COMPRESSIVE SENSING BASED ECG MONITORING WITH EFFECTIVE AF DETECTION

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ABSTRACT

Atrial fibrillation (AF) patients need long-term electrocardiography (ECG) monitoring to detect occurrence of AF. We can acquire ECG signals under low power by compressive sensing based sensor and detect AF by existing algorithms. However, the compression ratio of AF signal is low when DWT basis is applied for CS reconstruction. On the other hand the complexity of AF detection algorithms is high. In this paper, we propose a CS-based ECG monitoring system with effective AF detection. We exploit dictionary learning to improve 2.5x better compression ratio than existing works. With built-in AF detection, we can detect AF with 96.0% sensitivity and 97.2% specificity from highly compressed data, without any complex detection algorithm.

***Index Terms*—**Atrial fibrillation detection, ECG monitoring, compressive sensing, dictionary learning

1. INTRODUCTION

Atrial fibrillation (AF) [1] is the most common sustained cardiac arrhythmia, which increases the risk of stroke and mortality. AF symptoms of the AF patients may repeatedly occur and disappear. Therefore, we need to detect the occurrence of AF to help the doctors on pharmacological treatment. Electrocardiography (ECG) is a noninvasive and cost-effective tool which is commonly used in AF detection. Portable wireless ECG monitoring system is promising to run-time collect ECG signals for long-term AF monitoring.

The portable wireless ECG sensor is facing the problems of limited battery life. Since high data rate of ECG signals leads to large energy dissipation in transmission, data compression techniques are required to save transmitting power. However, the traditional measured-and-compressed sensors suffer from large energy losses due to the high complexity of compression unit. Compressive sensing (CS) [2] based ECG sensors [3] are emerging technique that samples signal under sub-Nyquist rate and compresses data without additional compression unit. The fact leads to lower power consumption than traditional sensors.

An intuitive framework of CS-based ECG monitoring system with AF detection is shown in Fig. 1. It directly cascades CS-based ECG compression system [4] and existing AF detection algorithms [5][6]. In CS sensor node, ECG signals are sampled under sub-Nyquist rate and transmitted under low power. In receiver, it reconstructs ECG signals by CS reconstruction algorithm and detects AF from the reconstructed signals. However, there are two problems with this system. First, the compression ratio in [4] decreases when it's applied to AF patients, whose ECG waveforms are more complicated due to variation between AF occurring and disappearing. Second, the AF detection block is high cost due to high computational complexity of AF detection algorithms. The work in [4] considers only CS-based ECG monitoring and the works in [5][6] consider only detecting AF from ECG signals.

In this work, we propose a CS-based ECG monitoring system with built-in AF detection for AF patients, as shown in Fig. 2. The present study not only considers both CS-based ECG monitoring system and AF detection, but improves the system by better compression ratio and lower hardware complexity. We exploit the dictionary learning (DL) [7] technique to AF ECG segments and normal ECG segments of the AF patient, respectively, to achieve two dictionaries. Collaborating these two dictionaries as sparsifying basis of CS, the compression ratio can be increased. Furthermore, a built-in AF detection can be accomplished by analyzing the distribution of the sparse coefficients projected on the sparsifying basis. Consequently, the system can simultaneously reconstruct ECG signal from CS-based sensor with high compression ratio and detect the occurrence of AF without extra hardware and energy cost. The compression ratio of the proposed method is 2.5x better than the one in [4]. Moreover, the proposed built-in AF detection method shows 96.0% sensitivity and 97.2% specificity in detecting AF from highly compressed data.

This paper is organized as follows. Section II will give an overview of related works on CS-based ECG compression and ECG-based AF detection. In Section III, we introduce the proposed CS-based ECG monitoring system with effective AF detection. The simulation results are discussed in Section IV. Finally, we give a conclusion in Section V.

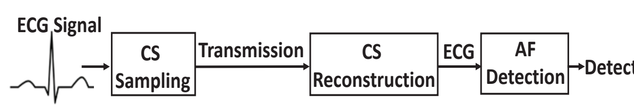

Fig. 1. Intuitive CS-based ECG monitoring system with AF detection.

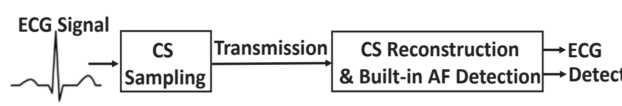

Fig. 2. Proposed CS-based ECG monitoring system with built-in AF detection.

