Performance of wrist based electrocardiography with conventional ECG analysis algorithms

DOI:
10.1109/ESGCO.2014.6847494

Performance of wrist based electrocardiography with conventional ECG analysis algorithms

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***Abstract*— Wrist worn activity monitors are becoming increasingly popular and could be greatly enhanced by the inclusion of additional physiological monitors. This paper investigates integrating wrist based electrocardiography into such devices. Results show that when no motion is present techniques and algorithms developed for traditional chest ECG can be directly re-applied to the wrist with a valid analysis present more than 90% of the time. With motion artefacts from keyboard typing this falls to 50%, still allowing significant re-use of existing approaches.**

I. INTRODUCTION

Wearable electronics are beginning to have a massive impact in the healthcare arena. The *fitbit* [1] and *Nike+ fuelband* [2] are two well known examples of wrist worn activity monitors for personalised and preventative healthcare. It is estimated that 90% of type 2 diabetes, 80% of heart diseases and 70% of strokes could be avoided with the use of suitable preventative techniques [3]. Given this, there is is now a major drive to integrate more physiological monitoring into similar wrist band devices. Cardiac monitoring is one such parameter, and the integration of this into wearable sensors is essential for studying heart function, cardiac arrhythmia, and oscillations during sleep, in the general population in a way not possible with traditional Holter monitors.

Several cardiac analysis algorithms have recently been implemented as low power consumption hardware circuits suitable for integrating into wearable and smart sensor devices [4], [5]. However these are all designed for traditional chest ECG. In contrast, for wearable applications the wrist is the most natural location to position the sensor, with a strong association with the use of watches. Pulse oximetry, typically placed on a finger, has long been used for non-chest heart monitoring, but it is severely corrupted by motion artefacts limiting its utility [6]. Wrist electrocardiography, the same as the ECG but with electrodes placed on the wrist, is a potential alternative [7] which is now of renewed interest, but which is yet to gain traction due to the signal collection and processing challenges present.

A recording of wrist ECG is shown in Fig. 1. The core cardiac information is clearly visible, although with a much reduced amplitude; typically 50 μV_{pp}. This is the same order of magnitude as brain signals recorded via the EEG and recent advances in EEG analysis have allowed the robust use of these low amplitude signals even in the presence of motion [8], [9]. It is now essential to map these into the electrocardiography domain and this paper begins the process by collecting wrist ECG and analysing it using two conventional QRS analysis algorithms. This demonstrates the extent to which chest measurement techniques can be directly mapped to the wrist and also quantifies how much of the wrist ECG data is corrupted by motion artefact.

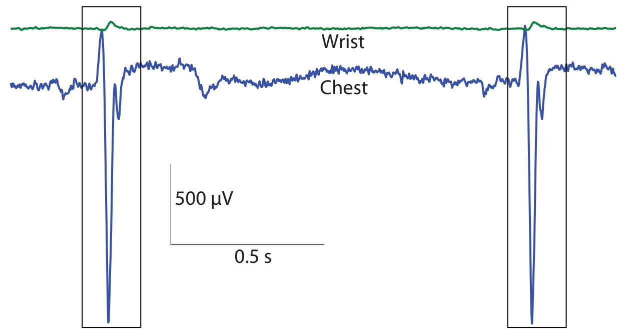

Fig. 1. Wrist ECG information is in the 50 μV_{pp} range requiring new sensors, devices and signal processing for wearable ECG applications.

II. METHODS

Three 45 minute wrist ECG recordings were carried out. Standard pre-gelled surface electrodes were placed on the wrist of the non-dominant hand: two on the upper forearm, and one underneath, corresponding to typical positions on a watch body and strap. A fourth electrode was placed on the chest for simultaneous conventional ECG monitoring. A cam*N*tech recorder was used (512 Hz, 10 bit sampling, 50 Hz notch) with one of the upper forearm electrodes as the combined reference and ground giving three recording channels. The upper and lower wrist channels were set to use an EEG signal range in order to accurately collect low amplitude signals. In two of the recordings the subject was asked to remain still, inducing minimum artefacts. The third recording was carried out while the subject operated a computer performing standard typing tasks including word processing, emails and Internet browsing.

