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ECG Signals Application Automated Apprehension and Allocation of Cardiovascular Abnormalities

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Abstract **- In this paper, a data-driven concordance access is proposed for automated apprehension and allocation of cardiovascular abnormalities. ECG arresting is represented by accomplished an complete dictionary that contains prototypes or atoms to abstain the limitations of pre-defined dictionaries. The data-driven accomplished dictionaries artlessly crop the ECG arresting as ascribe rather than extracting appearance to abstraction the set of ambit that crop the a lot of anecdotic dictionary. The access inherently apprentices the complicated morphological changes in ECG waveform, which is again acclimated to advance the classification. The allocation achievement was evaluated with ECG abstracts beneath two altered preprocessing environments. First category, QT-database is baseline alluvion adapted with cleft clarify and clarify the 60Hz ability band noise. Second category, the abstracts is added filtered application fast affective boilerplate smoother. The beginning after-effects on QT database confirms that our proposed algorithm shows a allocation accurateness of 92%.**
Keywords**: Electrocardiogram, concordance learning, dispersed coding, classification.**

I. INTRODUCTION

Electrocardiogram (ECG) is a painless, non-invasive and very effective tool to record and diagnose the electrical activity of the heart and has been used for several decades [1]. ECG deviations from the normal heart rhythm often caused by heart abnormalities. Several methods and approaches for ECG feature extraction have been reported in the literature. However, an accurate feature extraction from a wide variety of ECG morphologies is a challenging process [2].

Sparse representation has already been a subject of interest in processing the biosignals in different applications such as ECG data compression [3],[4], ECG classification [5],[6],[2],[7], and ECG anomaly detection [8]. Fixed orthogonal dictionaries such those created by using wavelet transform, discrete cosine transform, and Fourier transform can decompose any signal into its basis functions. Although these special dictionaries are mathematically simple [4], However, a linear combination of those dictionary atoms cannot be used to create an efficient sparse representation model [9]and they are not suitable for to represent signals with few redundancies. Learning the dictionary from the training data itself, allows the model to be suitable to a wide class of signals.

Sparse approximation is the process that allows to recover most of the signal information using a linear combination of a few atoms from a given dictionary.

Mathematically, let $Y = [y_1, y_2, \dots, y_N] \in \mathbb{R}^{n\times N}$, Y is the input $N - dimensional$signal to be processed.
A complete dictionary $D = [d_1, d_2, \dots . d_K] \in \mathbb{R}^{n\times K}$.The signal Y can be sparsely represented by sparse coefficient matrix$X = [x_1,\ x_2, \dots, x_N] \in \mathbb{R}^{K\times N}$.

$$Y = DX \tag{1}$$

Where X and D can be found by solving the following approximation,

$$< D, X > = \arg\min_{D,X} \|Y - DX\|_2^2, s.t. \forall_i \|x_i\|_0 < T \tag{2}$$

Where T is the sparse constraint factor, $\|x_i\|_0$ is the l_0-norm counting the nonzero elements of vector x_i.

II. METHODOLOGY

A. Preprocessing

The performance of classification is evaluated using QT database (QTDB) [10] which contains 3623, 3542, and 3176 cardiologist's annotations for QRS complexes, T waves, and P waves respectively. The QT database includes ECG signals which were chosen to represent a wide variety of QRS and ST-T morphologies and includes some records from MIT-BIH database. All records for this database are sampled at 250 Hz.

For each ECG signal, we followed the cardiologist annotations available online with the database to segment the heartbeat cycles in order PQRST. Due to the heart-rate variability, the cycles' durations are not the same in most cases. A time normalization is applied to each cycle taking the cycle with the longest duration as a reference. Linear interpolation and zero-padding the cycle in frequency domain were tested to normalize the cycle length and both methods comes with the similar time alignment.

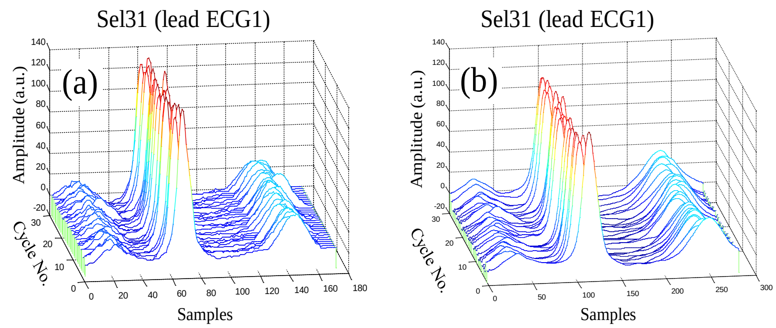

Fig.1 (a) Baseline drift corrected signal (Record sel30, lead ECG1). (b) After smoothing time normalization

