LOW-COMPLEXITY COMPRESSED ALIGNMENT-AIDED COMPRESSIVE ANALYSIS FOR REAL-TIME ELECTROCARDIOGRAPHY TELEMONITORING

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ABSTRACT

In order to implement a real-time electrocardiogram (ECG) telemonitoring, compressed sensing (CS) is a new technology that reduces the power consumption of biosensors and data transmission. Unfortunately, limited label data and computing resources hinder the real-time ECG telemonitoring. Prior experiments have shown that aligning ECG signals is a good way to solve the problem of limited label data. However, the reconstructed learning (RL) framework requires a lot of computing resources, and the compressed learning (CL) framework makes alignment difficult. In this paper, we propose a new compressed alignment-aided compressive analysis (CA-CA) framework that enables simple alignment and low-complexity requirements. From simulation results, we have demonstrated that our technology can maintain more than 95% accuracy while reducing training data (labeled data) by 70%. Therefore, compared to RL, the computation time and memory overhead of CA-CA are reduced by 6.6 times and 2.45 times, respectively. Compared with CL, the inference accuracy with a small amount of labeled data is improved by 13.5%.

Index Terms—Atrial fibrillation detection, real-time ECG telemonitoring, compressive sensing, compressive analysis, compressed alignment

1. INTRODUCTION

As population ages and chronic diseases increase, real-time telemonitoring and notification techniques for patients are becoming increasingly important [1]. On the other hand, doctors can diagnose the electrocardiogram (ECG) signals of most chronic diseases, so the ECG signal is suitable for real-time telemonitoring [2]. In addition, different people's ECG signals will also be different. Therefore, for a more accurate analysis, the ECG signal will be aligned to reduce the difference, as shown in Fig. 1. [3], [4]. However, the ECG sensors for real-time telemonitoring is power-hungry. Fortunately, the emergence of compressive sensing (CS) technology solves this problem. CS is a technique that combines both sampling and compression via random projections to reduce the power of data acquisition and transmission [5], [6]. Compared with digital wavelet transform (DWT) technology, the CS-based ECG sensor can extend the battery life-time by 37.1% [7].

Unfortunately, limited label data and computing resources are also major challenges in real-time ECG telemonitoring. Namely, doctors can't diagnose (label) each ECG signal by themselves due to the limited medical resources. On the one hand, in the reconstructed learning (RL) framework, it is necessary to reconstruct the compressed signal into the original ECG signal before analysis. However, the reconstruction process requires a lot of computing resources. On the other hand, in the Compression Learning (CL) framework, it bypasses the reconstruction process and analyzes directly in the compressed domain [8], [9]. However, CL is difficult or even impossible to align the signal on the compressed domain. Therefore, we need a new framework that does not need to be reconstructed and can be easily aligned.

In this paper, we propose a new framework for compressed alignment-aided compressive analysis (CA-CA) to reduce the number of labeled data and the complexity of the classification model. We implement this framework in ECG-based atrial fibrillation (AF) detection [10]. Our main contributions are summarized as follows:

I. Our proposed CA-CA framework can maintain more than 95% accuracy while reducing training data (labeled data) by 70%.

Fig. 1. Aligned ECG signal
Therefore, compared to RL, the computation time and memory overhead of CA-CA are reduced by 6.6 times and 2.45 times, respectively.

Compared with CL, the inference accuracy with a small amount of labeled data is improved by 13.5%.

The rest of this paper is organized as follows. Section 2 provides the background of this paper and reviews some related works. Section 3, we introduce the techniques of our compressed alignment-aided compressive analysis. The simulation results are discussed in Section 4. Finally, we give a conclusion in Section 5.

2. BACKGROUND

2.1. Compressive Sensing (CS)

CS is a novel technology that achieves higher sampling rates than Nyquist sampling. We can express the process of CS in matrix formation as

\[ \hat{x} = \Phi x, \]

where \( x \in \mathbb{R}^N \) is the input signal, \( \hat{x} \in \mathbb{R}^M (M<N) \) is the measurement, and \( \Phi \) is the sensing matrix whose entries are independent identically distributed (i.i.d) samples [5], [6]. Although the front-end CS sensor can save more power, the reconstruction of the back-end CS is more complicated.

