Feasibility of Long-Term Daily Life Electrocardiogram Monitoring Based on a Wearable Armband Device

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***Abstract*— A study on the feasibility of obtaining usable electrocardiogram (ECG) signals from a wearable armband during 24-hour continuous monitoring is presented. The wearable armband records 3-channel ECG and, unlike the conventional Holter monitors, it is convenient for long-term daily life monitoring because it uses no obstructive leads and it is based on dry (no gels) electrodes, which do not cause skin irritation. An optimal channel selector is presented, based on a linear classifier using features that are related to the ECG signal quality. In addition, this linear classifier is also used for artifact detection. The developed optimal channel selector and artifact detector are applied to 24-hour armband ECG recordings from 5 subjects. For reference comparison, the subjects also wore a Holter device. The armband obtained usable data during 51.07±13.54% (inter-subject mean ± standard deviation) of the non-bed recording time, and the mean heart rate was accurately (relative error with respect to the Holter less than 10%) estimated from the armband selected ECG channel from 94.39±3.41% of the usable data. During the bed recording time, the percentage of usable data was 93.54±2.92%, and mean heart rate was estimated accurately from 97.01±1.80% of those data. These results suggest that the armband device is potentially feasible for a long-term daily life heart rate monitoring based on the presented channel selector and artifact detector, especially during the bed time.**

I. INTRODUCTION

The diagnosis of most of the cardiac arrhythmias and other cardiac pathologies is based on electrocardiogram (ECG). Many of these pathologies produce paroxysmal symptoms, making a continuous monitoring necessary. One of the most popular approaches for continuous ECG monitoring is performed by using Holter monitors. These monitors use obstructive leads, and wet electrodes over the chest that cause skin irritation after few days, making them unsuitable for long-term daily monitoring. A daily long-term ECG monitoring would be interesting in different applications, including atrial fibrillation detection [1], sleep studies [2], stress assessment, and monitoring of chronic respiratory patients, especially when combined with respiration estimation [3].

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A wearable armband device for ECG monitoring is being developed in our lab at University of Connecticut, aimed to overcome the above mentioned limitations of Holter devices. This armband is designed to be worn on the left upper arm, and it incorporates 3 pairs of hydrophobic dry electrodes also developed in our lab [4] and uses them to record 3 ECG leads, one per pair, differentially. This armband device developed is more comfortable for the patient and it can be worn for long periods of time without skin irritation, resulting in being more convenient for daily long-term recordings than conventional Holter monitors. However, the armband setup is more challenging than the Holter setup. The electrodes are much closer to each other than in conventional Holter, which is usually based on electrodes distributed over the chest. Furthermore, the use of dry electrodes results in a poorer impedance matching in comparison to the use of wet electrodes. These disadvantages can result in less fidelity ECG signals. Besides the ECG signal, the armband setup records electromyography (EMG) signals from the local muscles, mainly from the left biceps and left triceps. Thus, the obtained ECG signal-to-noise ratio is lower in comparison to the one obtained with the conventional Holter setup. However, the quality of armband ECG signals was high enough to obtain respiratory rate using ECG-morphology features during lab-controlled no-movement conditions [3]. Nevertheless, the armband ECG signals have never been evaluated during 24-hour continuous recordings before.

In this paper, a pilot study on the feasibility of obtaining usable ECG signals from the wearable armband during 24-hour recordings is presented. The study includes the development of an automatic channel selector for using the highest quality ECG signal at each moment, as well as an automatic artifact detector for discarding those data which are not usable. Mean heart rate was extracted from the selected armband ECG channel and subsequently compared to the mean heart rate extracted from a conventional Holter device.

