Searching for Non-Sense: Identification of Pacemaker Non-Sense and Non-Capture Failures using Machine Learning Techniques

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Abstract

Abnormal or unexpected function of pacemakers due to mechanical failure of the implantation, electrical failures of the battery and electrodes, or physiological failures to respond to the stimulus may cause harm to a patient. A novel Bayesian decision tree algorithm is proposed to detect two types of pacemaker failures, nonsense and non-capture, without a priori knowledge of pacemaker type, model, or programming. A variety of pacemaker devices and modes were studied, including devices with single and dual chamber pacing; single and dual chamber sensing; and fixed rate and rate adaptive pacing. 12-lead ECG signals were acquired from 34 pacemaker patients at rest. These signals were annotated by a team of experts. A 10-fold cross-validation was performed on the data set to test the algorithm. Out-ofsample sensitivity and specificity of 87.8% and 98.7%, respectively, were achieved. This work shows that nonsense and non-captures pacemaker failures can be detected with high sensitivity and specificity without prior knowledge of the pacemaker type, model or programming, making this algorithm clinically relevant in emergency room environments where such pacemaker information may be unavailable.

1. Introduction

The goal of this research is to develop an automatic method for identifying pacemaker failures from time series data related to the patient's electrocardiogram (ECG) without prior knowledge of the type or model of the pacemaker. The application for the proposed algorithm is a patient monitoring system used in a hospital, transport, or emergency response environment.

Two types of pacemaker failures are investigated: non-sense (failure to detect a naturally occurring heartbeat) and non-capture (failure to stimulate the heart sufficiently to produce a paced heartbeat). If the patient does not exhibit symptoms of occasional non-capture, the condition may worsen over time. Additionally, a pacemaker failing to capture in a pacemaker dependent patient (one whose heart does not beat spontaneously) can lead to fatalities [1-3]. A pacemaker failing to sense may discharge at inappropriate times, causing fibrillation, leading to further harm to the patient [3, 4]. Detection of non-sense and non-capture by the patient monitoring system will provide earlier notification to the clinician when a cardiologist or pacemaker-programming device is not available to diagnose the condition.

False alarms are a significant problem with patient monitoring systems. Clinicians tend to distrust systems that alarm at every unrecognized pattern on an ECG. The algorithm proposed here must meet this requirement by weighing false alarms against missed events.

2. Methods

2.1. Data and preprocessing

GE Medical Systems – Information Technologies, provided data for this study. Research performed at Universitaetsklinik Freiburg (Freiburg, Germany) collected ECGs from 34 pacemaker patients, with a total of 5785 R-to-R intervals. Pacemaker devices and modes included devices with single and dual chamber pacing; single and dual chamber sensing; fixed rate and rate adaptive.

Data collected for each patient included a 12-lead ECG recorded from surface ECG electrodes through a CardioSys Exercise Testing System V3.01, with the patients at rest. The hardware detects pacemaker pulses by their high slew rate and replaces them with generated marker pulses representative of the actual pulse. The purpose of this replacement is to shut off the sensitive preamplifiers in the ECG circuitry during a potentially harmful slew rate input, and reduce recovery time to baseline.

All data was stored in the Massachusetts Institute of Technology-Beth Israel Hospital (MIT-BIH) Database format for ECG data [5]. The CardioSys Exercise Testing System software classifies the beats and annotates the patient's ECG file. The data contains annotations for pacemaker pulses and ECG annotations. Detected pulses and annotations were manually checked and corrected (if necessary) by a team of experts.

For this research, the data was processed into individual data intervals with labels of Normal, Non-Sense, or Non-Capture. Each data interval contains information about all events occurring between two QRS complexes. Non-sense and non-capture modes were expertly labeled, as the CardioSys either labeled these as "unknown" beats or had no event to label. In the 34patient data set, 13 cases of non-sense and 20 cases of non-capture were identified and labeled, with 5752 normal data intervals.

2.2. Features

The following features are chosen because they provide specific information relative to the proper functioning of the electrical and physiological aspects of the cardiac cycle. Each feature represents a particular measurement within the cardiac cycle.

The first feature, Pace Count, provides an identifier for normal data and examples of multiple non-capture beats in a row. Pace Count = 0 is assumed normal, because no pacemaker discharge occurred. A Pace Count > 2 is labeled non-capture because no acceptable rhythm has more than two pacemaker discharges within the selected interval, and at least one of the marked discharges has not received a physiological response. Additionally, this feature provides information for segregating the rest of the algorithm: Pace Count = 1 can be treated differently from Pace Count = 2.