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2. CS-BASED ECG COMPRESSION AND ECG-BASED AF DETECTION

2.1. CS-based ECG Compression

Signal can be measured with fewer samples than Nyquist rate in CS-based sensor. We can model the sampling process of compressive sensing in matrix formation as

$$\mathbf{y}_{M\times 1} = \mathbf{\Phi}_{M\times N}\mathbf{x}_{N\times 1}, \quad (1)$$

where $\mathbf{x}_{N\times 1}$ is the input signal with high dimension N, such as time domain signal sampled by traditional Nyquist-rate sensor, $\mathbf{\Phi}_{M\times N}$ is the sensing matrix, and $\mathbf{y}_{M\times 1}$ is the measurement with low dimension M ($M < N$). The CS-based sensor will obtain measurement $\mathbf{y}_{M\times 1}$ and transmit it. The compression is achieved by directly sampling less samples without extra compression unit. The receiver will reconstruct signal $\mathbf{x}$ from measurement $\mathbf{y}$..

The signal $\mathbf{x}$ need to be sparse enough to be reconstructed, where sparse signal means there are few nonzero terms in $\mathbf{x}$. Because most of natural signals are not sparse in time domain but in other domain, we can rewrite (1) as

$$\mathbf{y}_{M\times 1} = \mathbf{\Phi}_{M\times N}\mathbf{x}_{N\times 1} = \mathbf{\Phi}_{M\times N}\mathbf{\Psi}_{N\times P}\mathbf{s}_{P\times 1}, \quad (2)$$

where $\mathbf{\Psi}_{N\times P}$ is the sparsifying basis for signal $\mathbf{x}_{N\times 1}$, and $\mathbf{s}_{P\times 1}$ is the corresponding sparse representation vector. The $\mathbf{s}$ is said to be K-sparsity if there are K nonzero terms in $\mathbf{s}$. Then, we find $\mathbf{s}$ by solving sparse coding problem as

$$\min_{\hat{\mathbf{s}}} \left\|\hat{\mathbf{s}}\right\|_1 \; s.t. \mathbf{\Phi}\mathbf{\Psi}\hat{\mathbf{s}} = \mathbf{y}, \quad (3)$$

The (3) can be solved by the *l1* minimization algorithms, such as basis pursuit (BP) [8]. Then, $\hat{\mathbf{x}} = \mathbf{\Psi}\hat{\mathbf{s}}$.

To correctly reconstruct K-sparse $\mathbf{s}$ from $\mathbf{y}$, the measurement size M must be larger than $O(Klog(N/K))$[2]. A proper sparsifying basis $\mathbf{\Psi}$ is required to reduce sparsity K in $\mathbf{s}$. The facts leads to smaller measurement M. To evaluate the performance of compression, the *compression ratio (CR)* [4] is defined as

$$CR(\%) = \frac{N-M}{N} \times 100. \quad (4)$$

A higher compression ratio leads to lower transmitting power in CS-based sensor.

Therefore, the determination of sparsifying basis $\mathbf{\Psi}$ is a crucial problem. In [4], a discrete wavelet transform (DWT) basis is selected as the sparsifying basis $\mathbf{\Psi}$ for a CS-based ECG compression system. However, the DWT basis has low compression ratio when applying this system on AF patient due to complicated ECG waveform caused by the variation between normal ECG and AF ECG.

2.2. ECG-based AF Detection Algorithms

There are many existing algorithms for detecting AF from ECG signal. Reference [5] extracts RR interval feature from ECG and detects AF based on the irregularity of RR interval. It applies statistical features, such as Shannon Entropy and Turning Points Ratio, to analyze the randomness and complexity of RR interval. Reference [6] extracts P-wave feature from ECG and detects AF based on the absence P-wave.

Most of the AF detection algorithms need feature extraction from ECG and classification by applying statistic on the features. However, feature extraction leads to high computational complexity and the classification methods require large amount of training data to build the model.

3. PROPOSED CS-BASED ECG MONITORING SYSTEM WITH BUILT-IN AF DETECTION

3.1. Overview of the Proposed CS-based ECG Monitoring System with Built-in AF Detection

To solve the problems of DWT basis with application to AF patient, we introduce the dictionary learning technique to construct a proper sparsifying basis for ECG signal to improve the compression ratio. Furthermore, we proposed a method to built-in detect AF without additional detection block. The built-in AF detection scheme can solve the complexity problem of traditional AF detection algorithms.