II. METHODS

A. Signal acquisition and preprocessing

Armband signals were recorded from 5 healthy subjects continuously during 24 hours. For reference purposes, 3 ECG channels were simultaneously recorded by a conventional Holter available in the market: Rozinn RZ 153+ (Glendale, NY, USA). These ECG signals were down sampled to 250 Hz, considering that this sampling rate is enough for getting sufficiently time-accurate QRS detection marks, e.g., it is

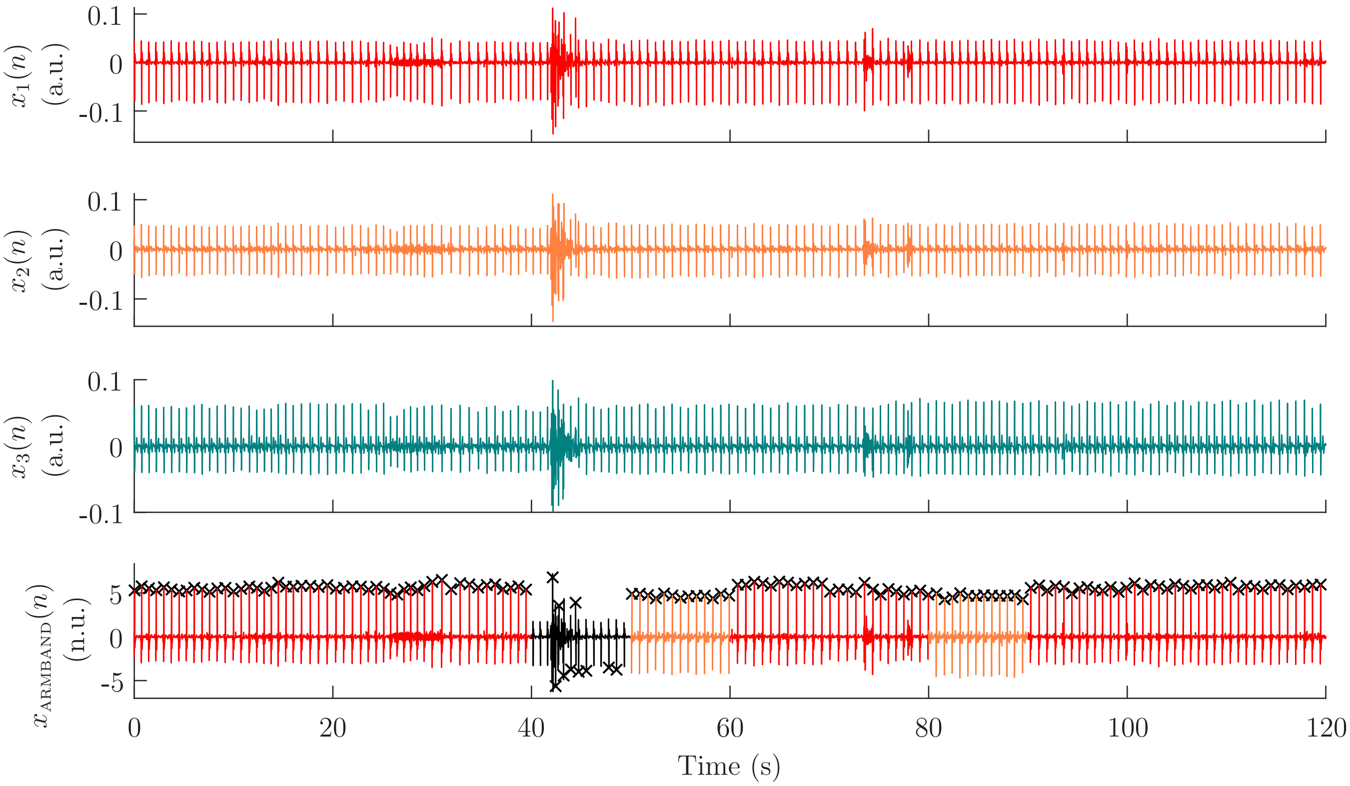

Fig. 1. Example of preprocessed armband ECG signals $x_1(n)$, $x_2(n)$, and $x_3(n)$ in red, orange, and green, respectively. Last row shows $x_{\text{ARMBAND}}(n)$, in the color that corresponds to the selected channel in each 10-seconds segment, and in black when the segment is considered an artfact (see segment from 40 to 50 seconds). Detected QRS complexes are shown with black 'x' marks over $x_{\text{ARMBAND}}(n)$.

the lowest recommended sampling rate for measuring the classical heart rate variability (HRV) indices [5].

