A Software-based Pacemaker Pulse Detection and Paced Rhythm Classification Algorithm

Eric D. Helfenbein, MS,* James M. Lindauer, MD,*
Sophia H. Zhou, PhD,† Rich E. Gregg, MS,‡ and
Earl C. Herleikson, MS‡

Abstract: A new pacemaker pulse detection and paced electrocardiogram (ECG) rhythm classification algorithm with high sensitivity and positive predictive value has been implemented as part of the Philips Medical Systems' (Andover, MA) ECG analysis program. The detection algorithm was developed on 1,108 paced ECGs with 16,029 individual pulse locations. It operates on 12-lead, 500 sample per second, 150 Hz low-pass filtered ECG signals. Even after low-pass filtering, this algorithm distinguishes between pacemaker pulses and narrow QRS complexes from newborns. An individual pulse detection sensitivity of 99.7% and positive predictive value of 99.5% was obtained by the multi-lead detector. A 10-second, 12-lead ECG database (n = 13,155) of paced (n = 2,190), non-paced adult (n = 8,070), non-paced pediatric (n = 1,209) and "noisy" ECGs with spike noise and muscle artifact (n = 1,686) was assembled and annotated by two readers. The overall performance in identification of an ECG as paced with any pacing present versus non-paced is 97.2% in sensitivity and 99.9% in specificity. The paced ECGs were classified by the mode in which the beats were paced, such as, atrial, ventricular, A-V dual, or dual/inhibited chamber (ie, combinations of atrial, ventricular and dual) pacing. An algorithm was developed for paced rhythm classification. The algorithm performance results show that accurate and robust pacemaker pulse detection and classification can be done in software on diagnostic bandwidth ECG signals. **Key words:** Resting ECG, diagnostic algorithm, pacemaker pulse detection, paced rhythm classification.

Implantable pacemakers, first introduced approximately 50 years ago, are being used with increasing frequency and have become more complex in their operation. There are approximately 1 million patients with implanted pacemakers in the United States and this number is increasing due to an aging population (1). The 12-lead resting electrocardiogram (ECG) continues to play a key role in pacemaker follow-up (2), but automated analysis is considered difficult due to pacemaker complexity and variability among models.

Approximately 2% to 5% of routine diagnostic

*From the Advanced Algorithm Research Center, Philips Medical Systems, *Milpitas, CA; †Oxnard, CA; ‡Andover, MA.*
Reprint requests: Eric D. Helfenbein, MS, Philips Medical Systems, 540 Alder Dr, Bldg 4, Milpitas, CA 95035; e-mail: eric.helfenbein@philips.com.

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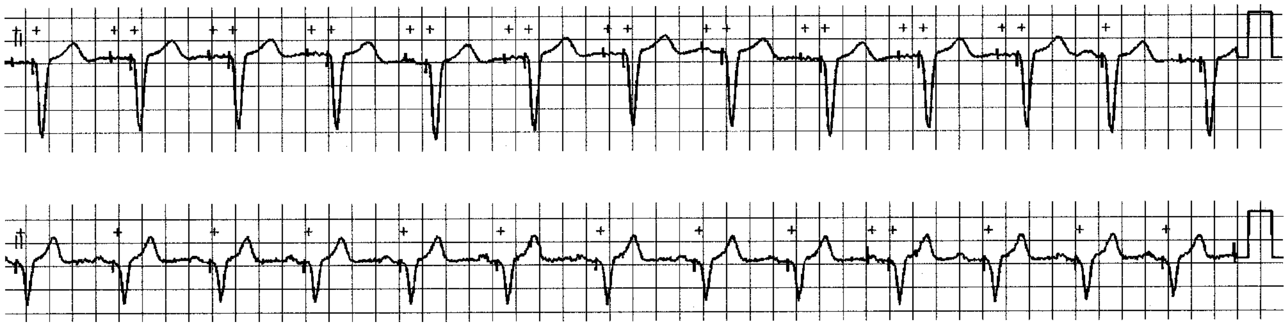

Fig. 1. Examples of dual pacing with intermittent inhibition of 1 chamber. In tracing (A), the atrial pulse is inhibited for the 12th beat. In tracing (B), the atrial pulse is inhibited, except for the 10th beat.

