Improving the Accuracy of Atrial Fibrillation Detection in Lossy ECG Streams

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Abstract

Continuous physiological monitoring is often the best available tool for detecting and treating asymptomatic, intermittent pathologies like Atrial Fibrillation. A particularly effective algorithm is based on the variance of inter-beat intervals. This algorithms relies on the detection of the QRS complex and is thus fairly robust to noise. Unfortunately, we find that the algorithm is very susceptible to lost data and can quickly degrade even when small parts of the ECG stream are missing. For home-based environments with small devices and wireless data transmission, data loss and noise are inevitable and as such an algorithm that is both robust to noise and lost data becomes necessary. In this paper we present a new Atrial Fibrillation detection algorithm that has the above stated desired qualities. We have run the original and the modified algorithms on a collection of patients from the Physionet database exhibiting Atrial Fibrillation. Even with data loss as little as 10% the original algorithm degrades rapidly and its output is only 2-3% similar to the no-loss case. The loss-conscious algorithm continues to provide output that is more than 90% similar to the no-loss case even for data loss rates as high as 30%.

1. Introduction

The cost of health care has been increasing at much higher rates than overall economic growth. It currently stands at 15% of GDP for the United States and at similar levels for other industrialized countries. Furthermore the graying of populations in the developed world promises to exacerbate current trends. As such, solutions are needed so we can continue to enjoy our current level of health coverage without bankrupting the system. Fortunately more than 80% of health care spending is associated with the relatively small percentage of the patient population (less than 20%) that suffers from certain chronic diseases. Chronic disease management lends itself nicely to remote care, thus appropriate technology developments offer the dual promise of reduced costs along with improved patient outcomes. One of the major candidates for at-home care is that of chronic cardiac arrhythmias, and in particular atrial fibrillation.

Figure 1. ECG recording of patient in Atrial Fibrillation.

Atrial fibrillation (AF) is a cardiac arrhythmia that causes the atria of the heart to flutter, leading to inefficient blood circulation between the atria and ventricles, and ultimately to blood clots and strokes. Unfortunately detection of the pathology can be difficult since it can be asymptomatic until it is too late. A typical ECG reading for a patient in Atrial Fibrillation can be seen in Figure 1. Atrial Fibrillation is reported to be responsible for 15-20% of all strokes[1] and is predicted to be associated with over 3 million hospitalizations by 2025[2]. Frequent ECG monitoring using Holter monitors can detect the condition but this approach is far too costly and cumbersome to be practical.

An exciting alternative is small, low-cost sensors with relatively long battery lives and wireless transmission capabilities. One of the disadvantages of these devices is higher levels of noise, and possibly lost data segments due to transmission and other errors.

To cope with the signals associated with such devices, AF detection algorithms need to be robust to morphology variations and high levels noise. One such algorithm is presented by Logan and Healey [3] and is based on the morphology independent, open-source QRS detector wqrs [4] and an analysis of R-R interval variance. Unfortunately this algorithm and others based on R-R interval

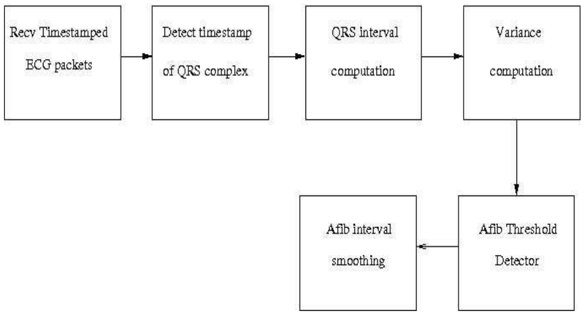

Figure 2. Original AF detection algorithm diagram.