B. Dictionary Learning

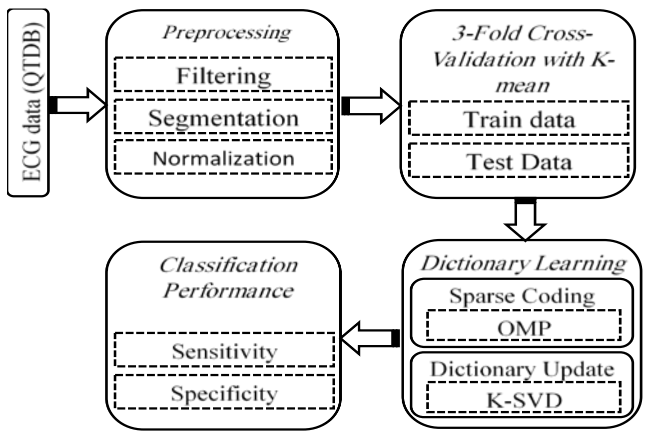

Fig. 2. ECG classification procedure with data-driven dictionary learning.

Fig.2 shows the general procedure followed in this paper. ECG data segmentation can be done using any QRS peak detection algorithm. To avoid any auto-misdetection of ECG heartbeats, we used the cardiologists' annotation points provided with the database to segment the ECG data into $N - dimensional$ stack of cycles (each cycle starts with the atrial activity and ends with the ventricle activity). Beat-to-beat (RR) duration or sampling frequency related segments around the QRS peak can be utilized to achieve a complete heart cycle segmentation. Sequence of adjacent heartbeats might have different morphological changes and most probably have different lengths. Length normalization as shown in Fig. 1(b) is performed for each individual cycle as required by dictionary learning process.

After normalization, a total of 6352 segments were extracted from the two leads QTDB. Since the segment duration related abnormality is neglected, we clustered the segmented data into normal and abnormal categories using three different approaches. Taking a reference normal cycle1 from the normal-sinus rhythm group as a reference and run cross-correlation between this reference cycle and the whole data cycles.

Class 1: all the cycles that shows 60% match and higher considered as normal. The rest is abnormal.

Class2: all the cycles that shows 80% match and higher considered as normal. The rest is abnormal.

Class 3:cycles were checked one-by-one and clustered into normal and abnormal classes.

The normalized cycles then partitioned into training and testing sets. 3fold cross validation assisted by k-mean clustering to insure that the training and testing data contains all types of ECG data. Table I below shows the data classes and data partitioning carried out in this work.

TABLE 1 QTDB DATASET FOR TRAINING AND TESTING.

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			Data 1	**Data 2**
Normal	Class 1	Train	780	908
		Test	390	454
	Class 2	Train	339	440
		Test	169	220
	Class3	Train	NA	815
		Test	NA	407
Abnormal	Class 1	Train	3455	3327
		Test	1727	1663
	Class 2	Train	3896	3795
		Test	1948	1897
	Class 3	Train	NA	3420
		Test	NA	1710

Data 1 (1st category): raw ECG data with power-line and base-line noise filtered.
Data 2 (2nd category): same as Data 1, filtered with fast moving average smoother.
NA: Not-available

C. Data-Driven Dictionary Learning

Sparse Coding Stage:

Used to find the sparse representation of input ECG cycle y_i, given the dictionary atoms $D \in \mathbb{R}^{n\times K}$, where D initially is a normalized iid Gaussian entries. Among the sparse approximation methods reported in the literature, we selected the orthogonal matching pursuit (OMP) [11] due to its simplicity and ability to well represent the data-driven dictionaries [3]. OMP is an iterated based method dedicated to choose the best matching atom d_k which satisfy the maximum inner product with y_i.

Dictionary Update Stage:

Singular value decomposition (K-SVD) is one of the popular algorithms for constructing dictionaries by learning. The goal of K-SVD is to find the optimal dictionary atoms. Nevertheless, a set of parameters have to be adapted to achieve a strong dictionary. Given the initial dictionary and the sparse representation matrix X created in sparse coding stage. In this paper, we followed the update procedure inspired by [12]. In which the dictionary atoms d_k (column) were updated sequentially along with the corresponding sparse vector x_k (row) as follows,

$$\langle d_k\,, x_k \rangle = \arg\min_{d_k\,, x_k^{row}} \| E_{-k} - d_k x_k^{row} \|_F^2 \tag{3}$$

Where the reconstruction error,

$$E_{-k} = Y - D_{-k} X_{-k} \tag{4}$$

D_{-k} is the dictionary with d_k (atom/column) removed, X_{-k} is the sparse coefficients vector with x_k (row) removed.