ECGs are acquired from subjects with implanted cardiac pacemakers. The automated diagnostic algorithm is expected to accurately identify the pacemaker pulses and to properly classify the basic rhythms of paced ECGs. The design of a paced ECG analysis algorithm consists of two stages, pacemaker pulse detection and paced rhythm analysis. The goal of pacemaker pulse detection is to accurately identify the location of pacemaker pulses in the ECG and to eliminate false detections due to muscle artifact, noise spikes, electrode artifact, and narrow QRS complexes. The goal of paced rhythm analysis is to provide an accurate and meaningful classification and interpretation describing the observed pacemaker's interaction with the cardiac rhythm.

Materials and Methods

Standard 12-lead resting ECGs were used in this study. The ECGs were acquired from a number of medical centers during 1995 to 2001 with Philips (Andover, MA) (formerly Hewlett-Packard) PageWriter Xli electrocardiographs. The ECGs were recorded on 12 simultaneous leads, for 10 s with diagnostic bandwidth (0.05-150 Hz) and stored at 500 samples per second. For purposes of developing and testing the pacemaker pulse detector and classification algorithm, 3 ECG databases were used.

Pacemaker Pulse Database

A pacemaker pulse database of 1,108 adult ECGs with a variety of pacemaker types and pacing modes was randomly selected for pacemaker pulse detection. This database contained 61 cases with atrial pacing, 746 cases with ventricular pacing and 301 cases with dual chamber pacers. The ECG records contained varying amount of noise and artifact. The "global" locations of 16,029 true pacemaker pulses across the multi-channel, 10-s ECGs were digitally annotated after visual examination using both 12-lead simultaneous rhythm strip printouts and a high resolution waveform display and annotation program.

Paced Rhythm Database

A paced-rhythm database was created with 2,190 paced ECGs. The ECGs in this database were classified into 5 groups based on observed paced rhythms. A 12-lead rhythm strip was used for ECG classification. There are 93 cases with atrial pacing, 1,385 cases with ventricular pacing, 477 cases with dual chamber pacing (both chambers paced when pacing present), 175 cases with dual chamber pacing with intermittent inhibition of one chamber (Fig. 1), and 60 cases with non capture/non sensing asynchronous pacing (fixed rate pacing with no pulse inhibition, usually due to placement of a pacemaker magnet) (Fig. 2) (3). The groups in this database contain both continuous and intermittent pacing.

Non-paced ECG Database

The non-paced ECG database contains a total number of 10,965 ECGs and was intended to stress the algorithm and to insure good specificity. This database includes 1,686 ECGs with extreme noise in one or more leads, 1,209 ECGs with narrow QRS complexes from newborns and the pediatric population randomly selected from an existing pediatric database, and 8,070 randomly selected non-paced adult ECGs.

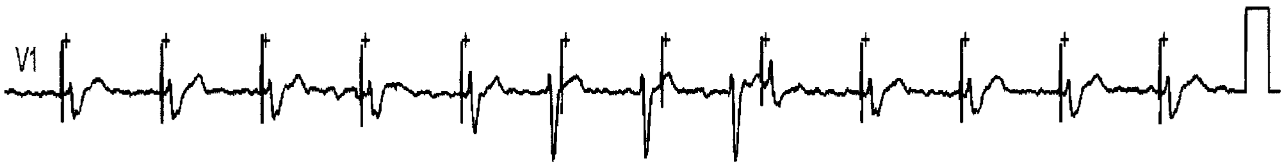

Fig. 2. Fixed-rate pacing with asynchronous rhythm due to pacemaker magnet placement. Pacemaker pulses are marked with (+).

Pacemaker Pulse Detection

Accurate detection of pacemaker pulse locations is required for pulse removal prior to QRS detection, for classification of the paced status of each beat (which will form the basis for paced rhythm classification and allow morphology analysis on atrial-paced and non-paced beats), and for identification of proper pacemaker function or malfunction. Because of the high-frequency nature of pacemaker pulses, their detection has traditionally been done in the front-end of electrocardiograph devices on high bandwidth signals (Fig. 3) (4). Many devices use special analog circuitry designed to detect the high signal slew rates typical of pacemaker pulses (5). These circuits, however, are prone to false detections. Other devices use a firmware based software algorithm in a front-end digital signal-processing chip or microprocessor that examines high-bandwidth, high-sample rate data, usually at the order of two to eight thousand samples per second (6). Another approach combines analog front-end detection with software pulse confirmation (7,8). The validity of the analog circuit detection is determined by examining low-pass filtered, diagnostic bandwidth signals for evidence of pulses. Analog detection without corresponding evidence is deleted, and assumed to be due to high frequency noise from the environment or artifact.