Each recording channel was analysed separately to determine R peak onset times. To compare performance two R detection algorithms commonly applied to chest ECG were used to analyse the data: firstly [10] based upon the derivative of the trace and an adaptive threshold; secondly [11] based upon fitting a low order polynomial for baseline removal and then applying a fixed threshold of 500 μV for the ECG trace and 40 μV for the two wrist traces. R onset times from both algorithms were used to determine the heart rate as measured on the chest and on the wrist, updated with each new detected R onset. This rate was post-processed using a 15-point median filter to eliminate brief transients present in the detections, and also used for the generation of standard ECG statistical measures.

978-1-4799-3969-5/14/$31.00 ©2014 IEEE.

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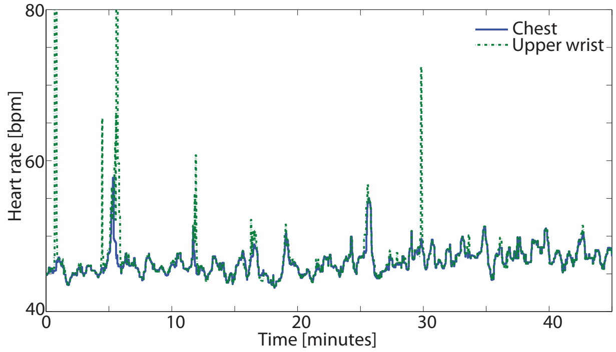

Fig. 2. Heart rate in record 1 measured using the algorithm [10] and ECG electrodes from the chest and upper wrist.

TABLE I PERCENTAGE OF TIME RR BASED HEART RATE MEASURED AT THE CHEST AND WRIST DISAGREE BY MORE THAN 2 BPM.

Algorithm		[10]	[11]
Record 1	Upper wrist	03.9%	17.2%
	Lower wrist	11.6%	38.0%
Record 2	Upper wrist	06.1%	09.3%
	Lower wrist	21.2%	37.6%
Record 3	Upper wrist	40.6%	42.8%
	Lower wrist	43.6%	53.2%

III. RESULTS

Fig. 2 shows a typical heart rate measured from the chest and upper wrist illustrating the common pattern of good agreement between the two sensing locations, but with transient periods of large disagreement. Table I quantifies how often the wrist based measurements differ from the chest measurement by more than 2 beats per minute. In the no motion records (1 and 2) the vast majority of the wrist data can be correctly analysed using the conventional ECG algorithms but re-applied to the new sensing locations. In the motion record (3), more data is corrupted, but large periods of valid analysis are still present. Within these valid analysis periods Table II shows the RR interval statistics for the chest and upper wrist locations, with a very good agreement present in all cases.

IV. DISCUSSION AND CONCLUSIONS

Two algorithms designed for chest ECG analysis have been re-applied to wrist ECG data, and Table I demonstrates that in the no motion case these algorithms can be used to generate correct heart rate measurements more than 90% of the time. New algorithm development is not necessary, and within the periods where the analysis is valid Table II shows that the wrist ECG can be used to accurately measure the RR interval mean and standard deviation. The algorithm of [10] outperforms [11] in all cases, but the performance of [11] is impressive given the use of a non-adaptive threshold (significantly simplifying a low power implementation). Likewise, despite being closer to the reference electrode and hence having smaller signals, the upper wrist based measurements outperform the lower wrist measurements in all cases. This is clearly the more promising sensor location for future wrist ECG developments.

TABLE II ECG RR STATISTICS FROM TIMES WITH VALID DATA (ALGORITHM [10] FOR R DETECTION).

RR interval		Mean [s]	Standard deviation [ms]
Record 1	Chest	1.29	46
	Upper wrist	1.28	48
Record 2	Chest	1.20	50
	Upper wrist	1.20	49
Record 3	Chest	1.25	78
	Upper wrist	1.23	79

In the typing task (record 3) the data analysis is valid for approximately half of the total collection time. In general wearable sensors applied in non-controlled and varying environments do not have continuously valid data, trading-off this off with the benefit of *time* to collect more data. This paper provides an initial quantification of how much wrist ECG data is valid, and dealing with new discontinuous data sets is an emerging research challenge in wearable sensing applications. For realising low power wearable devices it is important that conventional ECG analysis algorithms can be directly re-mapped to the wrist, and this also allows the sensor to switch between low power non-motion and high power motion-present algorithms depending on the current situation, maximising battery life.

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