Impact of Motion Artifact on Detection of Atrial Fibrillation in Compressively Sensed ECG using a Deterministic Matrix

Mohamed Abdelazez[1], Sreeraman Rajan[1] and Adrian D. C. Chan[1]

[1] Systems and Computer Engineering, Carleton University, Ottawa, Canada

Abstract—**Early detection of Atrial Fibrillation (AFib) is warranted to reduce the chances of patients developing complications. Compressive sensing (CS) of electrocardiogram (ECG) will facilitate long term monitoring with detection of AFib in the compressed domain eliminating the need for the expensive operation of reconstructing the ECG. This paper presented an AFib detector in the compressed domain and studied the effect of noise on it. ECG records from the Long-Term Atrial Fibrillation Database were contaminated with motion artifact from the MIT-BIH Noise Stress Database and compressed to 50%, 75%, and 95% levels. A 100 tree random forest was used to detect AFib in the uncompressed and compressed ECG at different noise levels. The random forest was evaluated using 5-fold cross validation and patient hold-out method. The random forest achieved a maximum of 81.87% F1 score at the 3 dB Signal to Noise Ratio (SNR) and 75% compression level in cross validation. Changing the SNR to -10 dB reduced the F1 score by 3.25%. The random forest achieved a maximum of 61.03% at 3 dB SNR and on uncompressed ECG in the hold-out test. Changing the SNR to -10 dB reduced the F1 score by 6.55%. The results show that it is possible to detect AFib in the compressed domain with noise impacting the performance.**

Keywords— **Compressive Sensing, Atrial Fibrillation, Machine Learning, Random Forest, Electrocardiogram**

I. Introduction

Atrial Fibrillation (AFib) is a type of cardiac arrhythmia that affects the atria, upper chambers of the heart, and is characterized by the uncoordinated contraction of the atria [1]. AFib may lead to other cardiac complications, stroke, and death if left untreated or without monitoring [2]. AFib increases the risk of heart failure by 3-folds, stroke by 5-folds and dementia and mortality by 2-folds [2]. AFib can affect individuals of all ages; however, it is more prominent in seniors [1]. In 2016, seniors outnumbered children for the first time in Canada [3]. The growing number of seniors in Canada will lead to an increase of healthcare cost due to AFib. AFib cost the United States healthcare system $26 billion in 2014 [4]. Early detection of AFib is warranted to prevent complications and to reduce healthcare costs.

AFib is typically diagnosed using an electrocardiogram (ECG), the electrical activity of the heart [1]. Patients suspected to have AFib are typically monitored using a Holter Monitor, a portable ECG monitor, over the course of few days; however, AFib episodes can occur randomly with days between episodes [1]. A long term solution to monitor patients is needed.

A single patient will generate 0.7 GBs per day considering 12-lead ECG recorded at 24-bits resolution at 250 Hz. The size of the data will grow with every patient which can lead to terabytes of data being generated daily. Transmitting large amount of data wirelessly can strain a communication network and reduce the battery life of monitoring devices. Additionally, storage facilities can be strained by the large amount of data. Analyzing the terabytes of data will also require an automated method.

Compressive sensing (CS) is a technique that has the potential to address the aforementioned challenges [5]. In CS, signals or images are sampled at a rate lower than Nyquist rate [5], thereby, reducing the amount of data required to be transmitted for the same duration of recorded ECG. As such, easing the strain on wireless communication networks, reducing the power requirements to transmit the data, and reducing the storage space requirements.

The operation of compression in CS is not computationally intensive and can be performed on low power devices [5]. On the other hand, the reconstruction of the compressively sampled ECG is a complex operation that requires solving an undetermined problem and is typically performed on high power computing devices [5]. Avoiding the expensive reconstruction step and analyzing ECG in the compressed domain may lead to quicker identification of AFib.

Previous studies have been performed on the feasibility of detecting AFib in compressively sensed ECG. The authors in [6] used fiducial based features to detect AFib in clean ECG. Fiducial based features may not be feasible to extract at high compression ratios and high levels of noise contamination due to ECG losing its characteristics. This paper addresses the gap in the research by presenting an AFib detector in compressively sensed ECG and studying the impact of noise on the detector.

