International Journal of Medical, Medicine and Health Sciences
ISSN: 2517-9969
Vol:10, No:8, 2016

Sparse Coding Based Classification of Electrocardiography Signals Using Data-Driven Complete Dictionary Learning

Fuad Noman, Sh-Hussain Salleh, Chee-Ming Ting, Hadri Hussain, Syed Rasul

Abstract**—**In this paper, a data-driven dictionary approach is proposed for the automatic detection and classification of cardiovascular abnormalities. Electrocardiography (ECG) signal is represented by the trained complete dictionaries that contain prototypes or atoms to avoid the limitations of pre-defined dictionaries. The data-driven trained dictionaries simply take the ECG signal as input rather than extracting features to study the set of parameters that yield the most descriptive dictionary. The approach inherently learns the complicated morphological changes in ECG waveform, which is then used to improve the classification. The classification performance was evaluated with ECG data under two different preprocessing environments. In the first category, QT-database is baseline drift corrected with notch filter and it filters the 60 Hz power line noise. In the second category, the data are further filtered using fast moving average smoother. The experimental results on QT database confirm that our proposed algorithm shows a classification accuracy of 92%.

Keywords**—**Electrocardiogram, dictionary learning, sparse coding, classification.

I. Introduction

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 are 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 [2], [5]-[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], a linear combination of those dictionary atoms cannot be used to create an efficient sparse representation model [9] and they are not suitable to represent signals with few redundancies. Learning the dictionary from the training data allows the model to be suitable to a wide class of signals.

Sparse approximation is the process that permits 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 and $\|x_i\|_0$ is the l_0-norm counting the nonzero elements of vector x_i.

II. Methodology

A. Preprocessing

The performance of classification is evaluated by 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 come with the similar time alignment.

Sh-Hussain Salleh is with the Centre for Biomedical Engineering, Universiti Teknologi Malaysia (FBME-UTM) (corresponding author; phone: +607-5535208; fax: +607-5535430; e-mail: hussain@fke.utm.my).

Fuad Noman is with the Centre for Biomedical Engineering, Universiti Teknologi Malaysia (FBME-UTM) (e-mail: mnfuad3@live.utm.my).

Chee-Ming Ting is with Center for Biomedical Engineering, and a senior lecturer in Universiti Teknologi Malaysia (e-mail: cming@utm.my)

Hadri Hussain is with Faculty of Electrical Engineering, Universiti Teknologi Malaysia (e-mail: hadri_hussain@yahoo.com).

Syed Rasul is a Consultant Cardiothoracic Surgeon, Department of Cardiothoracic Surgery, Sultanah Aminah Hospital (HSA), Johor, Malaysia (e-mail: leelarasul@yahoo.com)