The proposed CS-based ECG monitoring system with built-in AF detection is shown in Fig. 3. The *Phase 1* is an off-line training stage, we collect ECG data from the AF patient and divide them into normal ECG segments and AF ECG segments according to labels. By separately applying dictionary learning on each segments as training set, we construct two dictionaries for normal ECG and AF ECG, respectively. The *Phase 2* is an on-line working stage will sample and transmit ECG signal with CS-based sensor. In receiver, we exploit the two trained dictionaries from *Phase 1* as the sparsifying basis in CS reconstruction to improve compression ratio. At the same time, a built-in AF detection is applied to detect the occurrence of AF.

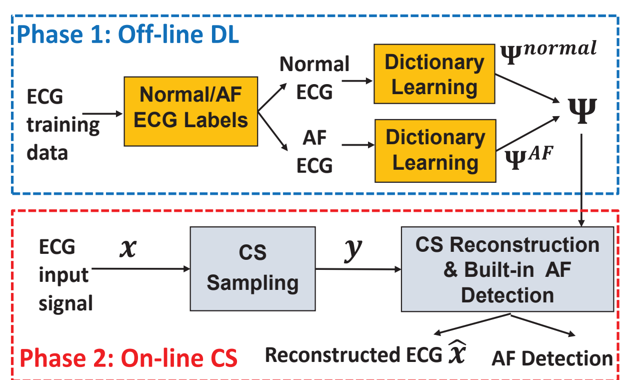

Fig. 3. Proposed CS-based ECG monitoring system with built-in AF detection.

3.2. Phase 1: Dictionary Learning for AF Patients

Dictionary learning (DL) is a technique to iteratively learn a "dictionary" from training data set. The goal is to make the projection of training data on this dictionary as sparse as possible. ECG signal can be well approximated using trained dictionary.

Let $\mathbf{T} = [\mathbf{t}_1 \ldots \mathbf{t}_L] \in \mathbb{R}^{N\times L}$ be the training data set and $\boldsymbol{\Psi} \in \mathbb{R}^{N\times P}$ be the desired dictionary. The dictionary can be obtained by solving the following optimization problem:

$$\min_{\boldsymbol{\Psi},\mathbf{c}} \frac{1}{L}\sum_{i=1}^{L}\left(\frac{1}{2}\left\|\mathbf{t}_i - \boldsymbol{\Psi}\mathbf{c}_i\right\|_2^2 + \lambda\left\|\mathbf{c}_i\right\|_1\right), \tag{5}$$

where $\mathbf{c}_i$ denotes the sparse coefficient of training data $\mathbf{t}_i$ projected on $\boldsymbol{\Psi}$ and λ is a weighting parameter. Reference [7] proposed a solution for solving (5) by iterative two steps, including sparse coding and dictionary update as shown in Fig. 4, to alternatively find $\mathbf{c}$ and $\boldsymbol{\Psi}$. In sparse coding step, it fixes $\boldsymbol{\Psi}$ and finds sparse representation $\mathbf{c}_i$ of training data $\mathbf{t}_i$ by Least Angle Regression (LARS) algorithm [9]. In dictionary update step, it fixes $\mathbf{s}_i$ obtained in previous step and updates $\boldsymbol{\Psi}$ by $\mathbf{c}_i$. After the iteratively two steps to update $\boldsymbol{\Psi}$ from training data, the dictionary $\boldsymbol{\Psi}$ is well trained.

In *Phase 1*, after collecting ECG training data from patient, we classify them into normal ECG and AF ECG set by labels. We obtain two trained dictionary $\boldsymbol{\Psi}^{Normal}$ and $\boldsymbol{\Psi}^{AF}$ by separately applying dictionary learning on normal ECG and AF ECG training set, respectively. The sparsifying basis $\boldsymbol{\Psi}$ by cascading $\boldsymbol{\Psi}^{Normal}$ and $\boldsymbol{\Psi}^{AF}$ is constructed as

$$\boldsymbol{\Psi}_{N\times 2P} = \left[\boldsymbol{\Psi}^{Normal}_{N\times P}\ \boldsymbol{\Psi}^{AF}_{N\times P}\right]. \tag{6}$$

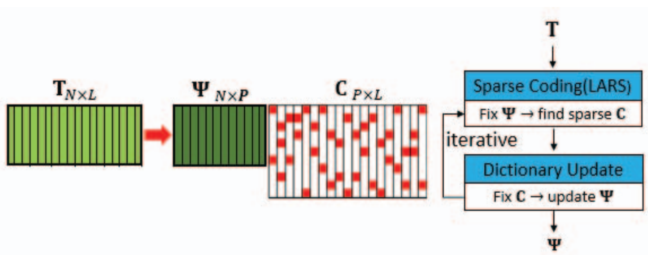

Fig. 4. Process of dictionary learning.