Applying SVD decomposition on the error $E_k = USV^T$, update the d_k atom using the eigenvector U_i with the largest eigenvalue. Then update the sparse coefficients vector x_k by multiplying the first column of V with the first value of S (the largest singular value of E). This updating procedure will lead to very few zero entries or non-sparse X. To solve this sparsity problem, [13] suggests a method to handle every entry of x_k independently updating only the non-zero entries to keep X sparse. Another approach of updating dictionary atom d_k is to update the sparsity of x_k first using $l_1 - norm$ penalty, more details can be found in [12].

From (1), the K-SVD assumes,

$$\tilde{x}_k = d_k^T E_{-k} \tag{5}$$

Rather than using a fixed value $l_1 - norm$ penalty, we suggest to adaptively set the penalty α to $\tilde{x}_k$ scale initialized by SVD decomposition.

Applying penalty α on $\tilde{x}_k$,

$$\tilde{x}_k^{\alpha} = \begin{cases} 1 & if \|\tilde{x}_i\| > \alpha\,, \quad i = 1, \dots, k \\ 0 & if \|\tilde{x}_i\| < \alpha\,, \quad i = 1, \dots, k \end{cases}$$

The x_k and d_k update equations [12] are,

$$x_k = sgn(\tilde{x}_k).\ \tilde{x}_k^{\alpha}.\left(\|\tilde{x}_k\| - \frac{\alpha}{2}\right) \tag{6}$$

$$d_k = \frac{E_{-k} x_k^T}{\|E_{-k} x_k^T\|_2} \tag{7}$$

III. EXPERIMENTAL RESULTS

A.Dictionary Parameters

During the stage of QTDB ECG cycles segmentation, we found that the cycle with longest duration has 284 samples. Note that the QTDB sampled at 250Hz. All cycles then normalized to the same length (284 sample).

Fig.3(a).Depicts the impact of dictionary learning iterations used in this paper on the signal to noise ratio (SNR), root mean squared error (RMSE), and the sparsity.Only 60 iteration were analyzed. For better results, more iterations should be done. With fixed complete dictionary size (K=284) it is obvious that when the iterations goes higher Fig. 3(a), it offsets by a decrease in the recovered ECG signal SNR. This decrease in SNR resulted from the noticed increase in the dictionary sparsity as in Fig. 3(c). Unlike Fig. 3(b),which shows rapid increase in recovered signal SNR as the dictionary size increases.

Fig. 4 shows the simple error based classifier used in this work. Given a test data and dictionary D (normal/abnormal), the encoding process estimates the sparse coefficients using OMP method with initially pre-determined sparse factor L. In which L determines the count of non-zero entries of X in solving the approximation problem (2). Experimental results of selecting L is shown in Fig. 3 (a, b, and c).

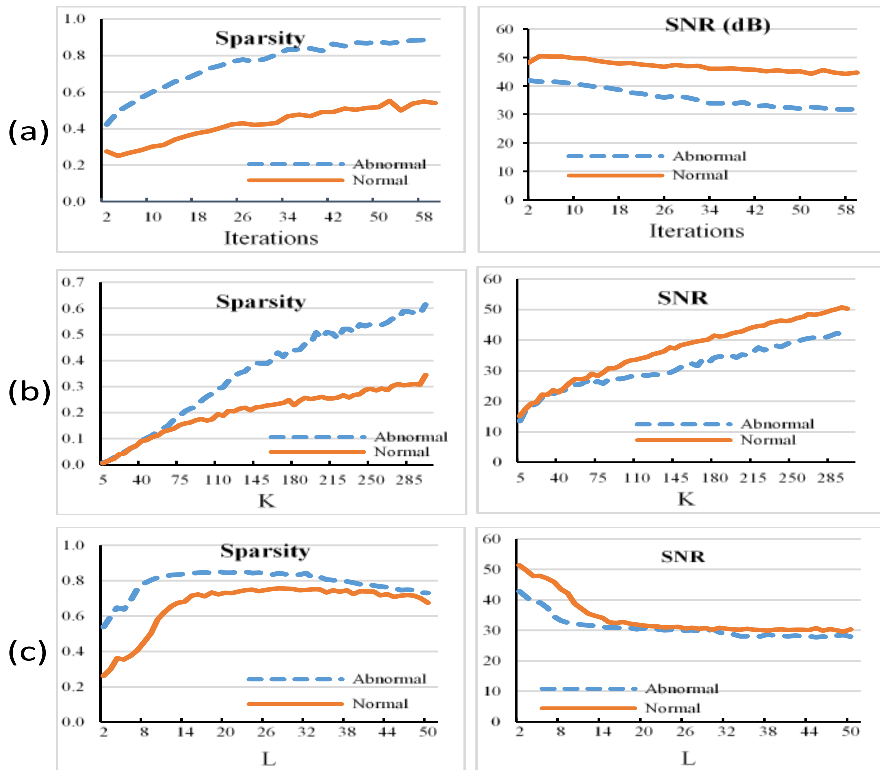

Fig.3 Normal and abnormal dictionaries performance on different set of training iterations