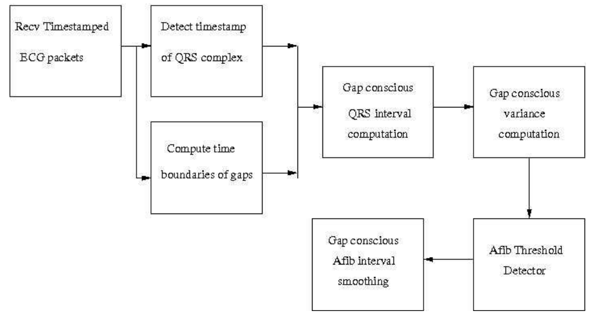

Figure 3. Gap conscious AF detection algorithm diagram.

statistics are highly sensitive to data loss. When segments of the ECG stream are missing, the outcome of the algorithm diverges significantly from the correct answer with results being only 2-3% similar to the correct answer.

In this paper we present an amended algorithm that takes data loss into account and reacts appropriately when data segments are missing. This improved algorithm continues to provide correct answers (more than 90% similar to lossless data analysis) even when data loss is as high as 30% of the total.

The rest of this paper is organized as follows. We present our algorithm in detail in Section 2. We then demonstrate its performance on data from the Physionet Database [5] in Section 3. In Section 4 we discuss the general principles behind our algorithmic changes and examine the kinds of loss patterns for which they are effective. We present related work in Section 5 and our conclusions in Section 6.

2. Gap conscious AF detection algorithm

Figure 2 shows a flow diagram of the AF detection algorithm used by our system. Our approach computes the variance of R-R intervals then applies a threshold and smoothing to this in order to detect AF.

In order to account for gaps we make changes to several of the modules. Figure 3 shows a flow diagram of the gap conscious algorithm. The first difference between this algorithm and the original approach is the computation of time intervals where data is lost. This information is then used by component that computes R-R intervals. This component accepts both streams of data and examines whether the distance between successive QRS complexes overlaps with data gaps. If the overlap exceeds 50% of the interval distance then the algorithm assumes that this interval is compromised due to data loss and drops it from the stream of intervals fed to the downstream components. The 50% overlap threshold was selected empirically. Other thresholds may work equally well. One interesting problem that needs to be addressed during this calculation is the possibility that an R-R interval may span multiple gaps. Thus the relevant metric is the sum of the overlaps between the interval and all the gaps with which it intersects.

Once the R-R intervals have been produced the next step is to compute the variance of those intervals over an appropriate time window. However, using a time window for the variance computation can result in significant divergence from the no-data-loss case. The reason is that in the presence of data loss, a time window may contain too few R-R intervals for the variance computation to be stable. Using a very large time window can address this but at the expense of suboptimal computation in the no-data-loss case. We have chosen to express the window in terms of the actual R-R intervals computed rather than time and have seen that this approach works well in practice.

Finally the smoothing component should take into account large gaps and mark those as areas of uncertainty rather than lumping them with the other two signal states (i.e. AF or normal sinus rhythm). Our current implementation does not do this since we knew that our patterns of loss would never result in excessively large data gaps.

3. Performance results

We have evaluated both the original and gap-conscious AF detection algorithms described in [3] and section 2 on a set of 23 patients from the MIT-BIH AF database (AFDB) [5]. We use two metrics to present our results. The first is the similarity of the results when analyzing the lossy data stream relative to the results of the original algorithm on the clean data stream. The second metric is the similarity of the results when analyzing the lossy data stream relative to the ground truth as reported in the MIT-BIH AF database. In the interest of space we show results only for the 10%, 20%, and 30% data loss cases even though our algorithm continues to perform well for loss rates as high as 50%.

We define percent similarity in the following way. Let P be the time period covered by the signal and over which we run our analysis. Let O_i be the afib intervals within the period P as computed by the original algorithm and

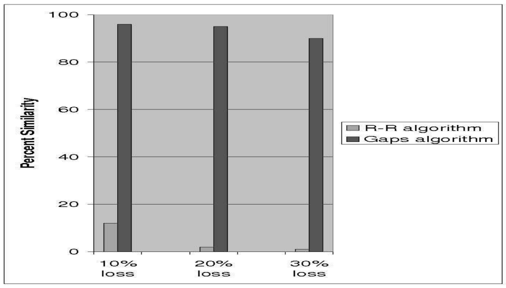

Figure 4. Percent similarity of the unmodified R-R algorithm and the modified Gaps algorithm when compared to the no-loss case.