II. Methods

A. ECG Data

The work presented in this paper used the publicly available Long-Term AF database (LTAFDB) found on Physionet [7], [8]. There were 84 records in the database with each record containing two-lead ECG recordings that spanned 24 hours. The first lead was used in this paper. The ECG in the database was sampled at 128 Hz and 12-bit resolution using an ADC with 20 mV range.

The ECG segments labeled as N and AFIB in the annotation file were used in this paper while the other segments were discarded. There were 32 days and 5.8 hours of ECG segments labeled as N and 36 days and 6.1 hours ECG segments labeled as AFIB.

The ECG was filtered using a zero phase third order bandpass Butterworth filter with cut-off frequencies of 0.67 Hz to remove baseline wandering as recommended by the American Heart Association (AHA) and 25 Hz to remove high frequency noise [1].

B. Contaminating ECG with Noise

The ECG was contaminated using the motion artifact from the publicly available MIT-BIH Noise Stress Test Database (NSTDB) found on Physionet [9]. NSTDB contained 30 minutes of motion artifact that was sampled at 360 Hz. The motion artifact was down-sampled to 128 Hz to match the sampling rate of the ECG using 'resample' function in MATLAB 2018b. Noise was added to achieve signal to noise ratios of 3 dB, 0 dB, -3 dB, -5 dB, and -10 dB. The noise was multiplied by a scaling factor calculated according to (1) – (4) to achieve the aforementioned SNR levels.

$$SF = \sqrt{\frac{Pn_d}{Pn_{org}}} \quad (1)$$

$$Pn_d = \frac{Ps}{10^{\frac{SNR_d}{10}}} \quad (2)$$

$$Ps = \frac{1}{A}\sum_{n=1}^{N} x_n^2 \quad (3)$$

$$Pn_{org} = \frac{1}{Q}\sum_{q=1}^{Q} a_q^2 \quad (4)$$

where SF is the scaling factor; Pn_d is the desired power of the noise segment; Pn_{org} is the original power of the noise segment; SNR_d is the desired SNR level; Ps is the power of the ECG segment; A is the number of samples in the ECG segment; x_n is the nth sample in the ECG segment; Q is the number of samples in the noise segment; and a_q is the q^{th} sample in the noise segment.

C. Compressive Sensing (CS)

CS compressed the ECG by multiplying it with a rectangular matrix, Φ, which had the size M x N, where $K < M < N$, K was the number of the significant samples in the ECG signal, and N was the number of zero samples in the ECG signal. The rectangular matrix was labelled as the sensing matrix. The sensing matrix used in this paper is known as deterministic binary block diagonal (DBBD) as proposed in [10]. The matrix was made from ones and zeros, so it had a low memory foot print. An example of DBBD matrix is shown in (5).

$$\Phi = \begin{bmatrix} [1 \ldots 1] & 0 & 0 & 0 \\ 0 & [1 \ldots 1] & 0 & 0 \\ 0 & 0 & \ddots & 0 \\ 0 & 0 & 0 & [1 \ldots 1] \end{bmatrix} \quad (5)$$

The number of ones in each row of Φ was indicated by m and was equal to the ratio of N and M, where M was the number of rows in DBBD and N was the number of columns in DBBD which was also the number of samples in the ECG. The compressed ECG was donated by y and was defined by (6).

$$y_{Mx1} = \Phi_{MxN} x_{Nx1} \quad (6)$$

The three levels of compression considered in this study were 50%, 75%, and 95%.

D. AFib Detection

A total of 134 features based on statistical measures, empirical mode decomposition (EMD), discrete wavelet transform (DWT), discrete cosine transform (DCT), and stationary wavelet transform (SWT) were considered. These features were chosen as they provided different representations of the signal. The features were calculated using MATLAB 2018b.

The features based on statistical measures of the ECG were the mean, median, kurtosis, and standard deviation.

The third and fourth intrinsic mode function (IMF) were extracted from ECG using EMD. The mean, median, skewness, range, kurtosis, and standard deviation of each IMF were calculated.

ECG was decomposed to the fourth level using DWT with the mother wavelet 'dmey'. The fourth level was chosen to represent the low frequency components, less than 7.5 Hz, of the ECG. The mean, median, skewness, range, kurtosis, and standard deviation was calculated for each decomposition level.

