EVALUATION OF REAL-TIME BIOSIGNAL QUALITY ANALYSIS FOR AMBULATORY ECG WITH ST-SEGMENT DEVIATIONS

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INTRODUCTION

Major cardiac complications, such as cardiac death and nonfatal myocardial infarction, are experienced by over half a million patients undergoing noncardiac surgery around the world each year [1]. These complications result in, at minimum, an increase in patient length of stay (LOS) and consequently an increase in the cost of health care provision [2].

Following findings from the Perioperative Ischemic Evaluation (POISE) trial [2], the Perioperative Ischemia Reduction (PROSE) study seeks to evaluate the effects of ß-blocker administration to noncardiac surgical patients experiencing myocardial ischemia. Myocardial ischemia is detectable via slow changes in the ST-segment of a patient's electrocardiogram (ECG) [3]. PROSE uses a commercially supplied myocardial ischemia detection system to monitor patient ECGs during ambulating recovery (i.e., ambulatory ECG) following noncardiac surgery; however, issues associated with ambulatory ECG signal quality resulted in a significant false alarm rate (one case presented 148 false positives within a 48 hour period)[4].

PROSE developed a supplementary 'white box' system that employed sliding windows to filter sudden spikes in ST-segment deviations [4]. Despite these efforts, the false alarm rate remained significant (e.g. 50 false positives were generated over the same 48 hour period mentioned above). The high false alarm rate renders the current PROSE setup impractical.

The findings presented in this paper are part of on-going efforts to design and implement a supplementary system that will reduce the false alarm rate (i.e. increase the specificity) of the commercial ischemia detection algorithms while maintaining sensitivity.

BACKGROUND

Gating False Alarms

Reduction of false alarms from the commercial ischemia detection system will be achieved through alarm gating based on signal quality. While the commercial system monitors patient ECG for ST-segment deviations, a parallel system will also monitor patient ECG with the aim of establishing a real-time estimate of the signal quality. The parallel system will then suppress alarms generated by the commercial system during periods of poor signal quality.

Biosignal Quality Analysis

The analysis of biosignal quality presents a challenge as the source signal is not completely known and varies between individuals [5]. Only the observed signal is available for analysis, which is often contaminated by unknown quantities of noise, such as electromyographic (EMG) artifacts and motion artifacts [6].

Previous work on biosignal quality analysis with respect to ECG has been typically geared toward robust heart rate detection, arrhythmia analysis or contaminant mitigation strategies. Biosignal quality analysis relating to heart rate detection and arrhythmia analysis frequently employ other cardiac measures (e.g. multiple leads [7], photoplethysmography [8]) in their analysis or focus on large artifacts [9], which would fail to detect smaller artifacts that impact analysis of ST-segment deviations. Mitigation strategies can likewise be ill-suited for ST-segment analysis, given their potential to distort aspects of the ECG waveform [10].

The real-time biosignal quality analysis algorithm outlined in [11] leverages the repetitive nature of ECG to perform quality analysis on a single ECG lead. The algorithm generates an average PQRST waveform (one complete heart beat in the ECG) from a sliding analysis window, which is used as an estimate of the patient's "true" ECG (i.e., without any noise contamination). This estimate of "true" ECG is compared with each observed PQRST waveform in the analysis window to estimate the signal-to-noise ratio (SNR). Additional details of the algorithm can be found in [11].

Status of Algorithm Validation

Development of the biosignal quality algorithm described above was validated using ECG recordings retrieved from the PhysioNet Long-term ST Database [12], [13] that did not contain motion artifact or ST-segment deviations (confirmed by visual inspection) [11]. As mentioned previously, the algorithm functions by comparing each PQRST waveform to an expected template and then regarding any differences as noise. Consequently, the changing ST-segment deviations affiliated with myocardial ischemia have potential to affect the performance of the algorithm; specifically, ST-segment deviations could be interpreted as noise, resulting in the algorithm falsely suppressing alarms.

This paper seeks to evaluate the performance of the biosignal quality analysis algorithm presented in [11] when it is applied to ambulatory ECG signals containing ST-segment deviations.