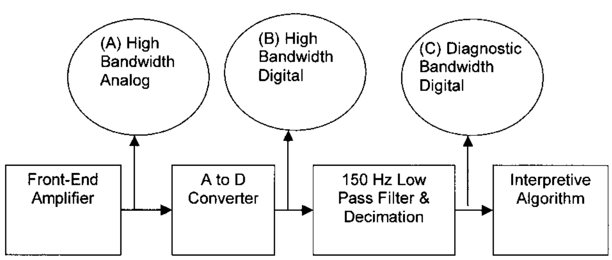

Fig. 3. Relevant key components in the ECG signal path in an electrocardiograph. Pacemaker pulse detection has been performed in locations (A), (B), and (A) and (C) together. We propose software detection on diagnostic bandwidth 500 sps signals in only (C).

In general, pacemaker pulse detection has not been performed by software only on low-pass (150 Hz) filtered signals. However, we wanted to explore the possibility of accurate pacemaker pulse detection based on diagnostic (0.05-150 Hz) bandwidth 500 sample-per-second ECG signals. Detection of pulses 0.5 ms wide on signals with a 2 ms. sample interval (ie, 500 sps) may initially seem infeasible; however, it is indeed possible because the low-pass filter broadens the pulse. If data acquisition, filtering, and decimation are performed correctly, the pulse will be represented with consistent amplitude and shape. However, the problem is that the filter attenuates the high frequency signal and greatly reduces the pulse amplitude, which makes it harder to detect. As the pulse gets narrower, the pulse seen after filtering becomes even more attenuated.

Current pacemakers generate small amplitude pulses with narrow widths, rather than the large, wide unipolar pulses seen in older pacemakers. The typical settings for current devices are in the range of 2 to 4 volt pulse output to the pacing electrodes with pulse width settings on the order of 0.2-0.5 ms. They are programmed to use minimal energy to conserve power, either adjusted manually by the clinician or with a capture test done daily by the device. The use of bipolar lead wires, conduction through the thorax, and the attenuating effect of projecting the bipolar pacing lead vector onto the standard 12-leads used for signal acquisition on the chest contribute to a significantly smaller pacemaker pulse signal being seen on the cardiograph.

The Association for the Advancement of Medical Instrumentation (AAMI) specification for cardiograph pulse detection at the input is 2 to 250 mV with 0.1 to 2.0 ms pulse width (9). Because these limits span a wide range, we wanted to determine what portion of this range was applicable to current pacers. Direct measurement of amplitude on the chest is difficult, because amplitude is dependent on the measurement system's bandwidth.

Working backwards from ECG records taken with a standard electrocardiograph from subjects with known pacemaker settings (3V, 0.2–0.4 ms width),

