Performance Study of Digital Pacer Spike Detection as Sampling Rate Changes

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Abstract

In this study, we first collected ECG data at 32 ksps and 500 sps from 51 patients with an implanted cardiac pacemaker. We also included 16 non paced ECGs with severe motion artifact and static interference. We then annotated the pacer pulses (locations and classifications) using special viewing software and divided the data into training and testing sets. We developed three digital pacemaker stimulus detection algorithms, one for each of three different sampling rates (500 sps, 8 ksps, and 32 ksps) by using similar detection concepts. After tuning them on the training sets at the corresponding sampling rates, we investigated their performances. Results showed that the detection algorithm based on the 12-lead 500-sps data stream has a good performance (Sensitivity or Se=77.51%; Positive Productive Value, or +P=90.32%). The 8-ksps detector has a better performance (Se=95.37; +P=99.77). The digital pacemaker detection algorithm for 32 ksps or higher data provided almost 100% true pacer spike detection (Se=99.51 and +P=100%). In summary, high speed sampling at 32ksps can provide accurate detection of modern pacers and leads to a significant improvement in detection of pacemaker stimuli compared to the reduced sampling rates used previously.

1. Introduction

Conventional analog hardware designs for pacemaker stimulus (spike) detection do not always perform well with modern pacemaker devices, historically having low sensitivity. Recent digital pacemaker spike detection algorithms based on 500-sps ECG data streams can be non specific on account of high-frequency interference. Clinically, improving body-surface ECG pacer spike detection is a high priority. To address this important issue, we designed a product, the Cardiac Science Atria 3100/6100 electrocardiograph, that digitizes body-surface ECGs at a high sampling rate in order to detect the short duration (e.g. 0.3 ms) pacer pulse signals and which also has the capability of storing the pacer data for further investigation. This study focuses on digital pacemaker spike detection solutions and their performance especially when different sampling rates are adopted.

2. Methods

(1) Data Collection

The digital data was acquired by Cardiac Science Atria 3100/6100 ECG units through the standard 12-lead hookup.

- This commercial product over-samples data at 8 ksps (kilo-samples per second) and then down-samples/decimates to 500 sps (samples per second) for traditional ECG processing, whereby the decimated 500-sps data stream can be directly used to identify the pacer spikes;
- The front end data acquisition also includes a high speed sampling module, i.e. 64/32-ksps, with a digital pacemaker spike detection system.

Both 500-sps and 32-ksps data streams were dumped onto memory media. The 8-ksps data stream in this study was decimated data generated from the 32-ksps data. The 500-sps data stream consisted of 8 leads, where the 8 ksps and the 32 ksps were acquired 2 leads at a time (II&V_1, II&V_2, II&V_3, II&V_4, II&V_5, and I&V_6) but included all 8 independent leads for every patient.

(2) Datasets

All data was acquired from live patients.

- Dataset 1 - 306 ECGs from 51 pacer-patients, including 16 patients with biventricular pacemakers [1];
- Dataset 2 - 6 normal ECGs with significant motion artifact;
- Dataset 3 - 10 normal ECGs incorporating spikes generated by a high energy static gun or clothing static.

49% of Dataset 1 (25 out 51 patients) was used for training and the remainder for testing along with Datasets 2 and 3.

Table 1 lists the cycles from Dataset 1 for atrial (A), ventricular (V), bi-ventricular (BiV), A-V sequential (A-V), and A-V sequential Bi-Ventricular (A-BiV) pacing.

(3) Annotation

The pacemaker spike locations were first marked by a

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high-sensitivity edge-detection algorithm followed by manual annotation through special viewing software. Both high-speed data in the 32-ksps and 500-sps streams, which were acquired at the same time, were used to help determine the "true" locations.

