A Point Process Local Likelihood Algorithm for Robust and Automated Heart Beat Detection and Correction

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Abstract

Robust and automated classification and correction of ECG-derived heart beats are a necessary prerequisite for an accurate real-time estimation of measures of heart rate variability and cardiovascular control. In particular, the low quality of the signal, as well as the presence of recurring arrhythmic events, may significantly affect estimation accuracy. We here present a novel point process based method for a real time R-R interval error detection and correction. Results of detection analysis over data from the benchmark MIT-BIH arrhythmia database demonstrate that the proposed algorithm achieves 99.97% accuracy (98.23% sensitivity, 99.98% specificity and 95.69% positive predictive value), outperforming state-of-the-art algorithms. Further results on simulated data demonstrate the efficacy of the detection and correction method.

1. Introduction

Heart rate variability (HRV) techniques [1] provide a window on the many physiological factors modulating the normal rhythm of the heart. In particular, they have been found useful for non-invasive assessment of the autonomic tone in a wide range of clinical a non-clinical scenarios. In order to provide reliable results, these techniques require uninterrupted series of normal R-R intervals. Peak detection errors – when the algorithm misses a beat and/or detects one when there is none – and ectopic beats often determine abrupt changes in the R-R interval series that may result in substantial deviations of the HRV indices, potentially affecting statistical outcomes.

If on one hand processing series contaminated by irregular R-R intervals might lead to inaccurate results, inclusion of only clean and ectopy-free R-R series may still pose some problems. For example, if the rate of occurrence of mis-detections or ectopic events is not uniform but it is dependent on specific parts of the protocol (e.g., those with frequent motion artifacts) or on the physiological state of the subject (e.g., states that may result in abnormal morphology of the QRS or in increased occurrence of ectopic events), then the exclusion of these periods might skew the resulting HRV indices [2, 3].

In some cases, it is therefore preferable to correct the corrupted R-R series to obtain a new artifact-free R-R series reflecting the underlying HRV dynamics. This new R-R series can then be used for for further processing using the HRV analysis techniques of choice. To date, this detection and correction of irregular beats has been mainly achieved by direct human expert evaluation and, more recently, by automatic techniques [2–10].

We have developed a novel point process based method for real-time R-R interval error detection and correction. Given an R-wave event, we assume that the length of the next R-R interval follows a time-varying history-dependent inverse Gaussian (IG) probability distribution [11]. We then use this model to assess whether the actual observation is in agreement with the resulting model or if, instead, the alternative hypothesis of an erroneous beat is more likely. In this paper we present the algorithm and we show its performance in comparison with three established methods for the detection of erroneous and ectopic beats.

2. Methods

2.1. Point-process model of the heart beat

Let $(0, T]$ denote the observation interval and $U = \{u_k\}$ the ordered set of consecutive heart beat times (for example, but not limited to, R-waves detected from an ECG) in that interval, i.e., $0 \leq u_1 < \cdots < u_k < u_{k+1} < \cdots < u_K \leq T$. We assume that given any beat event u_k, the length of the next R-R interval, $\tau - u_k$, obeys a time-varying history-dependent inverse Gaussian (IG) probability density [11]:

$$f(\tau - u_k \mid \mu, \lambda) = \sqrt{\frac{\lambda}{2\pi(\tau - u_k)^3}}\, \mathrm{e}^{-\frac{1}{2}\frac{\lambda\,(\tau - \mathrm{u_k} - \mu)^2}{(\tau - \mathrm{u_k})\,\mu^2}}$$

where λ is the shape parameter of the IG distribution while μ is the mean of the distribution of the next R-R interval. Given a vector of time-varying parameters $\boldsymbol{\theta}(t) = \{\theta_0(t), \ldots, \theta_{P+1}(t)\}$ and a history vector $\boldsymbol{H}_k =$

$\{w_k, w_{k-1}, \ldots, w_{k-(P-1)}\}$ containing information about P previous R-R intervals $w_i = u_i - u_{i-1}$, we define the history-dependent mean as a regression of the past P R-R intervals:

$$\mu = \mu\left(\boldsymbol{H}_k, \boldsymbol{\theta}(t)\right) = \theta_0(t) + \sum_{i=1}^{P} \theta_i(t)\, w_{k-i}\,. \qquad (1)$$

and the time-varying shape parameter as:

$$\lambda = \lambda\left(\boldsymbol{\theta}(t)\right) = \theta_{P+1}(t)\ .$$

A local maximum likelihood method [11] is used to estimate the unknown time-varying parameter set $\boldsymbol{\theta}(t)$. Given a local observation interval $(t-l, t]$ of duration l, we consider a subset $U_{m:n}$ of the R-wave events, where $m = \min\{k : u_k > t-l\}$ and $n = \max\{k : u_k \leq t\}$. At each time t, we find the parameter vector $\tilde{\boldsymbol{\theta}}(t)$ that maximizes the local log-likelihood, given the R-wave events recorded in the local observation interval:

$$L(\boldsymbol{\theta}(t) \,|\, U_{m:n}) = \sum_{k=m+P-1}^{n-1} w(t-u_{k+1}) \log\left[f\left(u_{k+1}-u_k \,|\, \mu(\boldsymbol{H}_k, \boldsymbol{\theta}(t)), \lambda(\boldsymbol{\theta}(t))\right)\right] \qquad (2)$$

where $w(\tau) = 0.98^{\tau}$ is an exponential weighting function for the local likelihood.

2.2. Detection of outlying heart beats

At time u_{k+1}, i.e., when the $(k+1)$-th R-wave is observed, it is possible to assess whether this observation is in agreement with the model resulting from the most recent parameter vector $\tilde{\boldsymbol{\theta}}(u_k)$. For conciseness, in the following, let $\mu_1 = \mu(\boldsymbol{H}_k, \tilde{\boldsymbol{\theta}}(u_k))$ denote the mean for the distribution of the first R-R interval following u_k, given the history and the model at time u_k, and let $\lambda_1 = \lambda(\tilde{\boldsymbol{\theta}}(u_k))$ denote the shape parameter, given the model at time u_k.

2.2.1. Normal beat

A straightforward way to assess whether the beat at time u_{k+1} is in agreement with the model is to evaluate the log probability density of observing the event u_{k+1} given the previous event u_k, the history $\boldsymbol{H}_k$ and the model $\tilde{\boldsymbol{\theta}}(u_k)$: $p = \log f(u_{k+1} - u_k \,|\, \mu_1, \lambda_1)$. In [9], this probability p was compared with a fixed threshold and, if lower, a beat was either inserted or deleted. While this approach works reasonably well, it has some flaws. In fact, a very low value of p might indicate an erroneous R-wave detection, an ectopic heart beat, but also a sudden physiologic change in autonomic control. Ideally, we would like to be able to detect and possibly correct the former two cases while preserving the latter. For this reason, in this work, we take a different approach: instead of setting a threshold for the score p, we compare its value with the values obtained from alternative hypotheses, assuming that the event at time u_{k+1} is erroneous or arrhythmic. Below, we analyze the following three cases in detail.

2.2.2. Extra beat

The first hypothesis that we consider is that the beat at time u_{k+1} is an extra event that was erroneously placed between two consecutive heart beats. This can happen, for example, when the detection algorithm mistakenly identifies a T wave as a ventricular contraction. The score of this event is $p_{\mathrm{e}} = \log f(u_{k+2} - u_k \,|\, \mu_1, \lambda_1)$ where u_{k+2} is the time of the event following u_{k+1}. If $p_{\mathrm{e}} > p + \eta_{\mathrm{e}}$, where η_{e} is a pre-defined threshold, the event at time u_{k+1} is labelled as an "e" (extra) beat.

2.2.3. Skipped beat

The second hypothesis is that between the events u_k and u_{k+1} there was an additional event that has been skipped. This can happen, for example, when the detection algorithm misses an R-wave because a superimposed artifact has drastically changed its morphology. In this case, the time elapsed between u_k and u_{k+1} should be compatible with the prediction of the model for the sum of two R-R intervals given the history at time u_k.

We assume that there are two stochastic events following u_k, the first at time τ' and the second at time τ, of which only the latter was observed and mistakenly labeled as u_{k+1}. According to our model, the distribution of the first R-R interval, $\tau' - u_k$, is simply $f(\tau' - u_k \,|\, \mu_1, \lambda_1)$. The distribution of the second R-R interval, $\tau - \tau'$, can be written as $f(\tau - \tau' \,|\, \mu_2(\tau' - u_k), \lambda_1)$, i.e., as an IG distribution whose mean μ_2 also depends on the first R-R interval. In fact, $\tau' - u_k$ enters the history vector $\boldsymbol{H}'(\tau' - u_k) = \{\tau' - u_k, w_k, w_{k-1}, \ldots\}$ and, through the regression in (1), affects μ_2. The total probability density function can be obtained marginalizing the unknown τ' in the joint probability density:

$$\int_{u_k}^{\tau} f(\tau - \tau' \,|\, \mu_2(\tau' - u_k), \lambda_1)\, f(\tau' - u_k \,|\, \mu_1, \lambda_1)\, \mathrm{d}\tau'. \qquad (3)$$