The R-to-R interval provides a measure for the interbeat period of the heart. An excessively long R-to-R interval may identify a heart not responding properly to a pacemaker discharge, or a lack of stimulation to the heart.

The R-to-Pace interval is the time between a QRS complex and the following pacemaker discharge. This measures the period of time the pacemaker allows for repolarization of the myocardium prior to the next discharge. In the event of a non-sense failure, the pacemaker will usually discharge too quickly after the QRS for proper repolarization.

The final feature, Pace-to-Pace interval, is the time between two pacemaker discharges occurring between successive QRS complexes. The Pace-to-Pace interval represents the time between atrial and ventricular discharges in a dual-chamber pacemaker. This interval is similar to the P-wave to QRS complex interval in the heartbeat, and is typically on the order of 0.12-0.20 seconds [6].

The R-to-R/Pace-to-Pace Ratio used by this research is a convenient way to characterize the relationship between the R-to-R interval and Pace-to-Pace interval. The ratio is taken by dividing the R-to-R interval by the Pace-to-Pace interval. This ratio provides information on whether the time between pacemaker discharges is appropriate for the length of time between heartbeats, and is useful for both non-capture and non-sense detection.

2.3. Hybrid rule-based and Bayesian decision tree

The classifier used in this research is a combination of expert rules and statistical pattern recognition. This approach allows the identification and rapid classification of easily separable cases while allowing more ambiguous cases to be determined by learned discriminant functions.

First, expert rules are implemented, based on a priori knowledge of the pacemaker and heart system. A data interval with Pace Count = 0 is considered a normal data interval as the ECG is spontaneous and not artificially paced and any data intervals with Pace Count > 2 are immediately identified as non-capture failures. This data interval may represent multiple failures in succession, or a single failure. Then, the data interval is classified into one of two categories: Pace count = 2 or Pace count = 1. Each of these categories has a discriminant function learned from training data.

For the case Pace count = 1, three possible conditions exist: A normal QRS complex initiated by a singlechamber pacemaker (either atrial or ventricular); a spontaneous QRS not sensed by a single-chamber pacemaker followed by another spontaneous QRS; or a spontaneous QRS complex following an episode of noncapture from a single-chamber pacemaker. The R-to-Pace interval is used to separate the non-sense and non-capture failures from the normal data in this category.

For the case Pace count = 2, several possibilities exist. The single normal case is a dual-chamber pacemaker operating properly to trigger a normal paced QRS complex. Failures include a single episode of non-capture by a dual-chamber pacemaker; single episode of non-capture by a single chamber pacemaker followed by a normal paced QRS; two episodes of non-capture by a single chamber pacemaker followed by a spontaneous QRS; and a combination of non-sense and non-capture by a single-chamber pacemaker followed by a normal paced QRS. All of these failures can be identified by an abnormal ratio of R-R interval / Pace-Pace interval.

A two-step approach is implemented to classify the data intervals. Initially, the classifier establishes whether the data interval is normal or a failure. If it is a failure, another classifier determines whether it is non-sense or non-capture. The category with the highest probability is assigned the label for the data interval.

For simplicity, Gaussian models are used to model all features. Normality tests of the data indicate Gaussian distributions, with some slight deviation. The training data is used to determine the mean, μ_i , and standard deviation, σ_i , of each feature within each class, ω_i ; and the prior distributions for each class $P(\omega_i)$:

$$\mu_{i} = \frac{1}{n} \sum_{k=1}^{n} x_{k} ,$$

$$\sigma_{i} = \sqrt{\frac{1}{n} \sum_{k=1}^{n} (x_{k} - \mu_{i})^{2}} ,$$

$$P(\omega_i) = \frac{\text{occurrences of class } \omega_i}{\text{total number of training data intervals}}$$

Based upon these measurements, the likelihood, $p(x|\omega_i)$, and posterior probabilities, $P(\omega_i|x)$, are:

$$p(x|\omega_i) = \frac{1}{\sqrt{2\pi\sigma_i}} \exp\left(-\frac{1}{2}\left(\frac{x-\mu_i}{\sigma_i}\right)^2\right).$$
$$P(\omega_i|x) = P(\omega_i) p(x|\omega_i).$$

The posterior probabilities are compared and the class with the greatest probability is selected for the data interval [7, 8].