METHODS

Generation of Analysis Windows

Analysis windows were composed of a combination of recorded ECG data from the Long-term ST Database and recorded motion artifact from the MIT-BIH Noise Stress Test Database [14]. Each analysis window contained 16 complete heart beats. ECG data consisted of 28 minutes and 47 seconds of a single patient's recording ('s20031'; channel 0), during which the ST-segment deviated from normal and achieved a maximum deviation of 322 µV before returning to normal. Figure 1 illustrates

ECG data with and without ST-segment deviations. ST annotation codes saved with the record in the Long-term ST Database were used to confirm the maximal ST-deviation and that the ST-episode was ischemic. Signals were deemed contaminant free by visual inspection.
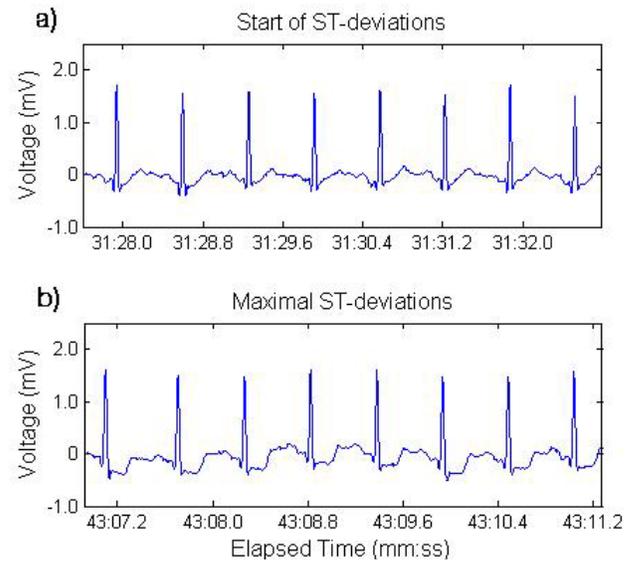
Figure 1: ECG taken from the Long-Term ST Database record 's20031'; channel 0. (a) ECG prior to an episode of ST-segment deviations, (b) the episode's maximal ST-segment deviations.

Motion artifact from the MIT-BIH Noise Stress Test Database ('em'; channel 3) was used to contaminate the ST-deviated ECG data. This is the same motion artifact recording as was used in [11]. The motion artifact was scaled and added to ST-deviated data to produce analysis windows with calibrated SNR levels by following the procedure outlined in [11]. The result was 200 analysis windows calibrated for each level of SNR between -10 dB and 10 dB in 5 dB increments for a total of 1000 analysis windows.

SNR Estimation

Each calibrated analysis window was run through the biosignal quality analysis algorithm, which averaged all beats within the window in order to estimate the window's SNR as described in [11]. This process analyses each of the 16 PQRST waveforms in the analysis window by subtracting the template provided

by the window's average PQRST waveform. The RMS difference between each beat and the template is taken as an estimate of the noise power, which is used to calculate the SNR. A total of 1000 SNR estimates (SNR_{window}) were generated for the calibrated SNR levels (SNR_{cal}).

RESULTS

Previous results revealed that there was indeed correlation between SNR_{window} and SNR_{cal} (r=0.93) when the biosignal quality analysis algorithm was run on ECG data without ST-segment deviations [11]. The relationship between SNR_{window} and SNR_{cal} for ECG data with ST-segment deviations exhibits the same correlation strength (r=0.93). The relationships between SNR_{window} and SNR_{cal} for both the normal ECG (without ST-segment deviations) and the ST deviated ECG (with ST-segment deviations) are shown below in Figure 2.
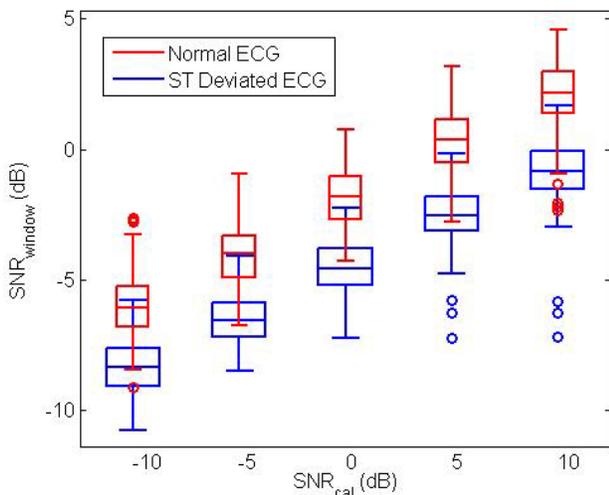
Figure 2: Comparison of SNR estimation algorithm outputs for ECG with and without ST-deviations.