Instead of attempting to solve (3), here we make the simplifying assumption that the resulting probability density function can be approximated by an IG distribution with mean $\mu_{1+2} = \mu_1 + \mu_2$ and shape parameter $\lambda_{1+2} = \lambda_1 \frac{(\mu_1+\mu_2)^3}{(1+\tilde{\theta}_1(u_k))^2\,\mu_1^3 + \mu_2^3}$ where $\mu_2 = \mu(\boldsymbol{H}'(\mu_1), \tilde{\boldsymbol{\theta}}(u_k))$.

Using these results, we can now evaluate the log probability density of observing a beat at u_{k+1} after a skipped beat at an unknown time $\tau' \in (u_k, u_{k+1})$: $p_{\mathrm{s}} = \log f(u_{k+1} - u_k \,|\, \mu_{1+2}, \lambda_{1+2})$. If $p_{\mathrm{s}} > p + \eta_{\mathrm{s}}$, where η_{s} is a pre-defined threshold, we assume that there might be a skipped ("s") beat.

2.2.4. Misplaced beat

The third hypothesis is that the beat at time u_{k+1} is misplaced, i.e., a beat at a different time in the interval

(u_k, u_{k+2}) has been mistakenly assigned to time u_{k+1}. This can happen, for example, when an artifact deforms the QRS complex and makes the detector misinterpret some random deflection for an R wave and miss the true R wave.

In this paper, for simplifying purposes, we will consider in this category also some types of ectopic beats, such as premature ventricular contractions that are followed by a complete compensatory pause. Even if, strictly speaking, ectopic beats are not mis-detections, it is often desirable to treat them this way. In fact, ectopic beats may significantly impair the results of many heart rate analysis techniques (such as spectral estimation) while, on the other hand, acceptance of only ectopic-free, short-term recordings may introduce significant selection bias [3]. For this reason, it is desirable to detect irregular beats and, possibly, replace them with fictitious regular beats in order to carry on the desired analysis.

A beat u_{k+1} is likely to be a misplaced one whenever the corresponding R-R interval does not fit the model while the sum of the two R-R intervals, $u_{k+2} - u_k$, does. Therefore, the score for the case of a misplaced beat is: $p_{\mathrm{m}} = \log f(u_{k+2} - u_k \mid \mu_{1+2}, \lambda_{1+2})$, and if $p_{\mathrm{m}} > p + \eta_{\mathrm{m}}$, where η_{m} is a pre-defined threshold, we assume that there might be a misplaced ("m") beat.

3. Results

We tested the performance of our algorithm on a set of real R-R timeseries with randomly deleted, shifted, and inserted beats. The method was able to detect, with remarkable accuracy, inserted and deleted beats, as well as beats that had been shifted by only a few tens of milliseconds. At the same time, the algorithm showed high specificity and did not trigger false alarms in response to sudden variations of the R-R intervals due to physiologic changes in autonomic control. An example of a test signal is presented in Fig. 1 which shows how the algorithm provides an optimal balance between the sensitivity needed to indicate small erroneous R-wave detections (m1, m2, m3, m5), as well as a real ectopic heart beat (m4), and the specificity to discern the cases to be corrected from factual, sudden physiologic changes in autonomic control (n1, n2).

In order to give reproducible and easy-to-compare performance measures of our method, we also tested its accuracy on the MIT-BIH Arrhythmia Database [12] and compared the results with three well-established approaches.

For this comparison, we did not consider the second part of the database (composed by less common types of arrhythmias) and, of the first part, we chose all the recordings having no more than 10 non-normal beats in any 1-minute window.[1] The reason is that we are interested in R-R series that are mildly affected by erroneous or ectopic events, and that can be recovered and further processed with HRV techniques. In a recording with an excessive number of irregular beats, the information about the underlying sinus rhythm cannot be reliably recovered and therefore the HRV indices cannot be assessed.

The first method that we implemented for comparison is the well-established algorithm by Berntson et al. [5] which uses two criteria to assess whether a heart beat is an artifact: Maximum Expected Difference (MED) and Minimal Artifact Difference (MAD). In order to allow the algorithm to adapt to non-stationary data, for each R-event u_k, MED and MAD were estimated using events in a 60 s sliding window preceding u_k.

