Performance Challenges in Current Multi-lead QRS Detection Systems

Maxim Dashouk, Zhe Zhang, Carolyn Lall, Yu Chen

Draeger, Andover, MA, USA

Abstract

Modern QRS detectors in patient monitoring systems must provide accurate results even when interfering noise is present. This task is complicated by the heterogeneous and non-uniform nature of the patient population. Certain beat morphologies demand a significant increase in the complexity of beat detection algorithms. At the same time, it is important to take a system-wide approach to the beat detection problem and include artifact rejection and baseline correction challenges. Here we emphasize the importance of such an approach to be able to successfully handle non-trivial input data. We also explain how this approach can improve the QRS detection performance in commercial patient monitoring systems. The performance benchmarks are presented by being tested on proprietary and public ECG databases.

1. Introduction

This paper outlines some performance challenges faced by QRS detection systems in commercial patient monitors. The QRS detection system is a vital part of the patient monitoring system. It is tasked with detecting ventricular contractions from surface electrocardiograms (ECG). Such information is used by advanced functions of a monitor, i.e. QRS classification and arrhythmia detection. Thus, together with ECG pre-processing, the QRS detection system confronts strict performance requirements. Failure to correctly detect QRS complexes propagates further into the analysis and undermines performance of the system as a whole.

Modern patient monitoring systems must operate under stringent performance requirements and client demands. On one hand patient monitors are regulated by standards established by AAMI [1], these standards outline minimum expected performance from the monitors. On the other hand improving computational capacity of embedded systems raises expectations of users in terms of additional features and capabilities, especially in high-end patient monitors.

The patient population is also constantly changing. Introduction of various cardiac assist devices, pacemakers and implantable defibrillators into the population affects the expected surface ECG in patient monitors. For example, ventricular assist devices change both the morphology and the amplitude of QRS complexes as seen on a surface ECG. To ensure reliable performance, manufacturers of patient monitors must be aware of these new clinical methods for treatment of heart related diseases.

In this paper, we discuss performance challenges faced by current multi-lead QRS detection systems. We particularly focus on QRS double-counting and false asystoles. Both challenges make significant contribution to overall satisfaction of a customer with a patient monitor. However, the challenges entail solving contradictory problems and demand additional algorithmic complexity in QRS detection systems. This paper addresses these issues in detail.

2. QRS double-counting

The authors use the term of QRS double-counting to define a QRS detection scenario when non-QRS elements of the surface ECG get detected as QRS complexes. One example is tall, abnormally strong P or T-waves that are counted as QRS complexes. Established methodology of QRS detection widely adopted by the patient monitoring industry [2] is vulnerable to such scenarios. In particular, the method utilizes non-linear techniques to transform and merge multi-lead ECG input to get a single signal to search for QRS candidates. What usually gets lost is the multi-lead diversity that could be used to otherwise improve the performance. T-waves might display different strength relative to QRS complexes in different leads. Figure 1 gives an example when T-waves are accentuated and exceed QRS complexes in a chest lead but they are relatively weak compared to QRS in a limb lead. Typically a patient monitor utilizes both chest and limb lead inputs. Therefore, it is practical to add rejection of tall T- and P-waves and other non-QRS morphology elements to the QRS detection system by exploiting morphological and strength differences between QRS and T- and P-waves in different input leads.

The task of distinguishing tall T-waves from ventricular contractions by differences in their morphology is, however, non-trivial in a real-world patient monitor. A patient monitor must detect QRS complexes in near-real-time [1]. Under this constraint, a QRS detection system cannot delay its results until it 'peeks' into the future beats. A developer of a tall T-wave rejection algorithm should rather focus on morphological and temporal differences between tall T-waves and abnormal QRS complexes. For instance, Figure 2 gives an example of beat with tall T-wave and a beat followed by a premature ventricular contraction (PVC). On the figure, the PVC can be discriminated from the tall T-wave both morphologically and by the distance from the preceding normal sinus QRS complex. Development of a tall T-wave rejection algorithm would therefore entail exploiting such differences that are valid over a wide patient population. This paper later introduces testing results of developing such an algorithm.