3. Application and experiments

The experiment setup consisted of a Matlab function that sorted the data into bins for ten-fold cross-validation to measure confidence in the results. Each method was implemented using the same set of bins for the data to produce comparable results.

Results of the research can be found in Table 1, below. The hybrid classifier has a sensitivity of 87.9% and a specificity of 98.7%.

		Classification		
		Failure	Normal	
Actual	Failure	29	4	
	Normal	77	5675	

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Table	1	– H3	/brid	classifier	confusion	matrix

Examples of incorrectly labeled events are seen in Figures 2 - 4. The first of these false failures is from a patient with a dual-chamber pacemaker that exhibits an abnormally long Pace-to-Pace interval during one beat. There is no immediate cause of this abnormality apparent in the ECG strip, Figure 1, below.

The statistical classifier interprets this as a non-capture episode because the first pacemaker discharge appears to lack a physiological response.

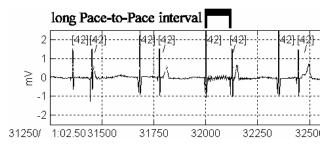


Figure 1– False Failure due to abnormally long Pace-to-Pace interval

Another type of false failure occurs when the patient's heart rate increases to the point where each successive beat becomes misinterpreted by the classifier as a non-sense episode. One example of this is shown in Figure 2.

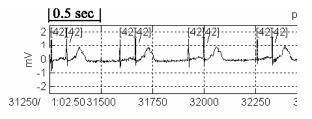


Figure 2 – False Failure, rapid heart rate classified as nonsense

This patient has an average heart rate of 96 beats per minute, however some of the beats occur more frequently. Approximately every third beat is misclassified for several seconds during this period of rapid heart rate. Accounting for the present heart rate may improve these false failure classifications, such as a manipulation of the R-to-Pace limit based upon the heart rate using a corrected time limit for the patient's Q wave to T wave interval [6], shown below.

$$QT_{CORRECTED} = \frac{QT_{ESTIMATED}}{\sqrt{(R - to - R Interval)}}$$

The type of missed failure is the case of a singlechamber pacemaker with a non-capture episode followed by a paced beat. In some instances of this situation, the ratio between R-to-R interval and Pace-to-Pace interval is similar to that of a normal beat triggered by a dualchamber pacemaker, as illustrated in Figure 3.

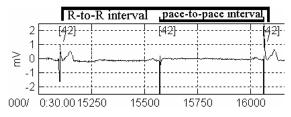


Figure 3 – Missed Failure, non-capture

This particular failure has a R-to-R/Pace-to-Pace ratio of 1.96. This particular case has an R-to-R interval 1.92 seconds, equivalent to a heart rate of 31.25 beats per minute, and on the edge of the distribution of normal R-to-R intervals.

Another type of missed failure occurs when the R-to-Pace interval for the non-sense case, as in Figure 4, is considerably longer than other cases. This may be confused as a non-capture failure by the statistical classifier. If the R-to-R/Pace-to-Pace ratio is similar to the previous case, the point may be labeled normal by the classifier.

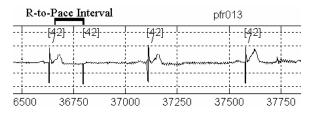


Figure 4 – Missed Failure, non-sense

Both types of missed failures are related to the R-to-R/Pace-to-Pace ratio used as a feature by the statistical classifier. A solution for this problem may be to separate the R-to-R interval and the Pace-to-Pace interval as individual features for statistical classification in addition to the ratio between the two.

4. Conclusions

This research shows that the proposed classifier is useful for detecting non-sense and non-capture. Further investigation into the false failures and missed failures has identified some shortcomings of the algorithm and paths for future improvement. Future enhancements to the algorithm will include utilization of the R-to-R interval and Pace-to-Pace intervals separately as well as the ratio between the two; investigation and correction of mislabeled data; additional ECG recordings that remain unlabeled at this point; and implementation techniques that have been presented by other research. The algorithm must also be updated to investigate biventricular and dual atrial pacemakers, which independently stimulate all four chambers, causing the potential of two atrial and two ventricular pacemaker discharges. Depending upon delays to surface electrodes and the programming of the pacemaker, these pacemakers may display three or four discharges on the ECG while operating normally [10-12]. This algorithm must be adapted to appropriately diagnose these newer pacemakers and accommodate changes in annotation systems designed to identify four-chamber pacemakers.

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