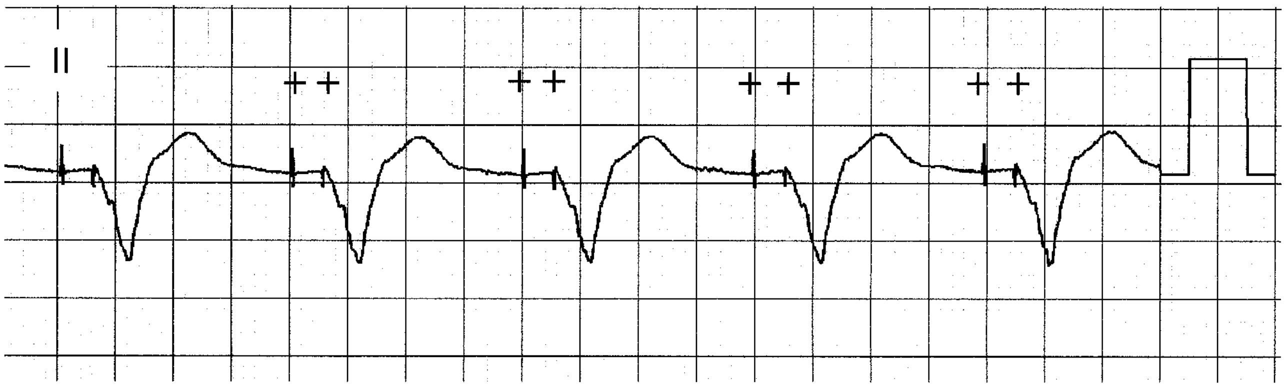

Fig. 4. Typical example of minimal energy dual-chamber pacemaker pulses in diagnostic bandwidth, 500 sps ECG. Pulse locations are marked with (+).

we estimated what surface voltages were necessary to generate the spike voltages observed in the tracings. Looking at the standard 12-lead with the maximum pulse amplitude of any lead, we estimated the surface voltage in the range of 2 to 4 mV. These values drop off to zero in leads perpendicular to the bipolar electrodes. These values correspond to the low end of the AAMI specifications.

After passing through the diagnostic bandwidth low-pass filter (150 Hz), the maximum pulse amplitude in the best lead is often attenuated to 400 to 800 μV. These values are given here to illustrate the potential difficulty in pulse detection at diagnostic bandwidth. If the pulses are small even on the best lead, the signals would be smaller on the other leads.

A typical example of minimal energy pacemaker pulses in diagnostic bandwidth 500 sample per second is shown in Figure 4, although in many cases the pulses are either significantly larger or

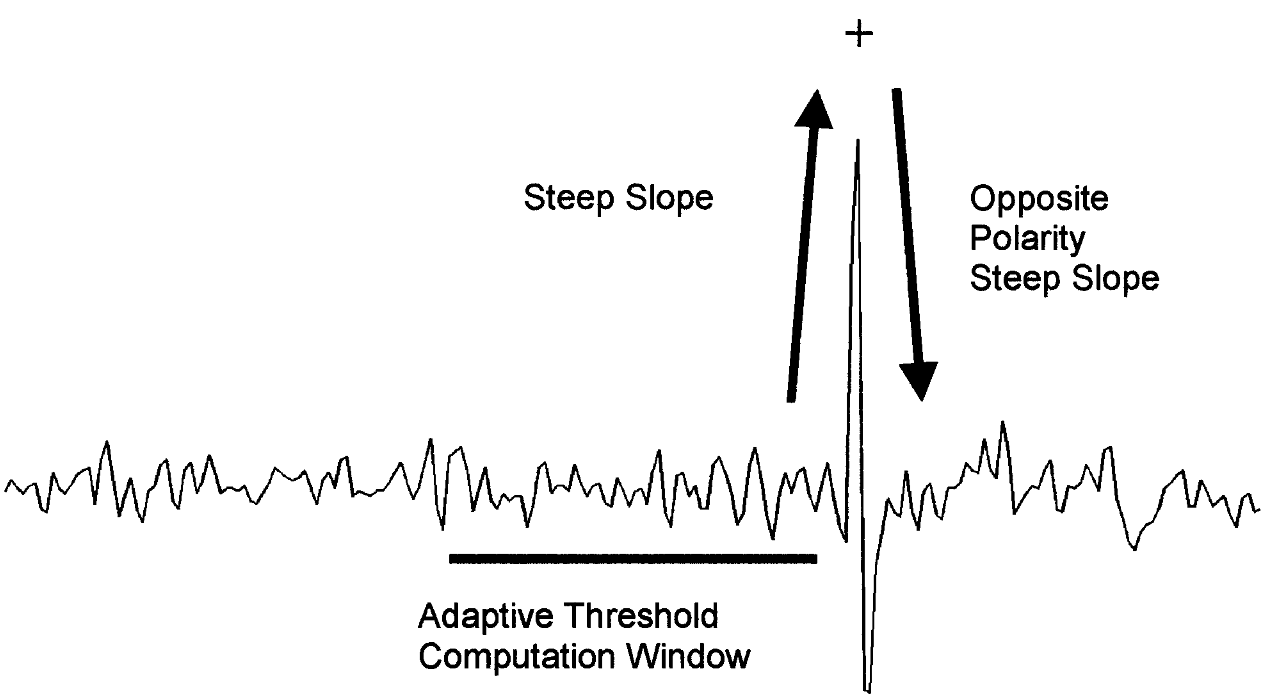

Fig. 5. Illustration of the pacemaker pulse detection algorithm. A steep slope exceeding a threshold must be followed by an opposite polarity slope within a time window for a pacemaker pulse (+) to be detected. The adaptive threshold is computed as a function of the maximum slope seen in a window preceding the detector.