DISCUSSION

The similarity between correlation coefficients for the ECG data without ST-segment deviations and the ECG data with ST-segment deviations is likely impacted by the fact that the motion artifact record used for contamination was the same for both cases. This similarity between correlation coefficients indicates that biosignal quality analysis

algorithm offers comparable performance both with and without ST-segment deviations.

The relationship visible in Figure 2 demonstrates a linear relationship between the estimated SNR values, SNR_{window}, and the actual level noise present in the signal. It can be seen that there is an offset and scaling difference between the estimated SNR values and their true value. Additionally offsets exist between ECG data with and without ST-deviations, which is likely due to variation in quality between records in the Long-term ST Database. Offsets can be easily accounted for when establishing thresholds for gating false alarms generated by the commercial system.

The spread of SNR_{window} values for a specified SNR_{cal} level is predominantly influenced by two factors. First, the SNR calibration procedure uses windows to scale the noise by finding the average motion artifact power over the whole window [11]. Thus within a calibration window, some portions of the signal will have more or less power than others.
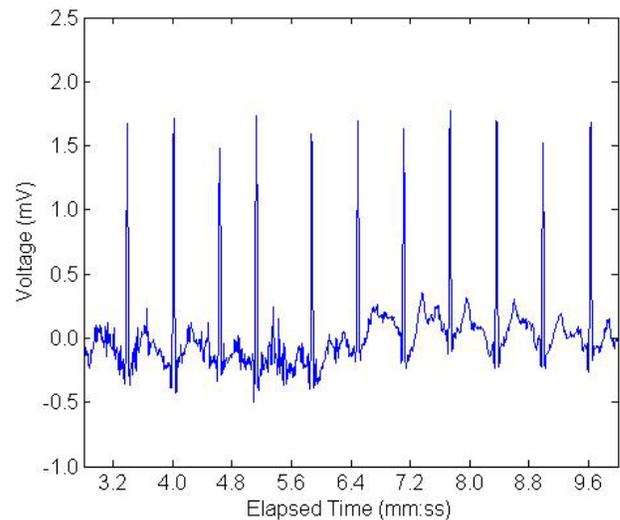
Figure 3: Differences in noise power within a single analysis window.

Figure 3 illustrates varying amounts of noise within a single calibration window. Consequently, some PQRST waveforms to which the noise is added will have higher SNRs than others. Second, the original ECG data were considered free from contaminants by visual inspection; however, this refers to significant contamination such as motion

artifact or severe baseline wander. While these signals have been deemed contaminant free, they still contain some small scale contaminants, which also affect the spread and SNR estimates for a given calibrated SNR level.

CONCLUSION

These results indicate that the biosignal quality analysis algorithm described in [11] is able to produce SNR estimates that reflect the quality of the signal under analysis, regardless of the presence of ST-segment deviations. The findings indicate that the biosignal quality analysis algorithm does not falsely interpret ST-segment deviations as noise. Therefore, these real-time estimates could potentially be used to gate alarms generated by a commercial myocardial ischemia detection system to suppress alarms generated during periods of poor signal quality with the aim of increasing the commercial system's specificity while maintaining its sensitivity.

Current SNR calculations are based on RMS estimates of signal and noise power; future work will examine the effects of alternate SNR metrics. Future work will also see the real-time implementation of the algorithm via QRS detection in lieu of using annotated records from the PhysioNet databases. Additionally, threshold values will be established for appropriate gating of the commercial myocardial ischemia detection system's alarm output. Ultimately, future work will see the implementation of a parallel biosignal quality analysis system for integration with the commercial detection system.

