Morphological Analysis on Single Lead Contactless ECG Monitoring Based on a Beat-Template Development

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Abstract

In an attempt to implement an ECG model that does not require active participation from the individual himself, contactless sensors are playing a relevant role in recent research. However, extremely high noise limited contactless applications. In this work we propose a method to make possible the morphological analysis based on single lead raw contactless capacitive ECG records. With respect to signal processing required, segmentation based on statistical parameters to discard invalid sections was applied, including artifacts removal filter, R-peak detection based on discrete derivative method, correlation analysis to discard ectopic beats, and smoothing statistical filter, to finally depict a sound noise-less beat template. The best configuration was proven to be placing the electrodes on the back (84% beats detected). Conversely, the best correlations among QRS complexes were obtained with wrist signals (71%, compared to 63% and 62% in forearm and wrist, respectively). A significant high number of beats are required for beat-template development, as well as for morphological analysis.

1. Introduction

Heart signal is probably the most deeply and frequently analyzed biological recording. Two devices are normally used to record heart activity: the Electrocardiogram (ECG), which is the most frequently used for standard clinical practice, and the 24h-Holter monitor o recorder, which is used in a further step of clinical study for long term monitoring (24 hours, 7 or 21 days). In both cases, the interface between the body and the registry device is a relevant element, limiting the quality of the final signal for clinical evaluation. Important efforts have been devoted in the last decades to improve the electrodes and the conductive capabilities by incorporating gels, and using even disposable electrodes that combine high technology conductive materials perfectly bundled to the electrode, with the economics of scale to allow single use. The inconvenience of using uncomfortable gels (the first case) or extremely adherent elements (disposable electrodes), prevent from using this kind of sensors daily control system for standard clinical follow up. Aiming to overcome this last limitation, new electrodes are being developed and tested, and recent articles suggest that currently the technology is ready for new paradigm, and even contactless. However, few of these previous works focus on morphological analysis due to the important noise component [1–5]. In this paper we present our work on how to denoise contactless capacitive sensors acquired signals, and how morphological analysis is then possible.

For this purpose, we used off-the-shelf commercial Plessey™ electrodes (capacitive sensors), where no special attention was paid with regard to the electromagnetic environment in order to simulate the usual domestic space (such as electricity noise, TV and other devices' electromagnetic interference). Different recordings in alternative conditions were analyzed based in two factors: position of the sensor in the body and measurement through clothes or directly to the skin. Special remark should be stated here with regard of the good quality of the signal when direct contact with the skin was applied (no conductive gel), where a clear signal was obtained when direct clinical interpretation was possible, with the only downfall of the level of the signal that required a significant amplification. In particular, a measurement performed with direct contact on the front wrist, provided a good signal, although it was not the case for the same position but over the back side of the body, where significant noise was present. In contactless recordings, signals were even weakened from previous, and noise contribution fully hidden direct visual inspection of the QRS shape and hence, only under certain circumstances R peaks were clearly recognized. Therefore, the main goal of this work was to determine the appropriate signal processing for the obtained signals, even in those cases where seem to be not visible at all, to allow clinical visual morphological inspection.

The next Section explains in detail the applied method to extract the QRS shape. This process starts with standard preprocessing, then a signal continuity detector is applied to identify segments with valid information, and finally R-peak and statistical denoising is applied.

2. Material and methods

This section comprises the information related to the physical elements used (device, sensors, and database).

Signals were registered using the digital output of a control interface box and capacitive electrodes from Plessey^{TM}. These sensors are non-contact electrometers, meaning that there is no direct DC path from the outside world to the sensor input, a condition that is somewhat analogous to the gate electrode of an MOS transistor. The sensor is protected by a capping layer of dielectric material to ensure that the electrode is isolated from the body being measured.

Database. An important set of recording completed the database used with more than 100 signals. Multiple sensor locations were evaluated to select the best configuration, both for user convenience and signal quality. The recordings included, not only a single contactless configuration with different clothes (nylon, cotton, wool and polyester), but also the direct-contact with the skin. Signals were registered in the *Hospital Universitario Virgen de la Arrixaca of Murcia* under clinical supervision, to enhance accuracy and maximizing the number of isopotential body lines being crossed.

Processing. MatLab^{TM} under windows environment was used for processing, measurement, and representation of the results.

2.1. Preprocessing

Initial preprocessing and signal conditioning are usually required for any processing method to be applied, especially for non-synthetically obtained records. For the case where no direct contact with the skin is applied, noise level can even be higher than the signal itself. Applied preprocessing included baseline wander and DC component removal, power supply notch filtering, and artifacts and other undesired high frequencies riddance. As an example of the signals recorded through this contactless procedure, Figure 1, shows an example corresponding to a wrist through cotton-clothes.

