The Effect of White Noise and False Peak Detection on HRV Analysis

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Abstract. Heart rate variability (HRV) is an established measure for cardiac health. Its use is widespread and many methods have been developed for its analysis. Little emphasis, however, has been given to the specific influence of noise from the electrocardiogram (ECG) on the heart rate (HR) series. There are explicit factors of noise that have been extensively studied on the ECG and much work has been published on their limitation or elimination. Despite all these solutions, however, often noise does end up in the ECG and is inevitably included in the derived HR series. It is of interest to investigate how this influences subsequent HRV analysis. We propose that the noise into the resulting HR series: Shifted R-peak (white noise) and false peaks. In this paper, we demonstrate how these two scenarios affect the outcome of the HRV analysis.

1 Introduction

HRV is computed from the variations in temporal distance between R-peaks of the electrocardiogram (ECG) [1,2]. In order for these peaks to be extracted from the original recorded signal, the QRS complex must be properly and accurately identified. The cancellation or elimination of noise in the ECG has been examined comprehensively by the medical and engineering communities and there has been a plethora of suggestions on general as well as specific noise reduction methods [3]. Although the problem has been greatly reduced, QRS points are still often measured with some amount of error.

Since the heart rate (HR) signal is detected from the ECG, it would be of interest to investigate how erroneous R-R intervals influence the subsequent HRV analysis methods in their accuracy. Previous studies have addressed this issue [4,5], but general observations are still lacking in the literature. In this paper, we investigate the performance of the most common linear HRV analysis methods on HR series that have been contaminated with varying amounts of noise.

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2 Noise Artifacts

The most common noise artifacts present in the ECG have been well highlighted in [6] and these will be examined in this paper. They include power line interference, electrode contact noise, motion artifacts, muscle contractions and baseline drift and amplitude modulation caused by respiration.

In the clinical and research context, there are three settings through which ECGs are digitally recorded: ECG monitoring, Holter devices and the treadmill stress test. Noise found in the ECG is commonly either filtered or discarded [6]. In the case of R-peak detection, noise that is not properly eliminated usually produces one of two errors in the HR series: false R peaks or lost R peaks.

Peak detection errors usually result in the introduction of white noise to the HR series. As false peaks are introduced or points are removed from the original ECG series, the true temporal occurrence of the R-peaks is slightly shifted in the resulting HR series. It is reasonable to claim then, that if the noise reduction method is not finely tuned and R-peaks are not identified properly, there is a larger amount of white noise present in the computed HR series. Below we list some of the most common forms of ECG noise, most of them described in more detail by [6].

a) Power line interference. This type of noise inserts 50 Hz or 60 Hz into the signal as well as harmonics that appear as sinusoids or a combination of sinusoids [6]. A sample of methods to reduce power line interference may be found in [7,8] and [9].

b) Motion artifacts. These are modulations in the baseline that are caused by change in electrode impedance at the site of contact of the electrode with the skin [6]. Often this is caused by respiration, perspiration or physical activity. A sample of noise reduction techniques may be found in [10-12].

c) Electrode contact noise. This occurs when the electrode contact with the skin is lost, usually leading to a loss in measurement [6].

d) Muscle contractions. These introduce milli-volt potentials to the signal [6]. This is also a common occurrence in Holter recordings and treadmill tests. A sample of muscle contraction noise reduction methods may be found in [13,14].

e) Baseline drift and respiration. This often has the appearance of a sinusoidal component at the frequency of respiration [6]. A sample of noise reduction methods may be found in [12, 15, 16].

f) Sampling. This kind of noise is due to quantization (digital recording). An acceptable minimum sampling rate found in most cases is 300 samples per second.

3 Methods

In the previous section we discussed the most common and significant sources of ECG noise. In this paper, our interest is how this noise affects the HR series. From the above discussion, we conclude that noise is inserted into the HR series in one of three ways: Shifted R-peak (which is commonly white noise), false peak detection and lost peaks. The third of these interferences does not really influence the outcome of the HRV analysis. Therefore, the results of the first two cases are reported here.