2.2. Principal Component Analysis (PCA) [11], [12]

The goal of PCA is to determine the most meaningful basis for re-expressing the data sets. The first step in PCA is to calculate the covariance matrix \( \Sigma \) of the data set \( X = [x_1, x_2, \ldots, x_m] \), where \( x_i \in \mathbb{R}^N \), and \( m \) is the number of data in the data set:

\[ \Sigma = \frac{1}{m} (X - \bar{x})(X - \bar{x})^T, \]

where \( \bar{x} \) is the mean of each row of \( X \), \( \bar{h} \) is a mx1 vector of all 1s, and \( [\cdot]^T \) denotes the transpose. The final step of PCA is to perform eigenvector decomposition on \( \Sigma \):

\[ \Sigma = UV \Phi^T, \]

where \( U \) is the eigenvectors of \( \Sigma \), and \( V \) is the eigenvalues of \( \Sigma \). Through the PCA, the eigenvectors are sorted by the magnitude of eigenvalues, which represent the variance on the eigenvectors. So we can get the eigenvector ordering, which can represent the data set information.

2.3. Related Works: Reconstructed Learning (RL) & Compressed Learning (CL)

In reconstructed learning (RL), measurement signals need to be reconstructed into the original signal before analysis. Although the reconstructed signal can achieve signal alignment, sparse signal reconstruction and ML inference in high dimensional original signal space are very energy intensive and time consuming [13].

In compressed learning (CL), it bypasses the reconstruction process and analyzes directly in the measurement domain. Since the distances between the points are retained by Johnson-Lindenstrauss lemma (JLL), the learnability is preserved [14]. Although CL can skip the process of reconstruction, it is difficult or even impossible to align the signal on the measurement domain.

3. PROPOSED COMPRESSED ALIGNMENT-AIDED COMPRESSIVE ANALYSIS (CA-CA)

To reduce both computation complexity and the required number of labeled data, the CA-CA framework is proposed, as shown in Fig. 2. The CA-CA process is as follows:

I. Find the coordinate of the reference point \( p \) (e.g. the peak of the ECG signal) from measurement signal.

II. Generate a circular shift matrix \( R_p \) based on the corresponding reference point coordinate \( p \).

III. Express compressed ECG signals on the same basis based on PCA and \( R_p \).

IV. Train the ML models and classification using the representation vectors generated from step III.

The detailed description of CA-CA is as follows. We use \( x, \hat{x}, \Phi, \) and \( U \) defined in section 2, to denote raw ECG signal, measurement signal, sensing matrix, and eigenvector, respectively.

3.1. Low-Complexity Approximate Reference Point Finding

The reference point we choose in this paper is the peak of the ECG signal (R-peaks). Although it is simple to find the ECG peak directly from the time domain signal, it is not easy to find the R-peak from the CS compression signal. Because we have to meet the limits of medical resources, we look for approximate reference points in a low-complexity way. In the first step, we simply extend the Eq. (1):

\[ \hat{x} = \Phi x = [c_1 c_2 \ldots c_n][x_1 x_2 \ldots x_n]^T = x_1 c_1 + x_2 c_2 + \cdots + x_n c_n, \]

where \( c_i \) is the \( i \)th column of \( \Phi \), and \( x_j \) is the \( j \)th entry of \( x \). It can be known from the Eq. (4) that the compressed signal \( \hat{x} \) is obtained by each point of the ECG signal and each
column of $\Phi$. Therefore, we can estimate the coordinate of the R-peak by the correlation of $\Phi$ and $\tilde{x}$

$$p \equiv \max_{i} \Phi_{i} \cdot (\Phi^T \cdot \tilde{x}),$$

(5)

where $\Phi^T$ is the transpose of $\Phi$. As mentioned above, R-peak is used as the reference point because it can be quickly estimated by low-complexity correlation methods. We make a tradeoff between the complexity and the exact coordinate of the ECG peak. Finally, use a low-complexity method to find the approximation $p$.

### 3.2. Circular Shift Matrix

After obtaining $p_i$ from Eq. (5), we can generate the circular shift matrix $R_p$, based on the corresponding reference point coordinate $p_i$,

$$R_p = [I^{N/2}_p \ldots I^{N/2}_p \ldots I^{N/2}_p]^T,$$

(6)

where $I_i$ is the ith column of the identity matrix ($I_{N \times N}$) and $j$th row of $R_p$. Since $R_p$ is shifted by the identity matrix, it is also an orthogonal matrix.