DC and baseline wandering. According to standard ECG detection papers [6, 7], low frequency signals may modulate ECG-recordings. This modulation can be seen as a trend in the main signal. For removing this trend, spline model was applied over one second window with 50% overlap. Generated trend signals were subsequently removed to the existing recording. This process was applied individually to every lead (a single lead for the contactless Holter, and 12 leads for the standard ECG).

High frequencies filtering. Typical ECG signals present frequency components mostly below 150Hz. This means that in order to preserve valuable signal waveforms, this range should be kept for clinical morphology analysis. As a consequence, a 256 order, 150 Hz low pass filter was applied. The order was selected to get a good performance for the experiments based on visual inspection of results in time and frequency domains.

Power interference notch filtering. Standard Notch filtering was applied to remove power interference fundamental components and harmonics. For the electrode locations under analysis, the notch filter was adjusted for 50, 100, and 150 Hz removal. Note that no further harmonic needed to be filtered because a previous 150 Hz low pass filter was applied.

2.2. Beat detection

The beat detection algorithm was developed in two stages. A first step identifies whether ECG signal is present, discriminating among segments with and without ECG, and a second process to identifies the main peak of the QRS.

Segment discrimination. A simple algorithm for detecting the presence/absence of ECG signals was developed.

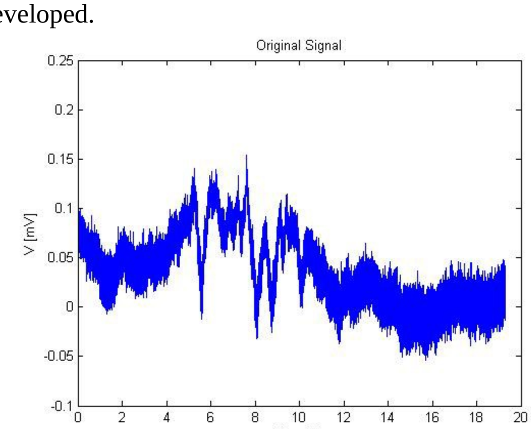

Figure 1. Example of recorded contactless signal.

This analysis allowed us to avoid useless processing, and reduced false detections in sections without any trace of real signal. According to our results, the Standard Deviation (SD) has proven to be, a simple but powerful discriminator of the presence of the effective ECG signal. Several analysis and benchmarks were compared, both with real signals and recordings far from the human body, as well as for different Segments Lengths (SL), and SD thresholds. Free parameters tuning was required based on existing registries, and accordingly, an empirical threshold for SD and optimal SL was selected.

Main peak detector. For the RR detection, an specific procedure was followed. The Green method discrete derivative [8] was used to detect R-peaks. The process was developed as follows: (a) discrete derivative was calculated for every lead; (b) all leads were multiplied to each other, hence amplifying the peak detection effect as the number of available lead increased; (c) a dynamic threshold was selected depending on the available number of leads and level of the signal. Every beat length could usually be measured between any of the different peaks, corresponding each of them to existing edges of the QRS waves. For that reason, all peaks corresponding to one single beat should be consolidated into one individual main-peak. All peaks inside a certain window were shielded behind the main peak. It is important to realize at this point that main-peak should not necessary be R-peak, and could also be an S-peak instead. A later processing can eventually detect any wave of the QRS complex.

RR interval. Detection of R-peak was calculated as the first peak under the QRS window defined previously. This step may not be always relevant, because the SS-interval it is as stable as the RR-interval as far as heart rate is concerned. However, in those cases where magnitudes of both waves are comparable (R and S), the main-peak detector may not be identified from the same wave on every beat.

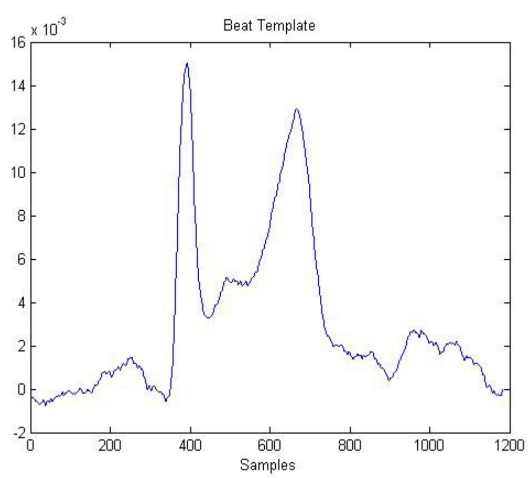

Figure 2. Beat template for morphological analysis.