In order to investigate the above, we inserted white noise (1%-20% of the mean value of the signal). It was then of interest to see how these various amounts of noise affected the discrimination between patient groups as well as the statistical significance of the results (p-value). The p-value indicates the possibility that the two data sets are not different. A similar method was applied in order to test the affect of false peaks on the HRV analysis. N false peaks were inserted to the timeseries, with N ranging from 1% to 20% of the total signal length. N new points were created each one by replacing an existing point with two new ones, with the sum of the two new points being equal with the value of the replaced point, generating in that way the effect of a false peak detection.

The HRV analysis methods which are applied in this study are the most commonly used in clinical and research settings [6]: the SDNN, the SDANN, the SDNNindex, the RMSSD, the pNN50 and the SDSD. We have also applied Local Linear prediction [17]. The SDNN is the standard deviation of the NN interval, where NN is equivalent to two successive R-peaks in the HR signal [6]. The SDANN is the standard deviation of the average NN interval that is calculated from short periods commonly 5 minutes in length and the SDNNindex is the mean of the 5-min SDNN computed over 24h [6]. The RMSSD entails measuring the successive beat-to-beat intervals and finding their distribution [6]. The pNN50 is the proportion resulting from the division of the number of interval differences of successive NN intervals greater than 50ms and the total number of intervals. The SDSD is the standard deviation of differences between successive NNs [6]. Local Linear prediction [17] predicts future samples of a time series $x_1, x_2, \ldots, x_n$ by using a linear combination of the previous k samples, where k is a specific window length.

Two sets of data are analyzed in this study. The first set, henceforth referred to as 'Data set 1' is composed of HRV signals of healthy young subjects, both male and female and a set of healthy elderly subjects, also both male and female. This data is drawn from the 'Fantasia' database (Physiobank), [18]. Both the younger subjects (21-34 years old) and the elderly (68-85 years old) have been thoroughly tested to establish cardiac health. The recordings are 120 minutes long and all subjects were resting in the supine position while watching the movie 'Fantasia'. The second set, henceforth referred to as 'Data set 2' is a collection of Holter recordings acquired from heart failure subjects and an analogous control group. The data of the Holter group is comprised of 24 hour recordings.

4 Results

Results are shown both in the case of white noise as well as in the case where false peaks are inserted into the HR series. We are interested in investigating how the differentiation between young and elderly subjects (Data Set 1) and control/patient subjects (Data Set 2) is affected by these white noise and how the insertion of false peaks effects the results of Data Set 1. The effects of false peaks on Data Set 2 are still under investigation and will be included in future work by the authors. The possibility of error in the classification is shown through the computation of the p-value (ANOVA test) and is taken as significant when $p < 0.05$. This method is applied since it is the most common among the clinical community in the statistical assessment of classification studies. The statistical significance of the methods applied is shown in Table 1. Due to space limitations, we only include one indicative figure of the results of the SDNN method. The results of all the other methods are summarized in Table 2.