ECG was also decomposed to the sixth level using SWT with the mother wavelet 'db5'. The mean, median, skewness, range, kurtosis, and standard deviation was calculated for each decomposition level.

DCT captures the energy components of the AFib in ECG. The mean, median, skewness, range, kurtosis, and standard deviation was calculated for the DCT representation of the ECG.

A 100 tree random forest was used to detect AFib in the ECG. A 100 tree forest was chosen as it provided the best trade-off between complexity and performance. Adding more trees only improved the performance by less than 1% while reducing the number of trees decreased the performance of the random forest substantially.

E. Training and Testing the AFib Detector

The ECG records from LTAFDB were divided into 30 s non-overlapping segments. Segments meeting the following criteria were considered for further analysis while the remaining segments were discarded:

- estimated SNR greater than or equal to 3 dB
- had mean greater than 1e-20 mV
- contained eight beats or more and less than 100 beats

The aforementioned criteria were chosen to discard noisy segments and segments that did not contain ECG. The estimated SNR was calculated according to the signal quality index (SQI) presented in [11], [12]. A total of 83,786 N and 91,890 AFib 30 s segments were considered for further analysis.

Each 30 s segment was contaminated with noise to the levels indicated in *section B*. The noise contaminated segments were then compressed to the levels indicated in *section C.* Features were then extracted from the uncompressed and compressed 30 s segments.

The records 10, 16, 19, 22, 47, 201, 202, 205, and 208 were held-out to create the test set with the remaining records considered as the training set. These test records were randomly chosen. Training and testing sets were created for every combination of noise levels and compression levels. The random forest was evaluated using 5-fold cross validation performed on the training set and by training on the training set and testing on the test set. The performance of the random forest was presented using F1 score as described in (7).

$$F1 = \left(\frac{Recall^{-1} + Precision^{-1}}{2}\right)^{-1} \times 100 \qquad (7)$$

The random forest was trained and evaluated on sets from similar noise and compression levels. As an example, the random forest trained using the training set with SNR of -10 dB and compression of 95% was tested on the test set with similar SNR and compression levels.

III. RESULTS

There was a total of 84,053 N and 72,642 AFib 30 s segments in each of the training sets. Each test set contained 7,837 N and 11,145 AFib 30 s segments. Table 1 lists the results of the 5-fold cross validation performed on the training sets at each noise and compression level combinations. Table 2 shows the F1 score for the held-out test sets.

Table 1 5-fold cross validation average F1 scores on the training sets for each noise and compression levels combinations

Compression/Noise Levels	3 dB	0 dB	-3 dB	-5 dB	-10 dB
Uncompressed	76.96	75.97	74.49	73.79	71.84
50% Compression	78.29	77.55	76.25	75.57	73.97
75% Compression	81.87	81.42	80.77	80.69	78.62
95% Compression	78.80	76.67	73.80	72.24	68.47

Table 2 F1 scores of random forests trained on the training sets and tested on the test sets from each corresponding noise and compression levels combinations

Compression/Noise Levels	3 dB	0 dB	-3 dB	-5 dB	-10 dB
Uncompressed	61.03	58.54	57.40	56.85	54.48
50% Compression	55.53	54.38	53.60	53.54	49.96
75% Compression	60.24	59.31	58.66	57.99	55.97
95% Compression	60.63	57.90	54.24	52.80	48.65

IV. DISCUSSION

This paper presented a non-fiducial AFib detector and studied the effect of noise on the detector. Cross-validation and hold-out testing was performed to assess the performance of the detector. Table 1 lists the average F1 scores of the cross validation performed on the training set corresponding to each noise and compression levels combinations. The average F1 scores were constantly greater than 70%. The impact of noise can be noticed with a drop of 5.12% between 3 dB and -10 dB noise levels in the uncompressed level. The impact of noise was most apparent in the 95% compression level. This has been attributed to the loss of information due to compression. An interesting observation is the increasing F1 score from the uncompressed level to the 95% compressed level at the 3 dB and 0 dB noise levels. This has been attributed to the effect of the sensing matrix on the ECG signal. The sensing matrix can be modeled as an averaging filter determined by the number of ones in each row. The light noise in the 3 dB and 0 dB is averaged out by the compression operation, thereby, improving the operation of the forest. The 75% compression had the largest increase from the uncompressed domain as it provided the best tradeoff between averaging of the noise and loss of information.