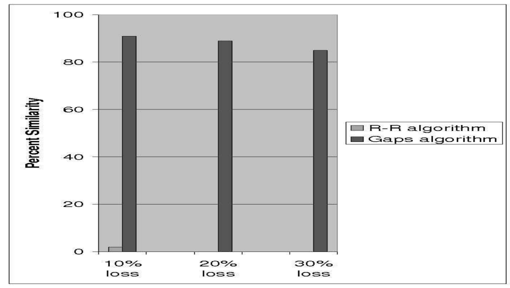

Figure 5. Percent similarity of the unmodified R-R algorithm and the modified Gaps algorithm when compared to the ground-truth.

assuming no data loss. Let N_i be the AF intervals within the period P computed by any algorithm when there is data loss. Then the similarity percent between the no-loss and lossy analysis is expressed by the formula:

$$(((P - \cup O_i) \bigcap (P - \cup N_i)) + (\cup O_i \bigcap \cup N_i)) -$$
$$(((P - \cup O_i) \bigcap \cup N_i) + (\cup O_i \bigcap (P - \cup N_i)))$$

Figures 4 and 5 show the performance of our improved algorithm relative to the original algorithm for data loss rates of 10%, 20%, and 30%. The left plot shows the performance of the algorithms relative to the original algorithm with *no data loss*. The right plot shows the performance relative to the ground truth as recorded in the MIT-BIH database. It can be seen that the original R-R algorithm quickly deteriorates even for small amounts of data loss, with similarity percentages dropping immediately to under 20% and deteriorating from there. For higher loss rates, the similarity percentage becomes negative [1]. Our modified algorithm has substantially better performance with similarity percentages staying above 90% when compared to the no-loss original algorithm, and above 85% when compared to the ground truth.

4. Discussion and loss pattern sensitivity

The intuition behind the gaps algorithm stems from the observation that loss of a data segment can severely affect the variance computation. The loss of ECG data around a QRS complex can result in the complex itself being missed by the QRS detector [4]. This in turn has the side effect that the surrounding complexes appear to be further apart in time than they really are, and the variance computation errs in believing the variance to be much higher than it really is. As such the original algorithm will find AF in areas of the signal which experience data loss since the missing QRS complexes result in higher variance for the remaining R-R intervals. By eliminating the R-R intervals that overlap with data gaps, and by stabilizing the variance and smoothing computations by requiring appropriate sized windows before they are computed, the gap-conscious algorithm overcomes the shortcomings of the original R-R algorithm and continues to yield good results even as data loss rates increase.

An interesting dimension to the problem of dealing with data loss has to do with the actual pattern of loss. For example a 10% loss rate can happen in a random, regular, or bursty pattern and each of those would have a different effect on the analysis algorithm. Our base results assume that data is lost in a bursty pattern since most ECG devices would exhibit this kind of loss. Burstiness stems from two factors. The first is that devices transmit packets of data rather than individual data samples so the minimum unit of loss is a packet. The second is that in most networking environments packet loss tends to come in bursts so it's usually a sequence of packets that gets lost rather than individual packets.

Nonetheless, we also looked at the other patterns of loss in order to determine how our algorithm would fare. We have discovered that when data loss happens in very small bursts (i.e. individual values) then both the original and the gap-conscious algorithm continue to perform quite well. The explanation for this behavior can be found in the workings of the QRS detector which can recover from extremely small segments of loss and still correctly discover and identify the position of the QRS complex. However, as the size of the burst increases then both algorithms deteriorate.