In the time-domain, we can use the $R_p$ to align the ECG signal, which can be expressed by the following equation:

$$x_a = R_p x,$$

(7)

where $x_a$ is the aligned ECG signal. Although the time-domain alignment only needs to be multiplied by a circular shift matrix, the compressed signal can’t be simply multiplied by a circular shift matrix to achieve alignment. Therefore, we propose a new technology that can be used for compressed-domain alignment.

### 3.3. Compressed-domain Alignment

We replace the traditional dictionary learning method with PCA, which allows the dictionary to retain more signal features. The PCA-based dictionary $\Psi$ is constructed from the first $L$ columns of eigenvector $U$:

$$\Psi = U(:, 1: L),$$

(8)

PCA-based dictionary keeps the most important information with the least vector. We first assume the aligned ECG signal $x_a$ has below representation $x_a = \Psi s_a$. Therefore, we can re-represent the Eq. (1) as:

$$\tilde{x} = \Phi x = \Phi \cdot R_p \cdot x_a = \Phi \cdot R_p \cdot \Psi s_a = \Theta s_a,$$

(9)

where $x = R_p x_a$, $\Theta = \Phi \cdot R_p \cdot \Psi$, and $s_a$ is the representation vector of $x_a$. The representation vector $s_a$ is obtained by

$$s_a = \Theta_{\tilde{x}} \tilde{x},$$

(10)

where $\{\cdot \}^*$ denotes the pseudo-inverse. Finally, we further implement the training and inference of machine learning models in the $s_a$.

### 4. SIMULATION RESULTS

We use a case study of atrial fibrillation (AF) [10] detection to validate the benefits of our proposed algorithm. The simulation settings are summarized in TABLE I. Raw ECG signals were recorded from the intensive care unit (ICU) of stroke in National Taiwan University Hospital (NTUH), and visually checked and labeled by doctors. Model selection for SVM (by LIBSVM [15]) is performed by cross-validated grid-search.

#### 4.1. Learning Performance Evaluation

Fig. 3 shows the average classification accuracy under the different number of training data with a compression ratio = 0.25. It can be seen that (I) Our proposed CA-CA can maintain more than 95% accuracy while reducing training data (labeled data) by 70%. (II) Our proposed CA-CA has higher accuracy than CL. This improvement is due to the

### TABLE I. SIMULATION SETTINGS

<table>
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<tr>
<th>Simulator</th>
<th>MATLAB</th>
</tr>
</thead>
<tbody>
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<td>Data Parameters</td>
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<td>Number of training / inference data</td>
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<td>Gamma ($\gamma$) Search Range</td>
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<tr>
<td>Cross-validation</td>
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</tbody>
</table>

Fig. 3. Comparison of classification accuracy under the different number of training data with a compression ratio = 0.25
alignment of the signal making the machine easier to learn. (III) The accuracy of our proposed CA-CA is slightly lower than RL. The reason is that the alignment of the compressed domain is caused by the approximation of Eq. (5).

4.2. Analysis of Computation Time

Fig. 4 shows the computation time under different compression ratios with the number of training data = 5000. It can be seen that (I) Our proposed CA-CA has less computation time than RL because it is no need to reconstruct the ECG signal. (II) Our proposed CA-CA computation time is slightly longer than CL because it requires additional pseudo-inverse and compression alignment.

4.3. Analysis of Memory and Computational Overhead

TABLE II presents the multiplication and memory overhead of different frameworks. Where N is the dimension of ECG data (input data), M is the dimension of measurement data, $d_R$ is the dictionary length, $K$ is the signal sparsity setting in reconstruction algorithm, and $n_{SV}$ is the number of support vector in SVM.

Under the simulation settings, TABLE III presents the overall comparison of different frameworks. It can be seen and proved again that (I) Our proposed CA-CA is a low-complexity framework because there is no need to reconstruct the ECG signal. (II) Because of the good data representation (aligned ECG signals), ML can get more detailed information. So our proposed CA-CA has higher accuracy. Therefore, compared to RL, the computation time and memory overhead of CA-CA are reduced by 6.6 times and 2.45 times, respectively. Compared to CL, the accuracy of CA-CA is improved by 2.65%.

5. CONCLUSION

In this paper, we present a novel compressed alignment-aided compressive analysis framework based on CS. We use compressed domain alignment technology to alleviate the shortage of medical resources. The proposed CA-CA differs from RL and CL in that it reduces both computational complexity and the required number of labeled data. The proposed idea can be extended to other disease detection and other biomedical signal processing, which makes the CS-based analysis system more efficient and powerful.

6. ACKNOWLEDGEMENT

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7. REFERENCES