Table 1. The total number of pacer cycles for five classifications from Dataset 1

Classification	A	V	BiV	A-V	A-BiV
Training Set	127	540	329	426	67
Testing Set	170	490	629	213	132

(4) Detection

Three algorithms were developed to find the pacer pulses. For the 8-ksps and 64/32-ksps data streams, edge/magnitude, timing detections and morphological recognition are used. The edge detection has a high sensitivity for pacer-like spikes, and a subsequent morphological recognition module controls the over detections and improves specificity. For the down-sampled 500-sps stream, only edge/magnitude and timing detections were employed because only a couple of samples associated with pacemaker spikes at the 500-sps stream were able to be used for detection. However, similar detection concepts were used for each individual detection module with corresponding changes due to the difference in the sampling rate. Also, each algorithm was tuned by using the training data (from dataset 1) from the same time.

It is an important feature of the algorithm to detect closely spaced pacemaker stimuli as sometimes is the case in biventricular pacing, where one electrode in the coronary sinus paces the left ventricle while another paces the right ventricle. A detection algorithm based on 500-sps data has low resolution and can see only one spike for the two adjacent ventricular impulses.

(5) A1V-type and A2V-type Measurements

Considering the majority of detection algorithms are currently not able to recognize bi-ventricular pacing, for comparing pacemaker detection methods, we introduce two statistical tactics to summarize the performance. An A2V-type calculation identifies all three spikes (AP, VP_1, and VP_2, see Figure 1) for each cycle; while an A1V-type measurement considers bi-ventricular pacing only as one spike event.

For an algorithm with the capability of recognizing bi-ventricular pacing (e.g. based on 8 ksps and 32 ksps), both A1V- and A2V-type measurements can be applied for comparison. A detection algorithm without the capability (e.g. based on 500-sps data) is only able to use A1V-type measurement approach for comparison. Table 2 and 3 show the A1V- and A2V- type measurements for the misdetection counts.

(6) Accuracy Calculation

We evaluated the algorithm performance based on the accuracy of pacemaker spike-by-spike detection, including sensitivity (Se) and positive predictive value (+P). Further, especially for a high-sampling rate detector, we measured the misdetections of five individual classifications for an algorithm in this report.

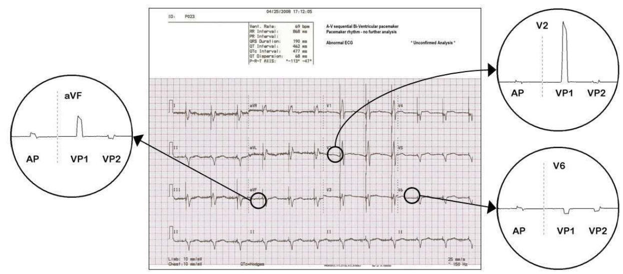

Figure 1. An example of an A-V Sequential Bi-Ventricular pacing ECG cycle

Table 2. Scheme for counting misdetections by using spike-by-spike detection evaluation for Bi-Ventricular Pacing.

Spike detected		Spike Misdetection Count	
VP_1	VP_2	A1V-type Measurement	A2V-type Measurement
√	√	0	0
√		0	1
	√	0	1
		1	2
Note: VP_1 = the first ventricular pacing spike, VP_2 = the second ventricular pacing spike. "√" indicates the particular pacing detected by the algorithm.			

Table 3. Scheme for counting misdetections by using spike-by-spike detection evaluation for A-V sequential Bi-ventricular Pacing.

Spike detected			Spike Misdetection Count	
AP	VP_1	VP_2	A1V-type Measurement	A2V-type Measurement
√	√	√	0	0
√			1	2
	√		1	2
		√	1	2
√	√		0	1
√		√	0	1
	√	√	1	1
			2	3
Note: AP = atrial pacing.				

3. Results

(1) Outcomes based on Dataset 1:

Performance statistics were calculated for both the training set and test set with all lead combinations counted (see Figures 2 to 5).