3.3. Phase 2: CS Reconstruction and Built-in AF Detection

In CS reconstruction of *Phase 2*, we apply basis pursuit (BP) algorithm [8] to get the sparse representation $\hat{\mathbf{s}}$ and reconstructed signal $\hat{\mathbf{x}}$ with this trained basis $\boldsymbol{\Psi}$ by $\hat{\mathbf{x}} = \boldsymbol{\Psi}\hat{\mathbf{s}}$ as shown in (2) and (3). Since this trained basis can sparsify ECG signal well, it has better compression ratio compared to DWT basis. Moreover, because the training data of *Phase 1* are selected from both normal ECG and AF ECG waveform, the basis $\boldsymbol{\Psi}$ can cover different ECG waveform of AF patients. There won't be performance loss caused by ECG variation in AF patients.

The sparse representation vector $\hat{\mathbf{s}}_{2P\times 1}$ corresponding to $\boldsymbol{\Psi}_{N\times 2P}$ in CS reconstruction. Traditionally, $\hat{\mathbf{s}}$ is only used to reconstruct signal $\hat{\mathbf{x}}$. However, there are some importance information in $\hat{\mathbf{s}}$ which can help us on AF detection. We define $\mathbf{s}^{Normal}$ and $\mathbf{s}^{AF}$ as the first P elements and last P elements of $\hat{\mathbf{s}}$, respectively, as

$$\mathbf{s}^{Normal} = [\hat{s}_1\, \hat{s}_2\, \ldots\, \hat{s}_P\,]^{\mathrm{T}}$$

and (7)

$$\mathbf{s}^{AF} = [\hat{s}_{P+1}\, \hat{s}_{P+2}\, \ldots\, \hat{s}_{2P}\,]^{\mathrm{T}}.$$

Note that signal $\mathbf{x}$ is the linear combination of columns of $\boldsymbol{\Psi}$, and the i^{th} entry of $\hat{\mathbf{s}}$ is the coefficient of i^{th} column of $\boldsymbol{\Psi}$. Hence, $\mathbf{s}^{Normal}$ and $\mathbf{s}^{AF}$ are the sparse coefficients corresponding to $\boldsymbol{\Psi}^{Normal}$ and $\boldsymbol{\Psi}^{AF}$ in (6), respectively.

In CS reconstruction, basis pursuit will make the non-zero terms in $\hat{\mathbf{s}}$ locate at s_i whose corresponding Ψ_i has high correlation to signal $\mathbf{x}$. Therefore, the distribution of non-zero terms in $\hat{\mathbf{s}}$ contains information about features of signal $\mathbf{x}$. The fact instigate us to exploit the distribution to detect AF. If $\mathbf{x}$ is AF ECG, it'll be more correlated to $\boldsymbol{\Psi}^{Normal}$ rather than $\boldsymbol{\Psi}^{AF}$, which results more non-zero terms in $\mathbf{s}^{normal}$ than $\mathbf{s}^{AF}$. The proposed criterion of $Detect$ function can be formulated as

$$Detect(\mathbf{s}^{normal},\mathbf{s}^{AF}) = \begin{cases} \text{AF ECG}, & if\ \|\mathbf{s}^{AF}\|_2 \geq \left\|\mathbf{s}^{normal}\right\|_2 \\ \text{Normal ECG}, if & \|\mathbf{s}^{AF}\|_2 < \left\|\mathbf{s}^{normal}\right\|_2 \end{cases} \tag{8}$$

where $\|\mathbf{s}\|_2 := \sqrt{\sum_i {s_i}^2}$.