ECG signals from the armband were found to be highly contaminated by noise, mainly due to the EMG from the local muscles. Thus, a strong band-pass filtering was applied in order to better isolate ECG data. The low/high cut-off frequencies of this filter were empirically set to 3/25 Hz. These filtered ECG signals are denoted $x_1(n)$, $x_2(n)$, and $x_3(n)$, in this manuscript. An example of these signals can be observed in Fig. 1.

B. Channel selection

Channel selection was performed in segments of 10 seconds based on several ECG signal quality indices (SQI) available in the literature. The features used by these SQI can be divided in two big groups: fiducial features and non-fiducial features [6]. The fiducial features are based on detecting the beats followed by studying the mean level and/or regularity of the resulting inter-beat (RR) intervals. However, the abnormal values of mean level and, especially of regularity of the RR intervals are the basis for many potential applications, such as arrhythmia detection, sleep studies, stress assessment and monitoring of chronic respiratory patients. Low signal quality based on abnormal values of mean level and/or regularity of inter-beat intervals may lead to the most valuable data for such arrhythmia applications being of low quality. Thus, no fiducial features were considered in this work. Nine non-fiducial features were computed in segments of 10 seconds: Multiscale entropy [7]; Shannon entropy [8]; Ratio between power in the frequency band 5-20 Hz with respect to the total power [9]; Self-correlation [10]; Shannon entropy, mean, and variance of the first intrinsic mode function [11]; Skewness, and Kurtosis [12].

In order to have a unique SQI per ECG channel and 10-seconds segment, a linear classifier was used. In order to train the classifier, all 10-seconds segments during the first hour from the first channel of each of the 5 armband recordings were visually inspected. These segments were labeled as artifact, normal, or none of the above. Subsequently, the nine non-fiducial features were computed from segments labeled as normal or artifact, and they were used for selecting 20 normal segments and 20 artifact segments per subject, by using k-means in order to obtain a good representation of the underlying distribution of the data. Thus, a total of 200 segments (100 normal and 100 artifacts) were selected. A feature selection was performed using those 200 segments by a forward wrapper approach, which consists of adding gradually one more feature and selecting the one which provides the highest accuracy, and stopping when the obtained accuracy is lower than that obtained with one less feature. Later, the linear classifier was trained on those 200 segments using only those features selected by the wrapper.

Subsequently, the selected features were computed from each of the 3 ECG channels. For each 10-seconds segment,

TABLE I

Mean and standard deviation (SD) of the percentage of segments with accurate heart rate estimates (less than 10% of relative error with respect to the Holter) from the wearable armband device; of the percentage of segments with usable armband data according to the artifact detector; and of percentage of segments with Holter usable data; during non-bed time and during bed time.

Subject	Non-bed time			Bed time		
	Percentage of segments with			Percentage of segments with		
	usable data	accurate heart rate	Holter usable data	usable data	accurate heart rate	Holter usable data
1	29.98%	88.80%	95.47%	89.15%	96.14%	80.56%
2	53.78%	94.95%	98.26%	93.39%	94.37%	98.83%
3	49.45%	96.22%	65.64%	92.83%	97.29%	93.72%
4	54.78%	94.22%	92.07%	95.65%	98.60%	98.95%
5	67.34%	97.78%	94.96%	96.69%	98.64%	98.31%
Mean	51.07%	94.39%	89.28%	93.54%	97.01%	94.07%
SD	13.54%	3.41%	13.40%	2.92%	1.80%	7.86%

the selected ECG channel was chosen by the linear classifier as the one being the furthest from the "artifact" class. These ECG segments were normalized in amplitude with respect to their standard deviation, and inverted in case that their minimum is greater than their maximum in absolute value. Then, a unique armband ECG signal $x_{\text{ARMBAND}}(n)$) was created by concatenating those selected segments. An example of this signal can be observed in Fig. 1.

C. Artifact detection

A 10-seconds segment from $x_{\text{ARMBAND}}(n)$ was considered an artifact if the linear classifier described in Section II-B classified it as an artifact (*i.e.*, the segment was classified as an artifact in the 3 ECG channels from the armband).