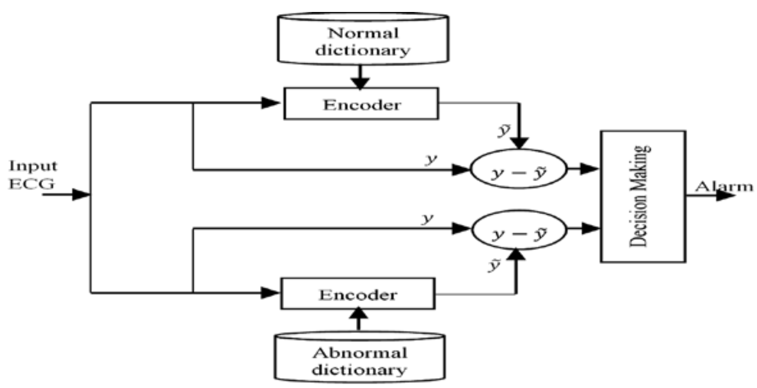

Fig.4. ECG reconstruction error based classifier block diagram adopted from [13].

B. Classification

The classification performance is assessed for its performance by calculating the Sensitivity $TP/(TP+FN)$ and specificity$TN/(TN+FP)$, where; TP - number of true positive detections (abnormal classified as abnormal), FN - number of false negative detections (abnormal classified as normal), FP - number of false positive detections (normal classified as abnormal), TN - number of true negative detections (normal classified as normal). In general, the sensitivity is the percentage of abnormal ECG cycles were correctly identified as abnormal. The specificity is the percentage of normal ECG cycles were correctly identified as normal.

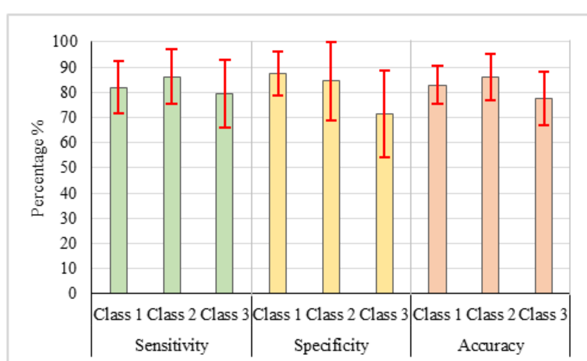

Fig.5 Classifier Average Performance.

The dictionary based classifier performance was evaluated using 3-fold cross-validation with around 70% of the data as training and 30% as testing. As shown in Fig. 5, the overall sensitivity, specificity, and accuracy were determined by averaging the results of 18 different dictionary parameter settings. The results show that sensitivity in some cases was $\approx 98\%$ and the specificity at best was 100%. Because of the trade-off between sensitivity and specificity, Table II depicts the best balanced performance combination which

TABLE 2 CLASSIFICATION PERFORMANCE ON QTDB DATABASE.

	Sensitivity	Specificity	Accuracy
Class 1	91.78	95.13	92.40
Class 2	92.09	94.67	92.30
Class 3	84.68	83.39	84.41

[14] has managed to detect and obtain twenty-points from the ST segment trained by support vector machine (SVM). The achieved average sensitivity of ischemic beat detection was 92.13% and [2] presented a patient-specific ECG heartbeats classifier assisted by Gini Index. A window of 61 samples centered at QRS peak is used to train the dictionary. Average accuracy of test data sets was 84.5% for only 9 ECG records selected from MIT-BIH database

IV. CONCLUSION

A dictionary based heart-beat classifier is presented in this paper. The proposed method utilizes the whole heart-beat cycle an input without feature extraction/selection. The ECG data reconstruction error used as decision rule for the classifier. Dictionary learning based methods provides good accuracies for ECG data classification. The experimental results indicates that the classifier built by this dictionary framework provide an accuracy of 92.4%, 92.3%, and 84.41% with class1, class2, and class3 data set respectively. The proposed dictionary learning algorithm has shown significant potential for further research that could provide for better accuracy of ECG data classification.

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