Loss bursts of between 0.1 and 2 seconds appear to be a "dead spot" where neither algorithm does well. The intuition behind this is that such loss patterns tend to have the

[1] Given our definition of similarity percentage it is possible to have negative similarity if the new detection algorithm introduces false positives in addition to missing real AF events.

worst possible impact on the number of QRS complexes that can be lost and can also affect the gap-overlap detector. A loss of this magnitude may not satisfy the 50% overlap criterion but still result in a missing QRS complex and an incorrect variance computation. As loss bursts get longer (above 2 seconds) the gap-conscious algorithm improves markedly as the uncertainty in the gap-overlap detection components is reduced. The original R-R interval algorithm continues to deteriorate as we have seen in the earlier section since it has no concept of gaps and thus can not take advantage of the fact that gaps are clearly defined when loss bursts are longer. Despite the existence of the dead spot we believe that the gap-conscious algorithm is likely to be highly effective in practice, since most expected loss patterns for any wireless devices would fall in the "large burst" category.

5. Related work

To the best of our knowledge, the specific problem examined in this paper has not received much previous attention. We expect the improvements shown by our algorithm would extend to any R-R-based AF detection algorithm.

Our AF detection algorithm is described in [3] and is loosely based on the R-R algorithm of Moody and Mark [6]. It is designed to detect AF using a custom sensor designed for long-term wearability. The ECG signal generated by this device is non-standard, has changing morphology and contains significant muscle noise. The algorithm uses a morphology independent QRS detector [4] to determine R-R intervals and detects AF based on R-R variance.

6. Conclusions

Designing algorithms for the detection of cardiac arrhythmias that are tolerant to data loss appears to be a significant but not well covered area of academic research. The proliferation of physiological sensors and long term continuous monitoring will result in large amounts of data that need to be automatically analyzed. It is highly likely that this data will contain time periods where the signal will either be overshadowed by noise or outright lost during collection and/or transmission.

We have presented a new algorithm for Atrial Fibrillation detection based on R-R interval variance that is tolerant of data loss. Our new algorithm provides answers that are substantially similar to the analysis of loss-free data even when loss rates for the input data stream are as high as 30%.

However, our algorithm is still susceptible to certain loss patterns. When data loss occurs in segments sizes between 0.1 and 2 seconds our gap overlap detection performs inadequately and as such the final result of the analysis deviates substantially from the ground truth. Nonetheless, the algorithm is extremely useful since it performs well for the common case of data loss where data collected by a device is packetized and transmitted to an analysis station. Expected patterns of loss in such a situation are highly likely to be in segments larger than the upper limit of our susceptibility window. In the future, we would like to extend our work so as to eliminate our window of vulnerability and also to cover the detection of other types of arrhythmias in lossy data streams.

References

[1] Sztajzel J, Sievert K, Landis T. New device diagnoses elusive irregular heartbeat after stroke. `http://www.americanheart.org/presenter.jhtml?identifier=3022130`, May 2004.

[2] Wattingney WA, B. CJ. Atrial fibrillation hospitalizations triple since 1985, will continue to climb. `http://www.americanheart.org/presenter.jhtml?identifier=3014151`, July 2003.

[3] Logan BT, Healey J. Robust detection of atrial fibrillation for a long term telemonitoring system. In Computers in Cardiology 2005. Lyon, France: IEEE Computer Society Press, 2005; .

[4] Zong W, Moody GB. A robust open-source algorithm to detect onset and duration of qrs complexes. In Computers in Cardiology 2003. Thessaloniki, Greece: IEEE Computer Society Press, 2003; 30:737–740.

[5] Goldberger AL, Amaral LAN, Glass L, Hausdorff JM, Ivanov PC, Mark RG, Mietus JE, Moody GB, Peng CK, Stanley HE. Physiobank, physiotoolkit and physionet: Components of a new research resource for complex physiological signals. Circulation 2000 June 13 10123e215 e200 ;Circulation Electronic Pages: http://circ.ahajournals.org/cgi/content-/full/101/23/e215.

[6] Moody GB, Mark R. A new method for detecting atrial fibrillation using r-r intervals. In Computers in Cardiology 1983. Ciudadela (Minorca), Spain: IEEE Computer Society Press, 1983; 227–230.

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