Fig. 6. Noisy 12-lead ECG illustrating the pacemaker pulse detector's immunity to noise. There were no false pulse detections when the single-channel detector was run on the individual leads.

smaller. Although the amplitude is small, the pulse has steep rising and falling slopes. Taking advantage of this characteristic, a slope-based pulse detection algorithm with an adaptive threshold was developed and patented (10). The basic concept is that the detector looks for a signal slope whose absolute value exceeds a threshold, followed by an opposite polarity slope exceeding the threshold within a short time window (Fig. 5). The adaptive threshold is computed as a function of the absolute value of the maximum slope seen in a preceding time window. The distinguishing feature of this detector is the steep slope requirement for the trailing edge of the pulse. This algorithm was adapted and enhanced for use in the current application. The algorithm can detect pacemaker pulses as small as 35 μV in clean ECG data, but is quite insensitive to muscle artifact and many other types of noise (Fig. 6).

Another difficult task is predicting *a priori*, which are the best leads for pulse detection. Because atrial and ventricular pulse projections are different, detection in multiple leads is a necessity. An efficient design and implementation of our algorithm allows the detector to be run independently on 12 simultaneous leads. A multi-channel resolver algorithm has been developed to turn the independent lead detections into a final set of "global" pace pulse locations for the entire ECG. Although the leads are not independent, cross-lead simultaneity improves noise immunity (Fig. 7).

Paced Rhythm Classification

The primary goal of paced rhythm classification is to identify the chambers paced, and whether capture, appropriate sensing or obvious malfunctions are present. The secondary goal of this algorithm is to identify non-paced beats that can be used for

Fig. 7. The multi-lead pacemaker pulse detection algorithm detects pacemaker pulses (+) in the presence of noisy ECG leads.

morphology analysis. To handle noise spikes (Fig. 8), a robust algorithm was designed with a tradeoff between sensitivity on paced ECGs versus specificity on the greater proportion of ECGs from subjects without pacemakers.

With given pacemaker pulse locations, P waves and QRS complexes, the algorithm associates pacemaker pulses with a beat, classifies pacemaker pulses as atrial or ventricular, classifies each beat, determines the paced rhythm from the string of beat classifications, and identifies constant rate pacing, noncaptured pulses or inappropriately timed pulses. All relevant intervals between pulses, beats, and P waves are examined. An alpha-trimming clustering algorithm is used to look for patterns and reduce the effects of false-positive noise spike detection.

Programmed Pacemaker Modes

The NASPE and British Pacing and Electrophysiology Group (NBG) standardized a set of 3-5 letter codes used to describe the programmed mode of a pacemaker (11–13). However, it is usually not possible to uniquely identify the programmed mode of the pacemaker in a 10-s ECG tracing, as a variety of intrinsic events are needed to exercise the device. A list of compatible modes could be identified, but this seems impractical. The observed pacemaker rhythm as a subset of programmed behavior can be well described by the classification algorithm.

Results

Pulse Detector Performance

For detection of individual pulses in the pacemaker pulse database, the pulse detection and multi-lead resolver algorithm achieved a sensitivity of 99.7% with a positive predictive value of 99.5%. The 54 of 16,029 pulses missed were usually due to periods of muscle or electrode noise that inhibited

