classified as "artifact". The effectiveness of our proposed approach to improve the robustness of the estimate was quantified by assessing the percentage reduction of the standard deviation of the estimate.

3. Results and Discussion

The obtained ROC curves are proposed in Figure 3A. Each point of the ROC curve corresponds to a different percentile used to threshold the RMSE and correlation values respectively. The two selected operating points are highlighted on the curves. Figure 3B presents the sensitivity, specificity and balanced accuracy subject by subject.

Results show that reasonable performances can be achieved by both approaches, but correlation outperforms RMSE by yielding a better sensitivity at the same specificity. When observing the subject-wise performance metrics, it can be appreciated that RMSE favors specificity, whereas correlation favors sensitivity: the best method can be defined according to the application of interest. Table 1 reports the percentage variation of the standard deviation of the estimate of the time of closure of the four cardiac valves using either reference labeling or template matching, with either correlation or RMSE. All methods produce a significant reduction of the estimated standard deviation, given that the original standard deviation is over 20 milliseconds. It can be observed that the proposed automatic, personalized approach decreases the variability of the estimate better than the labelling used as reference. It can be explained by the fact that heartbeats

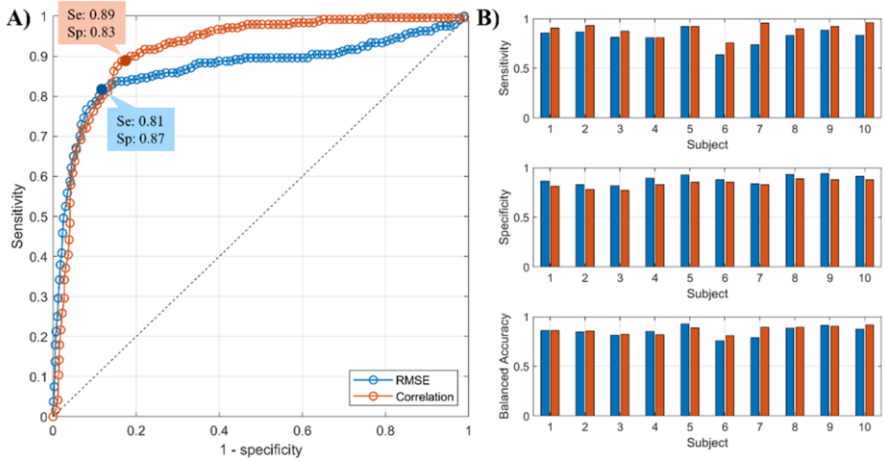

Figure 1. Performances of the motion artifacts detection algorithm. A) ROC curves using either RMSE or correlation for template matching. B) Sensitivity, specificity, and balanced accuracy for each subject.

without a simulated motion artifact are not necessarily free from artifacts: template matching removes heartbeats with a low correlation (or high distance) from the template independently on the type of artifact. From this perspective, the real performances may be even higher at a visual inspection. In the overall, the proposed approach proves effective in removing the motion artifacts and obtain a more robust estimate of the CTIs.

Table 1. Percentage variation in the standard deviation of the estimate of the time of closure of each cardiac valve using reference labeling, template matching (correlation) or template matching (RMSE).

	Reference labeling	Template matching (correlation)	Template matching (RMSE)
$\mathbf{RS_{1,M}}$	-8%	-22%	-20%
$\mathbf{RS_{1,T}}$	-14%	-19%	-20%
$\mathbf{RS_{2,A}}$	-7%	-17%	-18%
$\mathbf{RS_{2,P}}$	-7%	-17%	-17%

4. Conclusions

In this work, we propose an automatic method to detect motion artifacts in multimodal recordings devoted to estimate CTIs in chronic heart failure patients. The approach proved effective to improve the robustness of the estimate in a small sample population. The use of a fully personalized method improves the efficacy by being sensitive to the characteristics of the cardiac cycle of the subject and is suitable for telemonitoring, where a thorough assessment of the signal quality is required to obtain reliable biomarkers.

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