For that reason, fist peak detection inside the QRS window was required. RR interval is readily calculated as a difference between RR peaks, and heart rate was defined as the median of all RR intervals of the selected section.

2.3. QRS-wave conditioning

Once the R-peaks were detected, statistical signal filtering was performed. To accomplish this step, and by taking as a reference the R-peak, all peaks were individually treated and processed.

All beats were cross correlated to each other to identify relevant artifacts/noise still present at this stage, as well as other sources of morphological irregularities that may interfere to create a template beat, as those signals are not supposed to be part of a standard morphological view of the signal. Beat template was created averaging only well correlated beats (index over 0.5), yielding a statistically consistent ECG denoising. All other beats not presenting a significant correlations index were not considered for this purpose. Note that this threshold was much lower than the one used for direct contact ECG.

This ECG template is suitable for morphological analysis to evaluate diagnostic risk indexes, which is the main goal of the project supporting this work.

3. Experiments and results

Over one hundred signals of different lengths were processed by following the method described in the previous section. Preprocessing of the signal (detrend, baseline wander, and power interference denoising) effectively removed high noise components, even higher that the signal itself. Figure 3 shows an example of the resulting signal after notch filtering. Bearing in mind the signal weakness on contactless monitoring, a prior signal discriminator is required to avoid useless processing efforts and alarms.

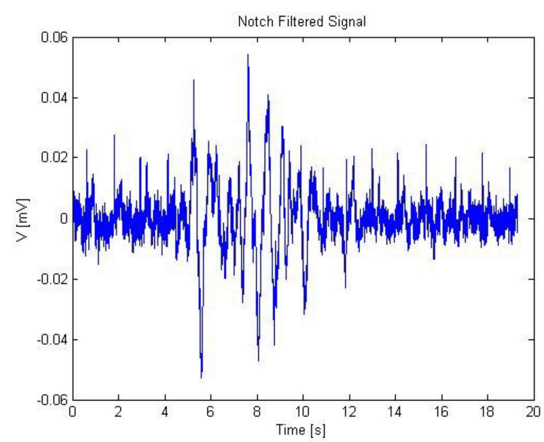

Figure 3. After notch filtering: signal and spectrum.

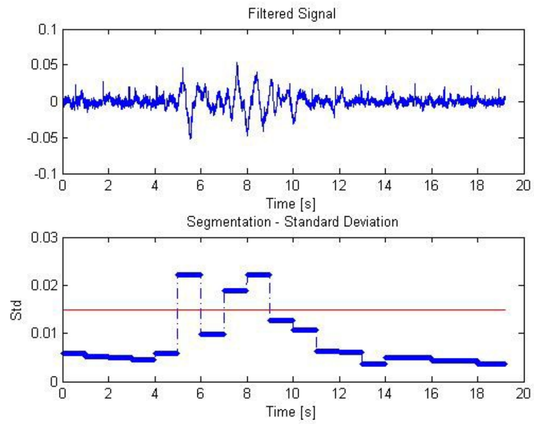

Figure 4. Segmentation and valid information detection. Top: signal. Bottom: segment discriminator where lower values correspond to valid information signal detected

Table 1. Detected beats and Correlations.

Position	Detected beats	Correlation
Wrist	70±7 %	71±34 %
Forearm	80±16 %	63±25 %
Back	84±14 %	62±11 %

A simple module was developed based on the SD over one second interval. It was empirically selected a threshold of 0,015. An example of the discriminator output is shown in Figure 4.

Standard beat detector, based on Green Method, and beat template conformation, based on statistical denoising, allowed final clinical evaluation with visual morphological information. Unequal results were obtained depending on sensor locations. Best outcome was obtained in terms of beats detected from electrodes located on the back, while best correlation among beats (improved morphological analysis) appeared when sensors were located on the wrist. Table 1 summarizes the results.

4. Discussion and conclusions

It is possible to use contactless sensors for clinical morphological analysis, and for the creation of diagnostic risk indexes, that could eventually trigger further evaluations. This result opens new frontiers in terms of new applications for monitoring cardiac activity, especially outside clinical environments.

It should be discussed here that the developed beat template lacks from representation of individual beat abnormalities, as it is built using only beats with significant correlation to avoid the undesirable artifacts. This limited the functionalities of this technique for clinical evaluation, and so it could not fully replace standard Holter functionalities. Further work and analysis on the free parameters tuning, based on a larger and more complete database of registries, will improve the generalization capability of the system developed. This additional effort should include a wider outlook in terms of diagnostic patterns, and formally learning techniques could be applied for enhance statistical significance and value of the proposed model.

Acknowledgements

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