Therefore, we can detect AF without any additional complex AF detection algorithm. All we need to do for AF detection is to compute $\|\mathbf{s}^{AF}\|_2$ and $\|\mathbf{s}^{normal}\|_2$ and compare them. In proposed framework, the CS reconstruction stage is no long for reconstruction only. We can simultaneously extract some important information from ECG signal as soon as CS reconstruction.

Nevertheless, the proposed built-in AF detection technique is only one of the example for classification in CS reconstruction. We can easily extend the technique to other signal feature processing in CS-based system by customized sparsifying basis $\boldsymbol{\Psi}$ corresponding to desired feature. Consequently, we make compressive sensing more powerful than just compress and reconstruct the signal.

4. SIMULATION RESULTS

4.1. ECG Database and Simulation Settings

We use the ECG data of AF patients in MIT-BIH Long-Term AF Database (LTAFDB) [10] for simulation. The database contains AF patients with labeled normal ECG and AF ECG signals. In *Phase 1*, the dimension of training vector N is set to be 256 and both the number of training vectors L of normal ECG and AF ECG training are set to be 2500. Each trained dictionary $\boldsymbol{\Psi}^{Normal}$ and $\boldsymbol{\Psi}^{AF}$ contains P=2N columns so that the combined sparsifying basis $\boldsymbol{\Psi}$ has 4N columns. In *Phase 2*, we fix the dimension of signal $\mathbf{x}$ at N=256. The sampling matrix $\boldsymbol{\Phi}$ is random Gaussian matrix. The dimension of measurement M and sampling matrix $M \times N$ varies according to the set of *CR*.

To evaluate compression and the recovery quality, we employ the *compression ratio (CR)* as in (4) and *percentage root-mean-square difference (PRD)* [11]. The *PRD* is defined as

$$PRD\ (\%) = \frac{\left\| \mathbf{x} - \mathbf{x} \right\|_2}{\left\| \mathbf{x} \right\|_2} \times 100 \quad , \qquad (9)$$

where $\mathbf{x}$ is the original ECG signal and $\hat{\mathbf{x}}$ is the reconstructed ECG signal. For AF detection, we use sensitivity and specificity to evaluate the detection performance. To evaluate the performance of AF detection, we use sensitivity and specificity to evaluate the performance, which are defined as

$$Sensitivity = \frac{\#\ of\ AF\ segments\ detected\ as\ AF}{Total\ AF\ segments(labels\ in\ database)}$$

$$Specificity = \frac{\#\ of\ Normal\ segments\ detected\ as\ Normal}{Total\ Normal\ segments(labels\ in\ database)}$$

4.2. Performance of ECG Recovery

In Fig. 5, we fix *CR* at 80% and compare the reconstructed ECG waveform by DWT basis [4] and proposed basis. The result shows that both the AF ECG and normal ECG waveforms reconstructed by proposed basis are better than that by DWT basis.

In Fig. 6, we provide the quantitative analysis of compression and reconstruction by *CR* and *PRD*, respectively. Larger *CR* implies better compression, and smaller *PRD* implies better reconstruction. The dimension of measurement *M* varies according to *CR*. The result shows that the proposed basis outperforms DWT basis in reconstruction of both AF ECG and normal ECG. Therefore, the proposed system is suitable for AF patients. If we target *PRD* at 2%, the proposed basis can reach 2.5x better compression ratio than DWT basis in [4].

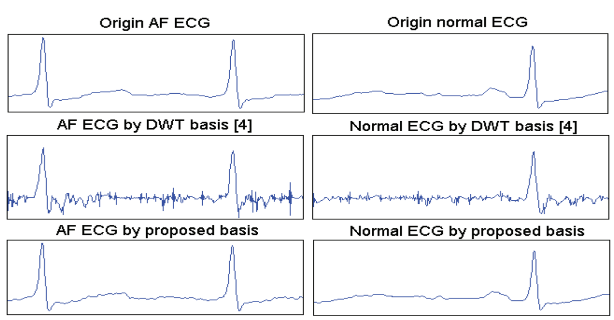

Fig. 5. AF and normal ECG reconstructed by DWT and proposed basis under *CR*=80%

4.3. Performance of Built-in AF Detection

To verify the performance of proposed built-in AF detection, we choose an AF patient (ID=117) who has a 15-hour ECG record. We train and test our method by normal/AF ECG labels in MIT-BIH database. In simulation, we sample ECG signals by CS at different *CR* and perform built-in AF detection in CS reconstruction with proposed criterion in (8).