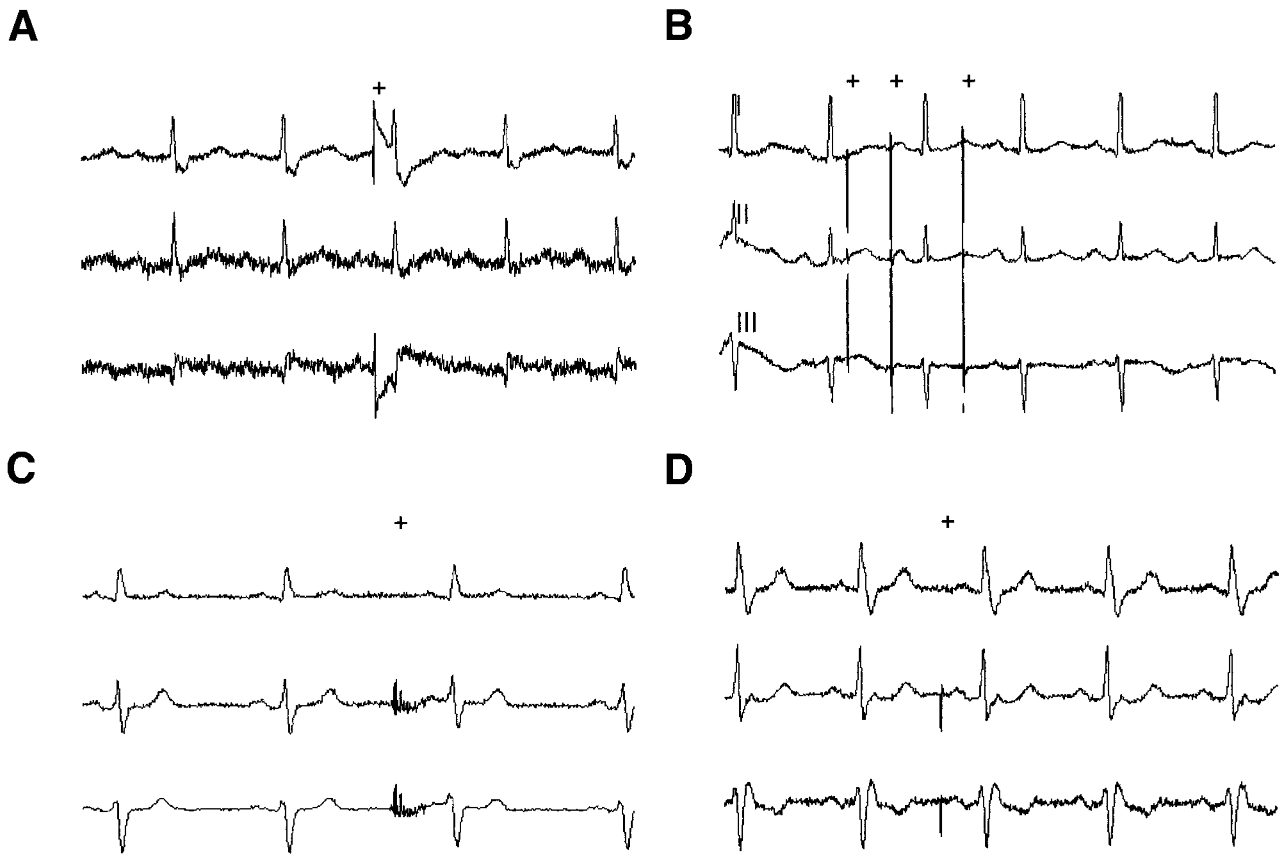

Fig. 8. Examples of noise spikes common in clinically acquired ECGs. Prevalence of these spikes detected as pacemaker pulses (+) requires a robust paced rhythm classification algorithm design.

the detector, or were extremely small atrial pulses. Of the 77 false positive detections, there were no false detections on adult QRS complexes. A few false positive detections were on muscle tremor spikes which managed to trigger the detector, but most were on sharp, isolated noise spikes of unknown origin. About half of these were during noise spike trains probably secondary to bad electrode contact. The rest were from isolated noise spikes.

Test Results on Narrow QRS Complex ECG Data

Eliminating false detection on narrow neonatal or pediatric QRS complexes is another major problem in algorithm development (Fig. 9). Running on diagnostic bandwidth ECG signals makes it even harder when pacemaker pulses are broadened by the low-pass filter. Our algorithm deals with this