D. Mean heart rate measure

The location of the QRS complexes of $x_{\text{ARMBAND}}(n)$ were automatically detected by an algorithm based on variable frequency complex demodulation and adaptive threshold rules [13]. The fiducial point of each QRS complex was set to that where the absolute value of the amplitude is maximum (R or S peak, depending on the lead morphology). The instantaneous heart rate was computed from these QRS locations as the inverse of the beat-to-beat intervals:

$$d_{\text{HR}_i} = \frac{1}{n_{\text{QRS}_i} - n_{\text{QRS}_{i-1}}} F_s, \tag{1}$$

where n_{QRS_i} denotes the ith QRS location sample. Subsequently, for each 10-seconds segment, the mean of d_{HR_i} series was computed. For comparison purposes, the mean heart rate was measured also from the Holter device by a similar procedure. The artifact detector and channel selector was not used in this case. Instead, the first channel was always used. In order to identify those segments with artifacts in this channel, two different QRS detectors ([14] and [15]) were applied. Those segments where these QRS detectors offer a different output were discarded from further analysis.

The percentage of 10-seconds segments where the mean heart rate estimated from the armband differs less than 10% from the mean heart rate estimated from the Holter was computed. The data used for training the linear classifier described in Section II-B (the first hour of each recording) was not used for this analysis in order to avoid a possible bias in the results. This analysis was performed separately for the bed time and for the non-bed time.

III. Results

The forward wrapper selected 8 out of the 9 examined features for the linear-classifier-based artifact detector and channel selector: Shannon entropy; Ratio between power in the frequency band 5-20 Hz with respect to the total power; Self-correlation; Shannon entropy, mean, and variance of the first intrinsic mode function; Skewness, and Kurtosis. Table I shows the percentage of segments for which usable data were obtained from the armband, according to the artifact detector (described in Section II-C), and the percentage of those usable segments for which an accurate mean heart rate was obtained (relative error with respect to the Holter less than 10%), during non-bed and during bed time. In addition, the percentage of discarded segments because QRS detectors were not consistent with the reference Holter ECG signal is also shown.

IV. Discussion

The feasibility of obtaining usable ECG signals from a wearable armband during 24-hour recordings has been analyzed. The armband developed in our lab at University of Connecticut records 3 ECG channels simultaneously. A novel channel selector was developed based on a linear classifier using some features that have been reported to be related to the ECG signal quality in the literature [6]. This channel selector chose an ECG channel in every 10-seconds segment. A new signal, composed of the selected ECG channel at each time was generated, and its QRS complexes were automatically detected. Furthermore, the linear classifier was used also to identify those 10-seconds segments containing artifacts, which were discarded from further processing.

The feature selection was performed by a forward-wrapper approach. All studied features were selected except the multi-scale entropy. This does not mean that the multi-scale entropy has no signal quality information, but that the information it contains is linearly redundant with the information of the other considered features. The mean heart rate was estimated in every 10-seconds segment from the armband and compared to the mean heart rate estimated from the Holter monitor, which was taken as Gold Standard. The estimation was considered accurate if it differs less than 10% from the estimation based on the Holter monitor. Note that this remains a strict criterion, as 10% in 10 seconds during usual rest heart rates (around 60 per seconds) means an error of only one beat. Table I shows that during non-bed time, the armband obtained artifact-free data for the 51.07% $\pm$ 13.54% (inter-subject mean $\pm$ standard deviation) of the segments, and the mean heart rate was accurately estimated in 94.39% $\pm$ 3.41% of those usable segments. Bed time is less challenging than non-bed time because the movements of the subjects are markedly reduced. Results are much better in terms of quantity of obtaining artifact-free data (93.54% $\pm$ 2.92%), and they are also slightly better in terms of number of segments offering accurate estimates (97.01% $\pm$ 1.80%).

V. CONCLUSION

Obtained results suggest that the armband device is suitable for a daily life heart rate monitoring, especially during the bed time. However, further studies must be elaborated including more subjects in order to extract stronger conclusions. These studies may include the use of signal processing techniques that may offer a higher signal-to-noise ratio by combining the information of the 3 different ECG leads, and specific studies for certain applications, such as arrhythmia detection, sleep studies, stress assessment, and/or monitoring of chronic respiratory patients.

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