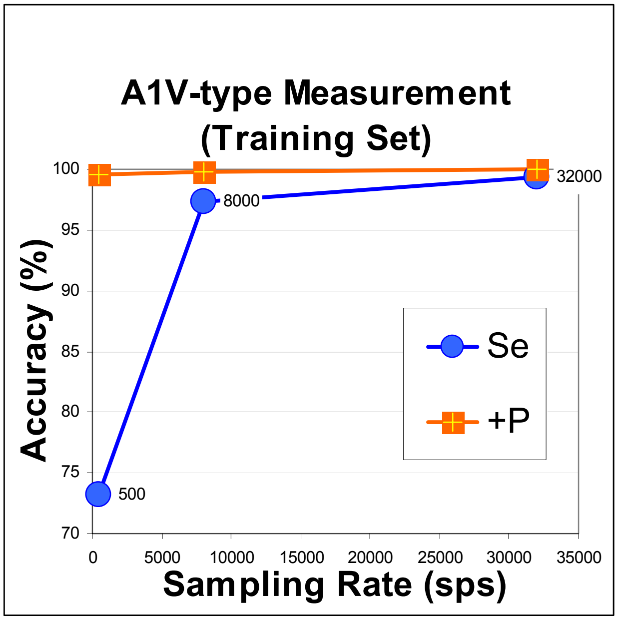

Figure 2. The A1V-type measurement for the training set (Spike Detection Evaluation)

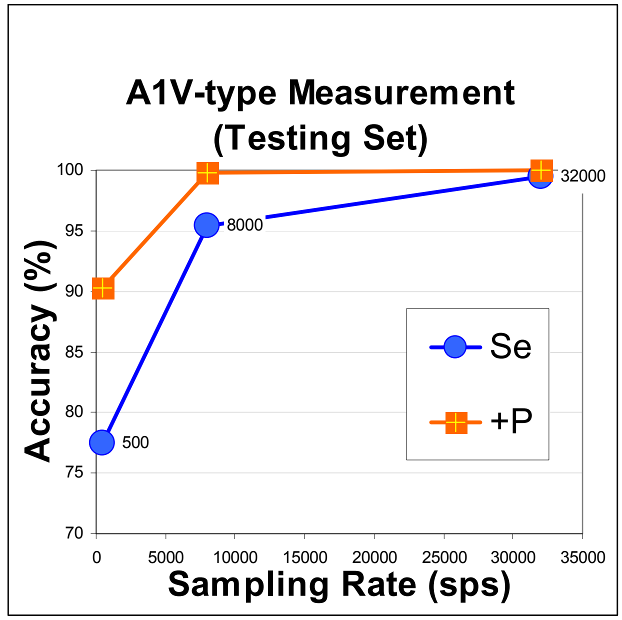

Figure 3. The A1V-type measurement for the testing set (Spike Detection Evaluation)

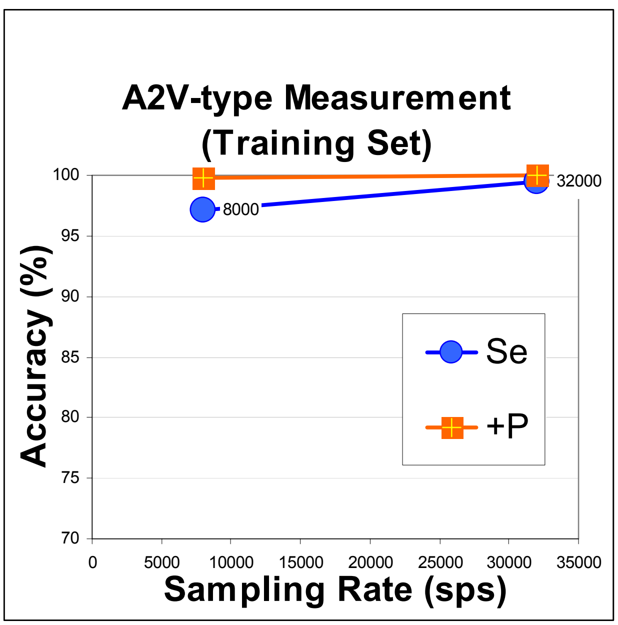

Figure 4. The A2V-type measurement for the training set (Spike Detection Evaluation)