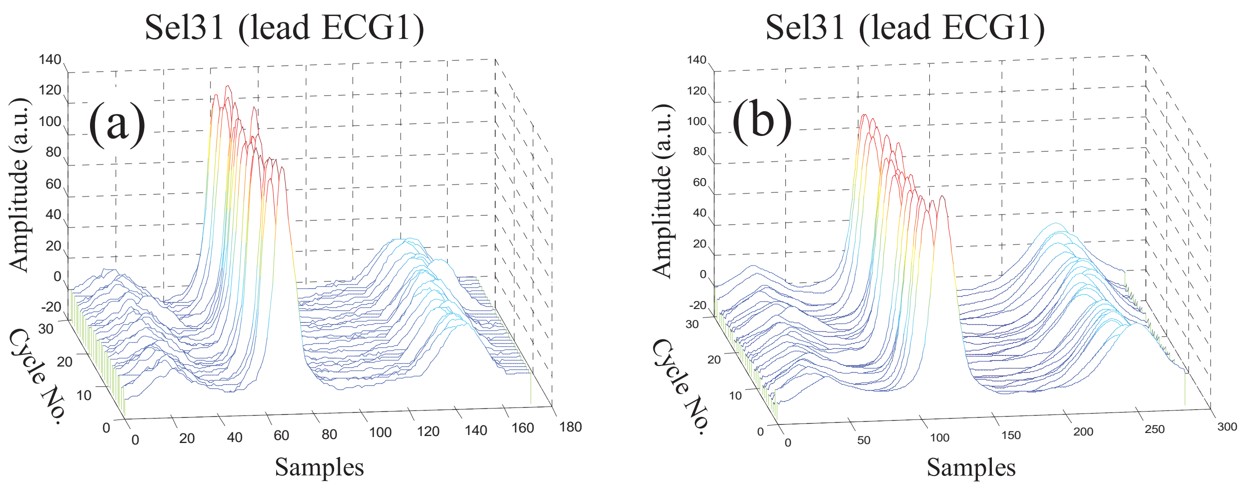

Fig. 1 (a) Baseline drift corrected signal (Record sel30, lead ECG1) (b) After smoothing time normalization

B. 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 QTDB database. Segment length normalization leads to neglect the heart rate related abnormality. Therefore, the extracted segments were clustered into normal and abnormal classes using three different approaches. A reference cycle[1] was selected from the normal sinus rhythm group and used to find the correlation coefficients with the entire data cycles.

- **Class 1**: all the cycles that show 60% match and higher are considered as normal. The rest is abnormal.
- **Class2**: all the cycles that show 80% match and higher are 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 are then partitioned into training and testing sets. 3 fold cross validation is assisted by k-mean clustering to ensure that the training and testing data contain all types of ECG data. Table I shows the data classes and data partitioning carried out in this work.

[1] Cycle or segment is the ECG signal begins from the P-Wave start till T-wave end.

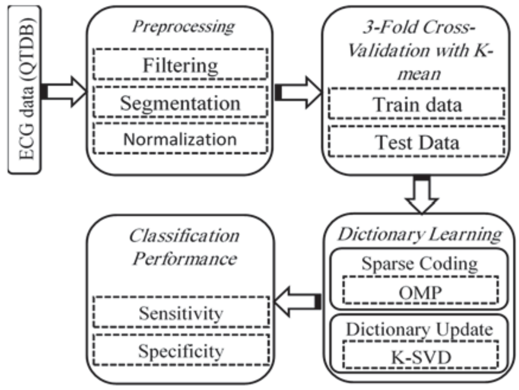

Fig. 2 ECG classification procedure with data-driven dictionary learning

TABLE I
QTDB DATASET FOR TRAINING AND TESTING

			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
	Class3	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: It is 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 iteration based method dedicated to choose the best matching atom d_k which satisfies the maximum inner product with y_i as,

$$\mathrm{a_j} = \arg \max_{\{d_k\},\ 1<k<K} \left|\langle r_{j-1}\,,\, d_k\rangle\right| \,, \qquad 1<j<L \tag{3}$$

where a_j is the selected atom, $\langle\,.\,\rangle$ denotes the inner-product, r_{j-1} is the residual at $(j-1)^{\text{th}}$ iteration with $r_0 = y_i$, d_k is the dictionary atom, and L is the sparse factor which determines the count of non-zero entries in X.

The iterated algorithm then updates the residual as,

$$S_j = D_j^T\left(D_j\, D_j^T\right)^{-1} \times y_i \tag{4}$$

$$r_j = y_i - a_j * S_j \tag{5}$$

where $D_j^T\left(D_j\, D_j^T\right)^{-1}$ is the Pseudo-inverse of the selected atoms.

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. The corresponding initial dictionary and the sparse representation matrix X are created in sparse coding stage. In this paper, we followed the update procedure inspired by Ref. [12] in which the dictionary atoms d_k (column) were updated sequentially along with the corresponding sparse vector x_k (row) as,

$$\langle d_k\,, x_k\rangle = \arg \min_{d_k\,,\, x_k^{row}} \|E_{-k} - d_k x_k^{row}\|_F^2 \tag{6}$$

where the reconstruction error,

$$E_{-k} = Y - D_{-k}\, X_{-k} \tag{7}$$

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,

$$\tilde{x}_k = d_k^T\, E_{-k} \tag{8}$$

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 adapted from [12] are,

$$x_k = sgn(\tilde{x}_k).\, \tilde{x}_k^{\alpha}.\left(\|\tilde{x}_k\| - \frac{\alpha}{2}\right) \tag{9}$$

$$d_k = \frac{E_{-k} x_k^T}{\left\|E_{-k} x_k^T\right\|_2} \tag{10}$$

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 250 Hz. All cycles then normalized to the same length (284 samples).