Table 2 shows the F1 scores on the held-out test sets. It is apparent that there is a decrease from the 5-fold cross validation results which has been attributed to the random forest learning the trends of the patients in the cross validation case and not the trends of AFib. The impact of the noise is also apparent in the hold-out testing. The increase of the F1 score across the compression levels is also evident, however, at a lower impact. As an example, the maximum increase of F1 score in the case of cross validation was 6.90% while the maximum in the case of hold-out test was 1.50%.

V. Conclusion

This paper showcased the potential of detecting AFib in compressively sensed domain and the impact of noise on detecting AFib. A random forest was trained on different compression levels and noise levels achieving a maximum of 61.03% F1 score when tested using hold-out method. The impact of noise was evident at all compression levels. Future work will explore noise detection and removal in the compressed domain and quantification of the impact of the filtering effect of compressive sensing using DBBD.

Acknowledgment

The authors would like to acknowledge Natural Sciences and Engineering Research Council and Vanier Canada Graduate Scholarship program for supporting this research.

Conflict of Interest

The authors declare that they have no conflict of interest.

References

[1] C. T. January *et al.*, “2014 AHA/ACC/HRS Guideline for the Management of Patients With Atrial Fibrillation,” *J. Am. Coll. Cardiol.*, vol. 64, no. 21, pp. e1–e76, Dec. 2014.

[2] A. Alonso *et al.*, “Incidence of atrial fibrillation in whites and African-Americans: The Atherosclerosis Risk in Communities (ARIC) study,” *Am. Heart J.*, vol. 158, no. 1, pp. 111–117, Jul. 2009.

[3] É. G. · C. N. · P. May 03, 2017 8:47 AM ET | Last Updated: May 7, and 2017, “Seniors now outnumber children in Canada, census figures show | CBC News,” *CBC*, 03-May-2017. [Online]. Available: https://www.cbc.ca/news/politics/2016-census-age-gender-1.4095360. [Accessed: 01-Feb-2019].

[4] A. S. Go *et al.*, “Heart Disease and Stroke Statistics—2014 Update A Report From the American Heart Association,” *Circulation*, vol. 129, no. 3, pp. e28–e292, Jan. 2014.

[5] D. L. Donoho, “Compressed sensing,” *IEEE Trans. Inf. Theory*, vol. 52, no. 4, pp. 1289–1306, Apr. 2006.

[6] G. Da Poian, C. Liu, R. Bernardini, R. Rinaldo, and G. D. Clifford, “Atrial fibrillation detection on compressed sensed ECG,” *Physiol. Meas.*, vol. 38, no. 7, pp. 1405–1425, Jun. 2017.

[7] A. L. Goldberger *et al.*, “PhysioBank, PhysioToolkit, and PhysioNet Components of a New Research Resource for Complex Physiologic Signals,” *Circulation*, vol. 101, no. 23, pp. e215–e220, Jun. 2000.

[8] S. Petrutiu, A. V. Sahakian, and S. Swiryn, “Abrupt changes in fibrillatory wave characteristics at the termination of paroxysmal atrial fibrillation in humans,” *EP Eur.*, vol. 9, no. 7, pp. 466–470, Jul. 2007.

[9] G. B. Moody, W. Muldrow, and R. G. Mark, “A noise stress test for arrhythmia detectors,” *Comput. Cardiol.*, vol. 11, no. 3, pp. 381–384, 1984.

[10] A. Ravelomanantsoa, H. Rabah, and A. Rouane, “Compressed Sensing: A Simple Deterministic Measurement Matrix and a Fast Recovery Algorithm,” *IEEE Trans. Instrum. Meas.*, vol. 64, no. 12, pp. 3405–3413, Dec. 2015.

[11] P. X. Quesnel, A. D. Chan, and H. Yang, “Signal quality and false myocardial ischemia alarms in ambulatory electrocardiograms,” in *Medical Measurements and Applications (MeMeA), 2014 IEEE International Symposium on*, 2014, pp. 1–5.

[12] M. Abdelazez *et al.*, “Signal Quality Analysis of Ambulatory Electrocardiograms to Gate False Myocardial Ischemia Alarms,” *IEEE Trans. Biomed. Eng.*, vol. 64, no. 6, pp. 1318–1325, Jun. 2017.