The second algorithm we used is based on the important contribution by Mateo and Laguna [8]. For each R-event u_k we evaluated Eq (1) from the original work (where t_k corresponds to our u_k) using a time-varying threshold $U_k = 4.3\,\sigma_k$ where σ_k is the standard deviation of the r_j values obtained for events in a 60 s sliding window preceding u_k. Then we classified the beat using the set of rules described in section II.A of the referenced paper.

Finally, we implemented the more recent method proposed by Rand et al. [10]. We followed the algorithm described in the original paper and used the values of parameters that they found optimal.

For each recordset of the MIT-BIH Arrhythmia Database considered, we ran the four algorithms described. As some of the algorithms use a 60 s sliding window to adaptively estimate their thresholds, we did not consider the beats in the first minute of the recordset. Table 1 reports the confusion matrices obtained for the four algorithms, whereas Table 2 shows their performance measures. Our methods outperforms the previous algorithms, especially in terms of a lower number of false detections, resulting in higher specificity and positive predicted value.

Table 1. Confusion matrices for the point-process method presented here (PP) and for the three state-of-the-art methods considered (Rand2007, Mateo2003, and Berntson1990) against the experts' annotations in the database (Annots). The label 'N' represent normal beats while '$\neq N$' contains all other types of beats.

		PP		Rand2007		Mateo2003		Berntson1990	
		N	$\neq N$	N	$\neq N$	N	$\neq N$	N	$\neq N$
Annot	N	23311	5	23218	98	23301	15	23296	20
	$\neq N$	2	111	2	111	5	108	2	111

Table 2. Performance measures of the four methods.

	PP	Rand2007	Mateo2003	Berntson1990
Accuracy	99.97%	99.57%	99.91%	99.91%
Sensitivity	98.23%	98.23%	95.58%	98.23%
Specificity	99.98%	99.58%	99.94%	99.91%
Pos.Pred.Val	95.69%	53.11%	87.80%	84.73%

[1] The recordset actually used were: 100, 101, 103, 105, 108, 112, 113, 115, 117, 121, 122, 123

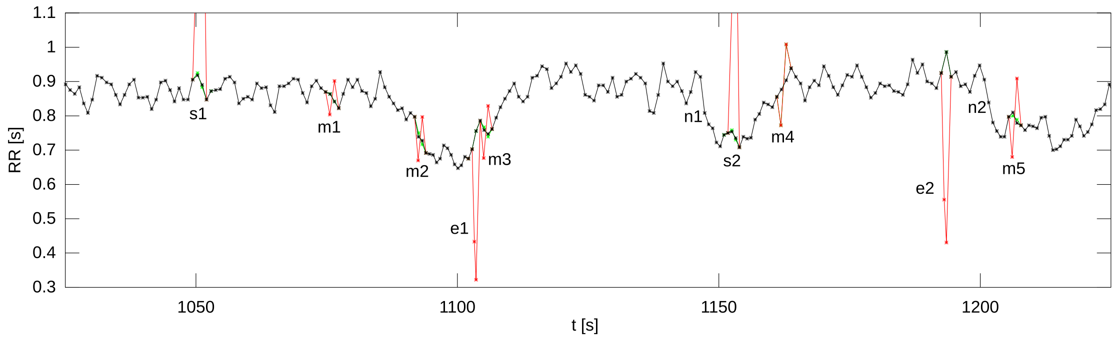

Figure 1. The plot shows an example of an original R-R interval series (green) where some R-events were removed (s1, s2), inserted (e1, e2) or shifted (m1–m3) to create an input corrupted series (red) to test the algorithm. The beat annotated with m4 represents an ectopic event already present in the original data while n1 and n2 are normal beats in proximity of a sudden physiologic change. The algorithm correctly recognizes all cases and appropriately corrects the beats (black).

4. Conclusions

The presented algorithm for beat detection and correction extends the previously developed point process framework to provide, simultaneously and in an on-line fashion, both arrhythmia classification markers and instantaneous indices of heart rate variability and cardiovascular control. Our results on simulated data demonstrate the efficacy of the detection method in recognizing missing, mis-detected, and irregular heart beats with remarkable accuracy even in scenarios that require discerning very small time resolution errors at millisecond scales. Results of detection analysis over data from the benchmark MIT-BIH arrhythmia database further demonstrate that our algorithm outperforms other previously proposed successful methods both in terms of accuracy, specificity and positive predictive value. Future efforts are aimed at refining and testing the correction criteria to propose the most appropriate beat events based on the features offered by the point process model. The complete paradigm, once tested extensively on simulated and real data, could be easily implemented in an on-line monitoring device.

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