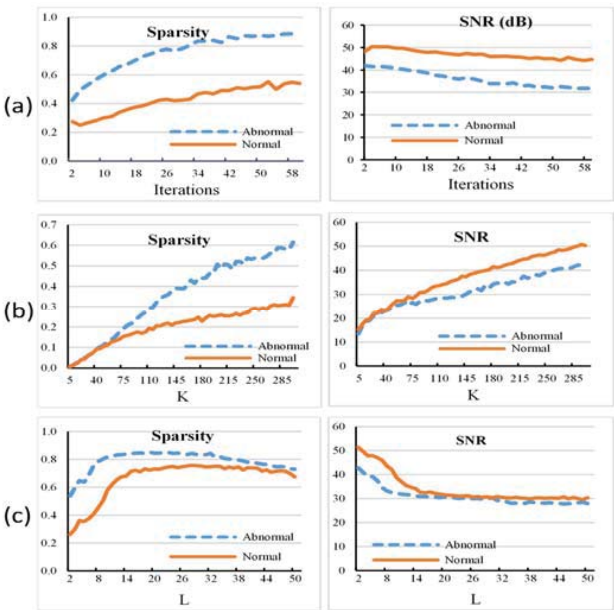

Fig. 3 Normal and abnormal dictionaries performance on different set of training parameters

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 iterations were analyzed. For better results, more iterations should be done. With fixed complete dictionary size (K=284), it is obvious that when the iterations go 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). On the contrary, Fig. 3 (b) shows that both the SNR and Sparsity increase as the dictionary size increases.

B. Classification

Fig. 4 shows the simple error based classifier used in this work. Given a test ECG data and the trained dictionaries (normal and abnormal), the encoder uses the OMP method to estimate the sparse coefficients by solving the approximation problem (3). Experimental results of selecting L is shown in Figs. 3 (a)-(c).

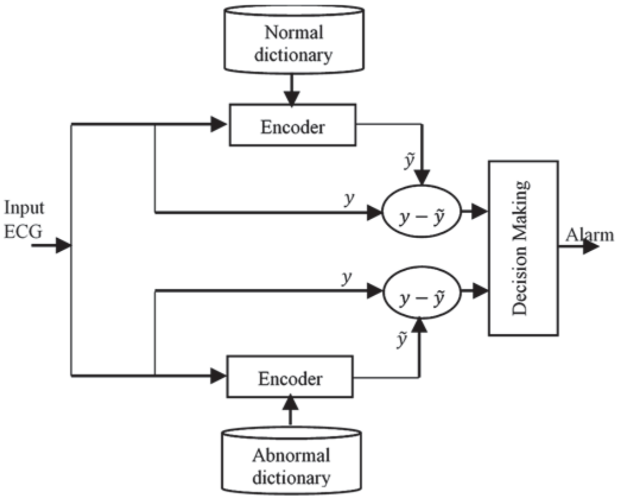

Fig. 4 ECG reconstruction error based classifier block diagram adopted from [13]

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.

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 ≈ 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.

Reference [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%.

Reference [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.

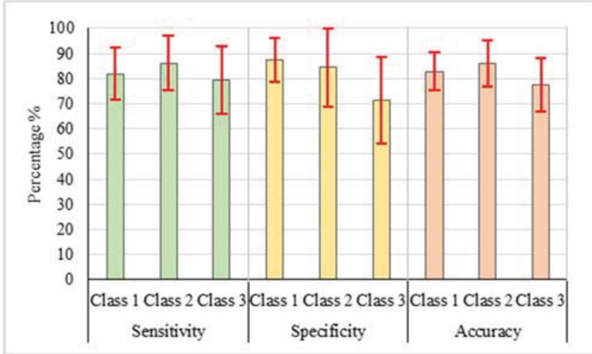

Fig. 5 Classifier average performance

TABLE II
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

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 indicate 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 have shown significant potential for further research that could provide for better accuracy of ECG data classification.