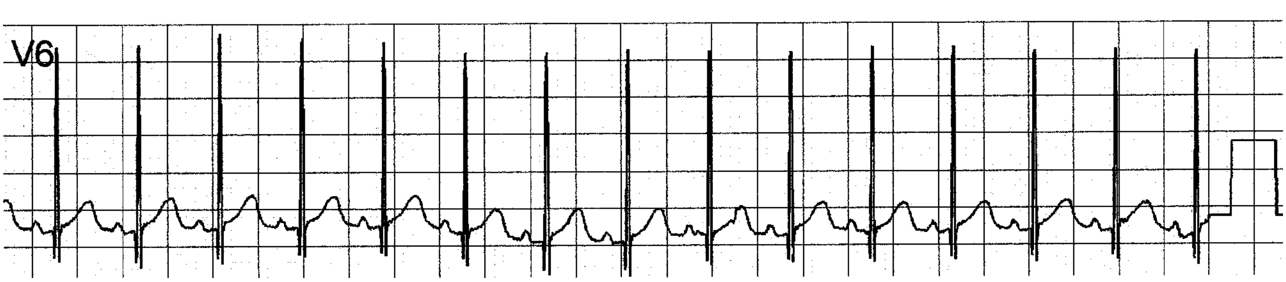

Fig. 9. Narrow QRS complexes from a 6-month-old girl. The pacemaker pulse detection algorithm distinguishes true pulses from these narrow complexes.

Table 1. Sensitivity and Positive Predictive Value of Paced Rhythm Classification

	No.	Sensitivity (%)	Positive Predictive Value (%)
Atrial	93	95.7	95.7
Ventricular	1385	95.5	97.1
Dual	477	95.4	91.2
Dual with intermittent inhibition of 1 chamber	175	57.7	76.5
Non sensing/asynchronous	60	65.6	95.2

problem successfully. When the multi-lead detector/resolver was run on 1,382 non-paced neonatal and pediatric ECGs, only 4 individual QRS complexes were falsely detected. A separate test has shown that our pacemaker pulse detector has excellent performance on pacemaker ECGs in the pediatric population.

Paced Rhythm Classification Results

Identification of a 10-s, 12-lead ECG as paced with any pacing present vs. non-paced achieved an overall performance of 97.2% sensitivity and 99.9% specificity. The 2.8% missed were usually due to presence of only a single paced beat. The 11 false positives were due to random noise spikes that happened to perfectly mimic a pacing mode.

As shown in Table 1, the 3 basic rhythms could be classified with 95% sensitivity with positive predictive value from 91 to 97%. Identification of dual pacing with intermittent inhibition of one chamber was more difficult, since one pacemaker pulse often made the difference in classification. Detection of asynchronous pacing is performed with a high positive predictive value.

Discussion

Our algorithm results demonstrate that accurate pacemaker pulse detection can indeed be performed on diagnostic bandwidth 500 sample per second 12-lead ECGs and used as the basis for paced rhythm classification.

The software only, diagnostic bandwidth approach to pacemaker pulse detection offers the following advantages. First, no analog hardware detection circuit is needed which translates to a lower device cost. Second, no special pacemaker pulse front-end signal processing is required, which reduces the device complexity. Third, the pacemaker pulse location markers from the front-end do not need to be stored and passed along since the pulse locations can always be found in the data, which enables subsequent re-analysis of the ECG record. Finally, since detection is conducted on readily available standard resting ECGs, no special high bandwidth pacemaker ECG database is required for detector development, testing, and future improvement.

Numerous automated pacemaker analysis and classification algorithms have been developed that require information from intracardiac electrograms and internal pacemaker activity (14–17). Another automated analysis algorithm uses a state transition approach employing data from a single lead, but does not identify failure modes (18). Garson has introduced a manual classification algorithm for paced ECG reading and teaching (19,20). Greenhut et al. (21) automated Garson's algorithm using both a surface and esophageal lead to perform cycle-by-cycle analysis. Our algorithm uses only the surface ECG.

We found that fully describing all aspects of paced ECGs without *a priori* knowledge of pacemaker programming or internal telemetry from the device is a challenging task for the ECG analysis algorithm. Device specific interrogator/programmers will always have an advantage over the resting ECG diagnostic algorithm because of their ability to interrogate the internal state of the pacemaker. Nevertheless, the 12-lead resting electrocardiogram will continue to be used routinely and for pacemaker follow-up on thousands of subjects with pacemakers. The detector and classifier we have developed meet this need through 1) identification of pacemaker pulse locations without the use of analog hardware, 2) identification of atrial-paced and non-paced QRS complexes for morphology analysis, 3) identification of asynchronous pacing, and 4) robust classification of the observed paced rhythm.

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