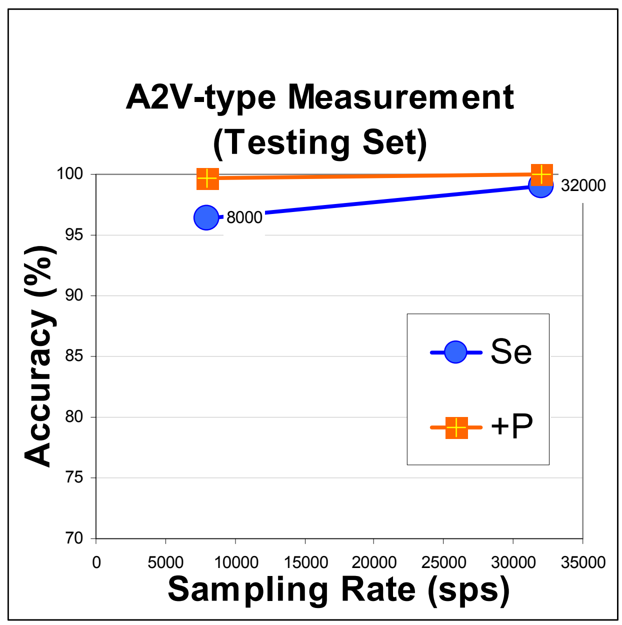

Figure 5. The A2V-type measurement for the testing set (Spike Detection Evaluation)

Further, Table 4 presents the performance of the detection algorithms for some lead combinations.

Table 4. The performance of the detection algorithm for some examples of the lead combinations (A2V-type measurement).

Lead Combinations	Accuracy (32-ksps stream)			
	Training Set (%)		Testing Set (%)	
	Se	+P	Se	+P
II & V_5	100.00	100.00	100.00	100.00
I & V_6	97.26	100.00	96.57	100.00

Lead Combinations	Accuracy (8-ksps stream)			
	Training Set (%)		Testing Set (%)	
	Se	+P	Se	+P
II & V_5	98.27	99.75	98.50	99.24
I & V_6	94.76	100.00	93.87	100.00

Moreover, Table 5 lists the misdetections for 5 pacer classifications of the spike detection algorithms with all lead combinations counted (8-ksps and 32-ksps streams).

Table 5. Misdetections of the detection algorithms for five classifications of spikes

Detectors for Data Stream	Training Set (%)				
	A	V	BiV	A-V	A-BiV
32-ksps	0.00	0.37	0.00	2.58	0.00
8-ksps	7.08	2.04	2.13	4.93	0.00

Detectors for Data Stream	Testing Set (%)				
	A	V	BiV	A-V	A-BiV
32-ksps	0.00	0.61	2.23	2.82	0.00
8-ksps	4.12	8.16	3.18	13.15	6.06

(2) Outcomes based on Dataset 2 and 3:

Over-detections were evaluated (see Table 6)

Table 6. Over-detections against Dataset 2 and 3

Datasets	Detector for 500-sps Stream	Detector for 8-ksps Stream	Detector for 32-ksps Stream
Dataset 2	179	0	0
Dataset 3		1103	80

4. Discussion

The detection algorithm based on the 12-lead 500-sps data stream has a good performance but is not able to identify Bi-Ventricular pacing due to its lower resolution. Also, it has an over-detection issue when noise is high.

The 8-ksps detector has a better performance. It is based on only two leads and might improve if more leads were to be used. For some pacemaker spike morphologies, it is hard to make the spike detection correctly.

The 32-ksps 2-lead detector has a near perfect detection performance. Lead combination selection, however, might change the performance. It could have a stable performance and be even better for static interference if one more lead is used.

Figures 2 to 5 and Table 3 show that over detection is not an issue for the detectors for 8-ksps and 32-ksps streams. The results support only to check misdetection for 5 pacer classifications of the spike detection without examining their over detection.

The Atria 3100/6100 can be used to collect both ECG and pacemaker stimuli, which can be processed for further study. Also, improved pacer spike detection algorithms from the study can be downloaded into the device to enhance performance in the field.

5. Conclusions

Recent advances in technology suggest that significant improvement in the detection of pacemaker stimuli is achievable. Digital pacemaker detection systems at 32 ksps or higher can provide almost 100% correct pacer spike detection information from body surface ECGs for routine clinical use.

Acknowledgements

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References

[1] Fairweather J, Johnston P, Luo S, Macfarlane P, Computer Analysis of Implanted Cardiac Pacemaker Rhythm, Computers in Cardiology 2007; 34: 193-6.

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