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Estimation of HRV Based on Low Frequency Data Transmission

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Abstract. Smart devices, including the popular smart watches, often collect information on the heart beat rhythm and transmit it to a central server for storage or further processing. A factor introducing important limitations in the amount of data collected, transmitted and finally processed is the life of the mobile device or smart watch battery. Some devices choose to transmit the mean heart rate over relatively long periods of time, to save power. Heart Rate Variability (HRV) analysis gives useful information about the human heart, by only examining the heart rate time series. Its discriminating capability is affected by the amount of available information to process. Ideally, the whole RR interval time series should be used. We investigate here how this discriminating capability is affected, when the analysis is based on mean heart rate values transmitted over relatively long time periods. We show that we still can get useful information and the discriminating power is still remarkable, even when the amount of the available data is relatively small.

Keywords. Sensors, smart watch, low rate transmission, HRV analysis

Introduction

Body sensors are widely used for recording physiological signals. Recordings can be of a predetermined time period, usually using less comfortable medical wearable devices, or for longer periods, using lightweight wearable devices, like smart watches. All devices need power to operate and frequent recharging is usually at least irritating or sometimes obstructive. To decrease power consumption, some smart watches and other mobile devices have chosen to transmit data with a lower frequency rate than the ideally desired one. This transmitting frequency is sometimes not enough for demanding and emerging applications, but enough for other purposes. In this paper, we investigate how the transmission frequency of heart rate affects the discriminating capability of HRV analysis. This work was motivated by the *Homore*[2] project, in which we use sensors and smart watches to monitor elderly people and improve their safety and quality of life.

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1. Methods

We used three data sets publicly available online on Physionet [1]: (a) *Normal Sinus Rhythm RR Interval Database (NSR)* [1]: includes beat annotation files for 54 long-term ECG recordings of subjects in normal sinus rhythm, (b) *Congestive Heart Failure RR Interval Database (CHF)* [1]: includes beat annotation files for 29 long-term ECG recordings of subjects aged 34 to 79, with congestive heart failure and (c) *Fantasia* [1,2]: twenty young (21--34 years old) and twenty elderly (68--85 years old) two hours recordings of healthy subjects.

The purpose of this work is to investigate how the heart beat collection and transmission frequency affects the discriminating capability in HRV analysis. The methodology followed is outlined, listed in steps: (a) We defined two categorization problems based on the data sets described above. In the first one, we use the first two data sets to categorize congestive heart failure patients and controls. In the second one, we use the third data set to categorize young and elderly subjects. (b) We selected popular HRV analysis indexes and computed how well each metric can discriminate the subjects in the two examined categorization problems. The p-value was used as an index to express how successful the categorization was. (c) Then, using that data, we simulated the mean heartbeat data collection process for specific periods T and constructed the corresponding time series with the mean heart rates, simulating what a mobile device does, when the mean heart rate is transmitted with period T. (d) We computed, again, the p-values, this time for the new series and compared the results.

For the HRV analysis we selected the following metrics: (a) *mean*: mean value of all samples [3], (b) *sdnn*: standard deviation of the time series [3], (c) *rmssd*: root mean square of successive differences [3], (d) *Shannon entropy (ShanEn)*: the famous entropy definition, as suggested by Shannon, (e) *Approximate entropy (ApEn)*: a popular estimate of entropy in m-dimensional space [4], *Sample Entropy (SampEn)*: another popular estimate in m-dimensional space [5], similar and complementary to Approximate Entropy.

2. Results

Table 1 presents the p-values computed by our experiments. On the left hand side the p-values discriminating congestive heart failure patients and controls can be found, whilst on the right hand side the corresponding p-values for the *Fantasia* data set are shown. With the notation *RR* we refer to the original signal. The rest of the values in the first column show the transmission rate of the constructed/simulated signal. Each column corresponds to one HRV metric.

For the *NSR-CHF* data sets, one can notice that p-values are generally increasing as the transmission frequency decreases. However, in all cases they remain in very satisfactory low levels. In *Fantasia* the problem seems to be more difficult, since in many cases, the p-value is over 0.05, not statistically significant. These cases are marked with a dash in the table. Both *sdnn* and *rmssd* presented low p-value, which was reasonably increased for low frequency rates. However, they remained in statistically significant levels. The entropy measures presented p-values slightly over the statistically significant level for the RR time series, something that became worse for simulated ones, especially for those with the lower frequency rates. Even though the classification was less effective in Fantasia data set, the main conclusion is the same: the statistically significant metrics remained statistically significant, whilst their p-values increased in a reasonably small degree.

Table 1. Discriminating capability for the two examined data sets

	NSR and CHF data sets						Fantasia					
	mean	*sdnn*	*rmssd*	*ShanEn*	*ApEn*	*SampEn*	*mean*	*sdnn*	*rmssd*	*ShanEn*	*ApEn*	*SampEn*
RR	10^{-6}	10^{-10}	-	10^{-2}	10^{-8}	10^{-6}	-	10^{-5}	10^{-5}	10^{-2}	10^{-3}	10^{-3}
5sec	10^{-6}	10^{-9}	10^{-2}	10^{-4}	10^{-4}	10^{-2}	-	10^{-7}	10^{-9}	10^{-2}	-	-
10sec	10^{-6}	10^{-9}	10^{-2}	10^{-5}	10^{-5}	10^{-5}	-	10^{-7}	10^{-6}	-	-	-
15sec	10^{-6}	10^{-9}	10^{-2}	10^{-5}	10^{-5}	10^{-7}	-	10^{-7}	10^{-6}	-	-	-
30sec	10^{-6}	10^{-9}	10^{-5}	10^{-5}	10^{-4}	10^{-7}	-	10^{-6}	10^{-8}	-	-	-
60sec	10^{-6}	10^{-9}	10^{-7}	10^{-5}	10^{-4}	10^{-7}	-	10^{-5}	10^{-8}	-	-	-
120sec	10^{-6}	10^{-9}	10^{-7}	10^{-5}	10^{-4}	10^{-7}	-	10^{-4}	10^{-7}	-	-	-

3. Conclusions

In this paper, we examined how the low frequency transmission of the heart rate signal affects HRV analysis. We employed time series of RR intervals and computed heart rate time series, simulating the transmission of the heart rate from a mobile device which sends the mean heartbeat every T seconds. We calculated the p-values for the original RR time series and the computed mean heart rates ones and compared the results. We showed that HRV analysis has remarkable discriminating power, even when the transmission rate is lower than the ideal one..

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