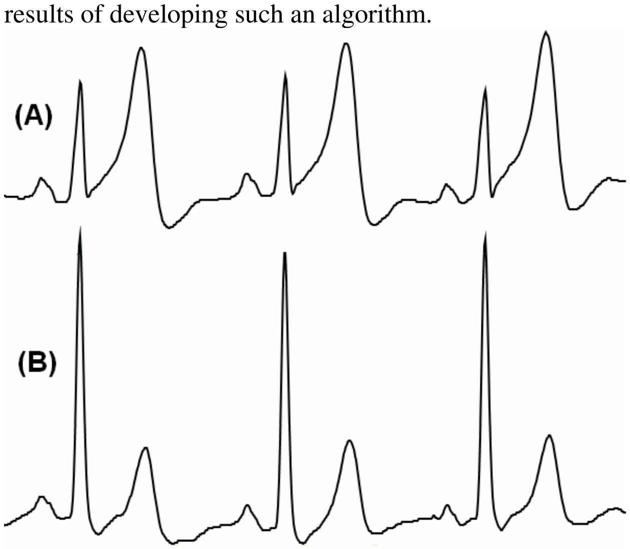

Figure 1. T-waves in this example are more prominent in a chest lead (A) than in a limb lead (B).

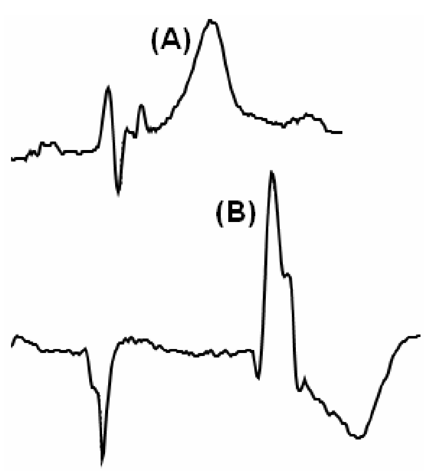

Figure 2. Tall T-wave (A) differs from PVC (B) both morphologically and temporarily.

3. False asystoles

False asystoles in patient monitors are caused in most cases by a surface ECG signal of insufficient strength. AAMI standards [1] state that a patient monitor must detect QRS complexes greater than 0.5mV and must not detect QRS complexes less than 0.15mV, with most commercial patient monitors using a dynamic QRS detection threshold between these two requirements. However, patient monitor users often expect the monitor to be able to correctly analyze signals of amplitude below the required AAMI standard when no noise is visibly present. This requirement conflicts with the fact that ECG monitors are designed to analyze noisy input (due to electric interference, motion artifacts, poor electrode preparation etc.) by considering only signals exceeding some minimum threshold to limit contribution of noise to the analysis.

The only way a manufacturer of ECG monitors can address demands of users to analyze insufficiently strong surface ECGs is by dropping the minimum QRS detection threshold. However, this introduces new challenges due to the fact that previously invisible morphological elements become detectable under new relaxed threshold requirements. The following sections discuss some of these challenges and possible ways to address them.

3.1. Ventricular standstill

Ventricular standstill, or P-wave asystole, is a life-threatening cardiac condition characterized by absence of ventricular electrical activity [3]. P-waves, however, might be present as on Figure 3. If an unsophisticated QRS detection system uses reduced minimum detection threshold, there is a high risk that P-waves will get detected and counted as QRS complexes due to absence any other periodic ECG features. As a result, a clinical staff will never be alerted by the patient monitor, the condition will be left untreated and the patient is not going to survive.

Figure 3. P-wave asystole rhythm is characterized by stopped ventricular activity but still contains P-waves.