Table I shows the sensitivity under difference CR. Under CR=90%, the sensitivity is 96.0% and the corresponding specificity is 97.2%. Hence, the proposed built-in AF detection technique is very accurate and effective in highly compressed data.

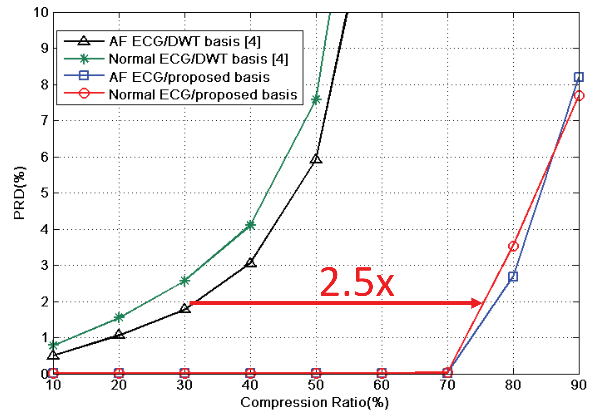

Fig. 6. Reconstruction performance of DWT and proposed basis under different CR.

TABLE I. SENSITIVITY AND SPECIFICITY UNDER DIFFERENT CR

CR	70%	80%	90%
Sensitivity	85.4%	92.4%	96.0%
Specificity	85.6%	86.0%	97.2%

5. CONCLUSION

We propose a CS-based ECG monitoring system with built-in AF detection. With the trained basis, we improve the compression ratio and perform built-in AF detection in CS reconstruction stage. The proposed detection scheme utilizes the ability of classification in CS reconstruction stage. The proposed idea can be extended to other feature processing, which makes the CS-based system more powerful than just compression and reconstruction.

6. REFERENCES

[1] V. Markides and R.J. Schilling, “Atrial fibrillation: classification, pathophysiology, mechanisms and drug treatment,” *Heart*, vol. 89, no. 8, pp. 939-943, Aug. 2003.

[2] E. J. Candes and M. B. Wakin, “An Introduction to Compressive Sampling,” *IEEE Signal Processing Magazine*, vol. 25, no. 2, pp. 21-30, Mar. 2008.

[3] L. T. Kuo, C. C. Hou, M. H. Wu, and Y. S. Shu, "A 1V 9pA analog front end with compressed sensing for electrocardiogram monitoring," in *Proc. IEEE Asian Solid-State Circuits Conf.*, Nov. 2015, pp. 1-4.

[4] H. Mamaghanian, N. Khaled, D. Atienza, and P. Vandergheynst, “Compressed Sensing for Real-time Energy-efficient ECG Compression on Wireless Body Sensor Nodes,” *IEEE Trans. on Biomed.*, vol. 58, no. 9, pp. 2456-2466, Sep. 2011.

[5] S. Dash , K. Chon , S. Lu, and E. Raeder, "Automatic real time detection of atrial fibrillation," *Annals of Biomedical Engineering*, vol. 37, no. 9, pp. 1701-1709, Sep. 2009

[6] R. Lepage, J. M. Boucher, J. J. Blanc, and J. C. Cornilly, "ECG segmentation and P-wave feature extraction: application to patients prone to atrial fibrillation," in *Proc. International Conference of IEEE Engin. Med. Biology Society (EMBS)*, vol.1, 2001, pp. 298-301.

[7] J. Mairal, F. Bach, J. Ponce, and G. Sapiro, "Online dictionary learning for sparse coding" in *Proc. International Conference on Machine Learning (ICML).* Jun. 2009, pp. 689-696.

[8] S. Chen, D. L. Donoho, and M. A. Saunders, "Atomic decomposition by basis pursuit," *SIAM J. Sci Comp.*, vol. 20, no. 1, pp. 33–61, Aug. 1998.

[9] B. Efron, T. Hastie, I. Johnstone, and R. Tibshirani. "Least angle regression," *Ann. Statist.*, vol. 32, no. 2, pp. 407-499, Apr. 2004.

[10] MIT-BIH Long-Term AF Database, https://www.physionet.org /physiobank/database/ltafdb/.

[11] Y. Zigel, A. Cohen, and A. Katz, "The Weighted Diagnostic Distortion (WDD) Measure for ECG Signal Compression," *IEEE Trans. on Biomed. Eng.*, vol. 47, no. 11, pp. 1422-1430, Nov. 2000.