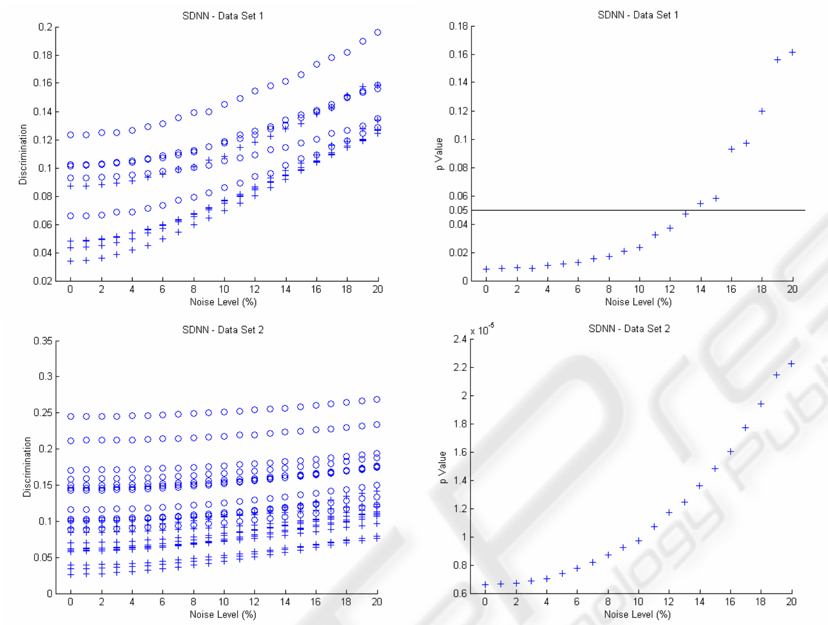

Fig. 1.1 White noise effects on the SDNN method on the discrimination of controls or younger subjects (*circles*) and heart failure or elderly subjects (*pluses*). The statistical possibility of error of classification for each data set is also shown

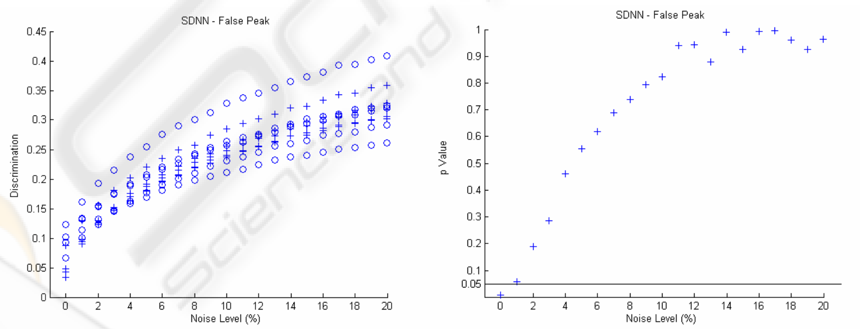

Fig. 1.2 False Peak effects on the SDNN method on controls (*circles*) and heart failure subjects (*pluses*). The statistical possibility of error of classification is also shown

As seen in Fig. 1, the data of Data Set 1 is greatly affected by noise after the 12% noise level. The same holds for Data Set 2 after roughly 6% noise is inserted. The outcome of the method is statistically significant for Data Set 1 up to roughly 13% noise insertion while for Data Set 2 all levels of noise produce statistically significant results. The insertion of false peaks to Data Set 2 immediately affects the discrimination between the two subject groups (even at 1% noise), as shown in Figure 1.2. This is also indicated by the fact that statistically significant results are found only when no noise is inserted. The above results are summarized in Table 1 and Table 2.

5 Discussion

The effects of noise on these methods have been experimentally examined in this study. It is of interest, however, to examine why these results have occurred. Although the standard deviation (SDNN) is the method of choice among most clinicians, there has been little interest in its robustness to all the above noise factors. As has been indicated here, it is clearly better than the others, as is the SDANN, which is similar but applied to 5-min intervals of the data. The RMSSD, which is also most common among clinicians, does not produce such encouraging results here, since it is a measure of spread and not a direct measurement of the deviation. The poorer performance of the SDNNindex is most likely attributed to the individual examination of small segments of holter data, which is unstable and usually contains the most noise of all recording equipment. Overall, we believe these are interesting results and we are currently examining the effects of such noise on other classification methodologies, which, although not as popular in the clinical setting, do provide research interest.

Table 1. Maximum noise level at which statistical significance of data is maintained

Method	White Noise		False Peaks
	Data Set 1	Data Set 2	
SDNN	13%	All	None
SDANN	All	All	Varies
SDNNindex	-	9%	None
RMSSD	7%	All	None
SDSD	8%	18%	None
LLP	11%	All	4%

Table 2: Maximum noise level at which classification of data sets is maintained

Method	White Noise		False Peaks
	Data Set 1	Data Set 2	
SDNN	12%	6%	None
SDANN	All	All	2%
SDNNindex	-	2%	5%
RMSSD	6%	2%	None
SDSD	5%	2%	None
LLP	3%	2%	None

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