The way to avoid such scenarios is to introduce additional complexity to the QRS detection system to detect established P-wave asystoles. Figure 3 highlights similarity between consecutive P-waves in their morphology and also their periodicity. A straightforward P-wave asystole detection algorithm would analyze a number of consecutive QRS candidates and intervals between them. Once it establishes that all the candidates are similar between each other and resemble P-waves by most significant P-wave criteria and also highly periodic, then all such QRS candidates cannot be valid QRS complexes and they have to be rejected from this point on. In addition, one should be aware of wide but weak periodic QRS complexes that might resemble P-waves during P-wave asystole. This scenario presents additional challenge for a P-wave asystole rejection algorithm.

3.2. Third-degree atrioventricular block

Third-degree atrioventricular (AV) block (i.e. complete heart block) is a potentially life-threatening arrhythmia that can progress to ventricular standstill without warning [3]. Figure 4 presents an example of complete heart block taken from the same patient as on Figure 3 immediately before the ventricular standstill.

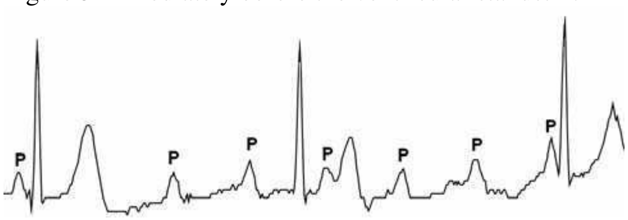

Figure 4. Third-degree AV block is characterized by P-waves (marked with ‘P’) contracting at their own rate independently from the ventricles.

During complete heart block, atrial and ventricular activities occur at their own rates and they do not affect each other [3]. From the QRS detection standpoint, low ventricular rate of ~30 beats per minute combined with atrial rate at least twice as high presents a challenge for a QRS detection system with reduced minimum detection threshold. P-waves mistakenly detected as QRS complexes might establish themselves as a dominant beat type due to their prevalence in the rhythm with low-rate ventricular contractions. As a result, a life-threatening condition is not detected and an incorrect heart rate is given.

Similarly to ventricular standstill, complete heart block demands introduction of additional morphological analysis into the QRS detection system. The analysis shall focus on morphological differences of P-waves from a wide range of QRS complexes. Once P-waves are discriminated, the third degree AV block detection algorithm would reject any QRS candidate that resembles a P-wave according to a predefined set of features. Again, a normal sinus rhythm with PVCs serves as a counterexample of what the complete heart block rejection algorithm must be aware of so that not to confuse it with the third-degree AV block.

3.3. Artifacts and baseline wander

An ECG patient monitoring system is required to be robust to noisy inputs. The main contributors of noise are electrical interference, motion of a subject and electrode preparation. While electrical interference is usually of high-frequency nature and can be suppressed using conventional filtering techniques, motion results in low-frequency distortions of the surface ECG signal. Some distortions, like baseline wander can be filtered given tolerance to output delay. But other distortions present a non-trivial challenge to development of a QRS detection system. In Figure 5, a non-cardiac muscle contraction creates an artifact, that would usually be detected as a QRS complex due to its resemblance to a PVC. Recognizing such artifacts normally demands additional delay to analyze surrounding context of the event. Also, a developer faces a challenge to avoid rejection of true PVCs that morphologically resemble motion artifacts. However, advanced artifact rejection algorithms can be developed to assess the signal quality of each lead to determine which lead(s) have minimal artifact distortion and are suitable to be used in QRS detection. An example of such an approach is described in [4]. There, an additional feedback loop is introduced to an ECG analysis system that exploits multi-lead diversity to reject various low-frequency artifacts.

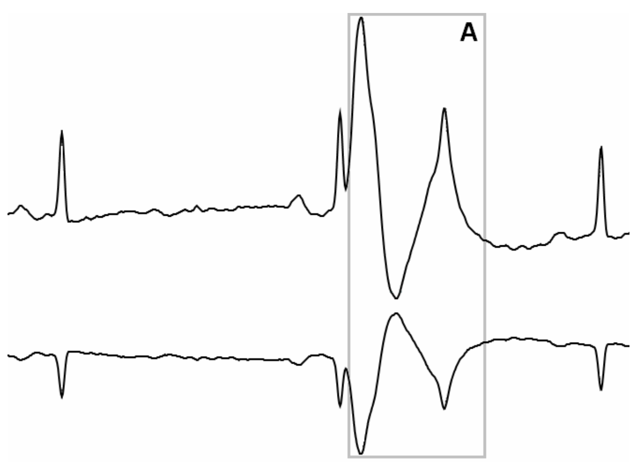

Figure 5. A low-frequency artifact (A) introduced by muscle contraction.