REFERENCES

[1] P. J. Devereaux, "Perioperative cardiac events in patients undergoing noncardiac surgery: a review of the magnitude of the problem, the pathophysiology of the events and methods to estimate and communicate risk," *Canadian Medical Association Journal*, vol. 173, no. 6, pp. 627–634, Sep. 2005.

[2] P. J. Devereaux, H. Yang, S. Yusuf, K. Guyatt, K. Leslie, J. C. Villar, D. Xavier, S. Chrolavicius, L. Greenspan, J. Poque, P. Pais, L. Liu, S. Xu, G. Málaga, A. Avezum, M. Chan, V. M. Montori, M. Jacka, and P. Choi, "Effects of extended-release metoprolol succinate in patients undergoing non-cardiac surgery (POISE trial): a randomised controlled trial," *The Lancet*, vol. 371, no. 9627, pp. 1839–1847, May 2008.

[3] F. Badilini, M. Merri, J. Benhorin, and A. J. Moss, "Beat-to-beat quantification and analysis of ST

displacement from Holter ECGs: a new approach to ischemia detection," in *Proceedings of Computers in Cardiology*, 1992, pp. 179–182.

[4] B. Haider and H. Yang, "PROSE 3: Early Ischemia Detection Using Digitized ST Values," in *Rehabilitation Engineering and Assistive Technology Society of North America (RESNA) Conference*, Toronto, ON, 2011.

[5] A. D. C. Chan, M. M. Hamdy, A. Badre, and V. Badee, "Wavelet Distance Measure for Person Identification Using Electrocardiograms," *IEEE Transactions on Instrumentation and Measurement*, vol. 57, no. 2, pp. 248–253, Feb. 2008.

[6] T. He, G. Clifford, and L. Tarassenko, "Application of independent component analysis in removing artefacts from the electrocardiogram," *Neural Computing & Applications*, vol. 15, no. 2, pp. 105–116, Apr. 2006.

[7] G. D. Clifford, D. Lopez, Q. Li, and I. Rezek, "Signal quality indices and data fusion for determining acceptability of electrocardiograms collected in noisy ambulatory environments," in *Computing in Cardiology*, 2011, pp. 285–288.

[8] C. Yu, Z. Liu, T. McKenna, A. T. Reisner, and J. Reifman, "A Method for Automatic Identification of Reliable Heart Rates Calculated from ECG and PPG Waveforms," *J Am Med Inform Assoc*, vol. 13, no. 3, pp. 309–320, Feb. 2006.

[9] S. J. Redmond, N. H. Lovell, J. Basilakis, and B. G. Celler, "ECG quality measures in telecare monitoring," in *30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2008, pp. 2869–2872.

[10] A. Fasano, V. Villani, and L. Vollero, "Fast ECG baseline wander removal preserving the ST segment," in *Proceedings of the 4th International Symposium on Applied Sciences in Biomedical and Communication Technologies*, New York, NY, USA, 2011, pp. 56:1–56:5.

[11] P. X. Quesnel, A. D. C. Chan, and H. Yang, "Real-time biosignal quality analysis of ambulatory ECG for detection of myocardial ischemia," in *2013 IEEE International Symposium on Medical Measurements and Applications Proceedings (MeMeA)*, Ottawa, ON., 2013.

[12] A. L. Goldberger, L. A. N. Amaral, L. Glass, J. M. Hausdorff, P. C. Ivanov, R. G. Mark, J. E. Mietus, G. B. Moody, C.-K. Peng, and H. E. Stanley, "PhysioBank, PhysioToolkit, and PhysioNet Components of a New Research Resource for Complex Physiologic Signals," *Circulation*, vol. 101, no. 23, pp. e215–e220, Jun. 2000.

[13] F. Jager, A. Taddei, G. Moody, M. Emdin, G. Antolic, R. Dorn, A. Smrdel, C. Marchesi, and R. G. Mark, "Long-term ST database: A reference for the development and evaluation of automated ischaemia detectors and for the study of the dynamics of myocardial ischaemia," *Medical and Biological Engineering and Computing*, vol. 41, no. 2, pp. 172–182, 2003.

[14] G. B. Moody, W. E. Muldrow, and R. G. Mark, "A noise stress test for arrhythmia detectors," presented at the Computers in Cardiology, 1984, vol. 11, pp. 381–384.