ACKNOWLEDGMENT

Authors would like to convey the deepest acknowledgment to Universiti Teknologi Malaysia (UTM), Center for Information and Communication Technology (CICT-UTM) and Ministry of Higher Education (MOHE) – Malaysia for supporting this research under TRGS grant number R.J130000.7845.4L840 and Science-Fund number R.J130000.7945.4S127 (MOSTI).

REFERENCES

[1] Di Marco, L.Y. and L. Chiari, *A wavelet-based ECG delineation algorithm for 32-bit integer online processing.* BioMedical Engineering OnLine, 2011. 10(23): p. 19.

[2] Baali, H. and M. Mesbah. *Ventricular ectopic beats classification using Sparse Representation and Gini Index*. in *Engineering in Medicine and Biology Society (EMBC), 2015 37th Annual International Conference of the IEEE*. 2015.

[3] Lee, S., J. Luan, and P.H. Chou. *A new approach to compressing ECG signals with trained overcomplete dictionary*. in *Wireless Mobile Communication and Healthcare (Mobihealth), 2014 EAI 4th International Conference on*. 2014.

[4] Lee, S.J., J. Luan, and P.H. Chou, *ECG signal reconstruction from undersampled measurement using a trained overcomplete dictionary.* Contemporary Engineering Sciences, Vol. 7, 2014, no. 29, 1625 - 1632 HIKARI Ltd, 2014.

[5] Mathews, S.M., L.F. Polanıa, and K.E. Barner. *Leveraging a discriminative dictionary learning algorithm for single-lead ECG classification*. in *Biomedical Engineering Conference (NEBEC), 2015 41st Annual Northeast*. 2015.
[6] Tseng, Y.L., K.S. Lin, and F.S. Jaw, *Comparison of Support-Vector Machine and Sparse Representation Using a Modified Rule-Based Method for Automated Myocardial Ischemia Detection.* Comput Math Methods Med, 2016. 2016: p. 9460375.
[7] Li, Q., C. Rajagopalan, and G.D. Clifford, *Ventricular Fibrillation and Tachycardia Classification Using a Machine Learning Approach.* IEEE Transactions on Biomedical Engineering, 2014. 61(6): p. 1607-1613.
[8] Adler, A., et al., *Sparse Coding with Anomaly Detection.* Journal of Signal Processing Systems, 2014. 79(2): p. 179-188.
[9] Wang Tian, J., Y. Zheng Bao, and Z. Yang. *An overcomplete dictionary design algorithm for sparse representation of piecewise stationary signals*. in *Communications (APCC), 2012 18th Asia-Pacific Conference on*. 2012.
[10] Laguna, P., et al. *A database for evaluation of algorithms for measurement of QT and other waveform intervals in the ECG*. in *Computers in Cardiology 1997*. 1997.
[11] Tropp, J.A., *Greed is good: algorithmic results for sparse approximation.* IEEE Transactions on Information Theory, 2004. 50(10): p. 2231-2242.
[12] Seghouane, A.K. and M. Hanif. *A sequential dictionary learning algorithm with enforced sparsity*. in *Acoustics, Speech and Signal Processing (ICASSP), 2015 IEEE International Conference on*. 2015.
[13] Elad, M., *Sparse and Redundant Representations: From Theory to Applications in Signal and Image Processing*. 2010: Springer Publishing Company, Incorporated. 376.
[14] Mohebbi, M. and H.A. Moghadam. *An Algorithm for Automated Detection of Ischemic ECG Beats Using Support Vector Machines*. in *Signal Processing and Communications Applications, 2007. SIU 2007. IEEE 15th*. 2007.