4. Results

The authors designed an enhanced QRS detection system that addresses the challenges described in this paper. The system includes additional measures to: a) prevent double-counting of tall T-waves and P-waves as QRS complexes, b) detect complete heart block and P-wave asystole, and c) reject low-frequency motion artifacts.

The authors emphasize the importance of using modern clinical data to reflect current population trends for this study. For this purpose, the pool of test ECGs is largely composed of proprietary database records which include data from telemetry, ICU and OR patient monitors. In addition, public databases were added to the pool [6]. Overall, the test database spans approximately 1000 different patients and approximately 290 000 QRS candidates.

Testing of the enhanced QRS detection system was conducted in three stages. First, the baseline QRS detection system that does not address any of the problems outlined in the paper is tested against the ECG database. Second, the QRS detection threshold was reduced to illustrate improvements in false asystole handling. Finally, the complete enhanced system is tested to reduce the number of false beats introduced by dropping the minimum QRS detection threshold.

The results of the last two stages of this testing are presented on Table 1. The table presents the percentage of false beats detected and missed beats for the last two stages of the testing.

	Stage 2: Lower QRS Detection Threshold	Stage 3: Enhanced QRS Detection System
False beats	0.29 %	0.04 %
Missed beats	0.03 %	0.03 %

Table 1: Percentage of false and missed beats in the last two stages of the testing.

Table 1 confirms that dropping the minimum detection threshold (Stage 2) solves the problem of missed beats due to false asystoles but introduces more noise to the system, which is reflected the increased false beat rate. Additional algorithms added in Stage 3 that analyze QRS candidates by their morphology and timing resolve the issue with minimum negative effect on missed QRS complexes.

5. Conclusion

This paper highlights problems that arise in development of QRS detection systems for patient monitors. Demand to reduce false asystole alarms in real-life clinical environment by reducing minimum signal detection level conflicts with low tolerance to false QRS complexes. Such contradictory system requirements can only be resolved with algorithms that reject false QRS candidates, based on their morphology and timing. Additional steps to limit contribution of motion artifacts must also be taken. The presented enhanced QRS detection system addresses the challenges discussed in this work. The included results illustrate the effect that each of the solutions contributes to the overall performance of the QRS detection system.

References

[1] American National Standard. Cardiac monitors, heart rate meters, and alarms. ANSI/AAMI EC13:2002.

[2] Pan J, Tompkins W. A real-time QRS detection algorithm. IEEE Trans. Biomed. Eng. 1985;BME-32:230-6.

[3] Huff J. ECG Workout. Excercises in Arrhythmia Interpretation. 5th ed. Lippincott Williams & Wilkins; 2006.

[4] Zhang Z, Lall C, Chen Y. Stability analysis of QRS features to evaluate signal quality for multi-lead QRS detection. To appear in IEEE EMBC; 2011; Boston.

[5] Kojic EM, Hardarson T, Sigfusson N, Sigvaldason H. The prevalence and prognosis of third-degree atrioventricular conduction block: the Reykjavik study. *J Intern Med.* Jul 1999;246:81-6.

[6] PhysioBank. www.physionet.org/physiobank/

[7] Duda R, Hart P, Stork D. Pattern Classification. 2nd ed. New York: John Wiley & Sons; 2001.

Address for correspondence:

Yu Chen, PhD

Algorithm Manager
Monitoring, Systems & IT
Draeger Medical
6 Tech Drive, Andover, MA, 01810, USA.
yu.chen@draeger.com.