Information Sciences 345 (2016) 340–354

Contents lists available at ScienceDirect

Information Sciences

journal homepage: www.elsevier.com/locate/ins

Deep learning approach for active classification of electrocardiogram signals

M.M. Al Rahhal[a], Yakoub Bazi[a,*], Haikel AlHichri[a], Naif Alajlan[a], Farid Melgani[b], R.R. Yager[c,1]

[a] ALISR Laboratory, College of Computer and Information Sciences, King Saud University, P. O. Box 51178, Riyadh 11543, Saudi Arabia
[b] Department of Information Engineering and Computer Science, University of Trento, Via Sommarive, 14, I-38123 Trento, Italy
[c] Machine Intelligence Institute, Iona College, New Rochelle, NY 10801, USA

ARTICLE INFO

Article history:
Received 23 April 2015
Revised 1 December 2015
Accepted 29 January 2016
Available online 5 February 2016

Keywords:
ECG signal classification
Feature learning
Denoising autoencoder (DAE)
Deep neural network (DNN)
Active learning (AL)

ABSTRACT

In this paper, we propose a novel approach based on deep learning for active classification of electrocardiogram (ECG) signals. To this end, we learn a suitable feature representation from the raw ECG data in an unsupervised way using stacked denoising autoencoders (SDAEs) with sparsity constraint. After this feature learning phase, we add a softmax regression layer on the top of the resulting hidden representation layer yielding the so-called deep neural network (DNN). During the interaction phase, we allow the expert at each iteration to label the most relevant and uncertain ECG beats in the test record, which are then used for updating the DNN weights. As ranking criteria, the method relies on the DNN posterior probabilities to associate confidence measures such as entropy and Breaking-Ties (BT) to each test beat in the ECG record under analysis. In the experiments, we validate the method on the well-known MIT-BIH arrhythmia database as well as two other databases called INCART, and SVDB, respectively. Furthermore, we follow the recommendations of the Association for the Advancement of Medical Instrumentation (AAMI) for class labeling and results presentation. The results obtained show that the newly proposed approach provides significant accuracy improvements with less expert interaction and faster online retraining compared to state-of-the-art methods.

1. Introduction

The Electrocardiogram (ECG) signal is a noninvasive test widely used for reflecting the underlying heart conditions. A careful inspection of its behavior is essential for detecting cardiac arrhythmias particularly in long-term recordings (usually over a period of 24 h). Therefore, the utilization of computer-based methods represents an important solution that can benefit cardiologists in the diagnosis.

In the last decades, several pattern recognition methods were developed for arrhythmia detection and classification [1–4,27,33,43]. Usually, these approaches are based on three main steps which are preprocessing, feature extraction; and classification. First, the ECG signals are enhanced by eliminating various kinds of noise and artifacts (i.e., baseline wanders,

* Corresponding author. Tel.: +966 506469808.
E-mail addresses: yakoub.bazi@gmail.com, ybazi@ksu.edu.sa (Y. Bazi), hhichri@ksu.edu.sa (H. AlHichri), najlan@ksu.edu.sa (N. Alajlan), melgani@disi.unitn.it (F. Melgani), yager@panix.com (R.R. Yager).
[1] Visiting Distinguished Scientist, King Saud University, Riyadh, Saudi Arabia.

http://dx.doi.org/10.1016/j.ins.2016.01.082
0020-0255/

power line interference, and muscle contraction) [41,51,55,59,60]. After this step, the ECG waveforms, also known as PQRST, consisting mainly of P wave, QRS complex and T wave are extracted by means of segmentation [9,46,50]. Then several handcrafts features are calculated from these waveforms. In general, the available feature representation methods include, but are not limited to, morphology [14,18], temporal information [15,35], wavelet transform [61,63], high-order statistics (HOS) [35], Hermite basis function [37], and hidden Markov modeling (HMM) [12]. Then feature reduction techniques such as principal component analysis (PCA), independent component analysis (ICA), and linear discriminant analysis (LDA) are usually applied to reduce the dimensionality of the feature representation [42,62,63]. Finally, the obtained features are used to learn the decision function of a classifier such as neural networks (NN) [34], probabilistic NN [58], recurrent NN [17], support vector machines (SVMs) [1,27], least square SVM [19], path forest [40] and Gaussian processes (GPs) [1,44].

Despite these great efforts, it has been shown recently [14,27,64] that automatic methods do not perform well if the recommendations of the Association for the Advancement of Medical Instrumentation (AAMI) for class labeling and results presentation are closely followed as a possible solution for standardization. Specifically, the AAMI standard defines five classes of interest: normal (N), ventricular (V), supraventricular (S), fusion of normal and ventricular (F) and unknown beats (Q). Regardless of the class definition, this standard essentially recommends for performance evaluation the adoption of inter-patient scenario (i.e., training and test ECG beats are extracted from different patients), which is not usually adopted in most of the works published in the literature. This requirement renders the automatic classification task very challenging due to the strong shift between the distributions of training and test subjects. Although, various handcrafted feature representations as well as many classifiers were considered as mentioned previously, the results obtained by automatic methods remain up till now unsatisfactory.

To overcome the above issues, semiautomatic methods allowing expert interaction are introduced as an alternative promising solution. Basically, these approaches start by training a global classifier on a large dataset and another local-classifier on the first few minutes from the test record labeled by an expert [5,15,41,32,34]. Then the outputs of both classifiers are fused using voting rules to classify the entire record. However, one major drawback of these methods lies in the selection scheme which does not take into consideration the importance of these beats in improving the classification accuracy. Indeed, it is not guaranteed that the selected first few minutes can efficiently model the statistical distribution of the data.

This paper proposes a novel approach for the active classification of ECG signals based on deep learning [8]. The idea of deep learning also known as feature learning (proposed for the first time by Hinton [25]) is about learning a good feature representation automatically from the input data [26,56,54,13,65]. Typical deep learning architectures include deep belief networks (DBNs) [26], stacked autoencoder (SAE) [54], convolutional neural networks (CNNs) [52]. Recently, compared to shallow architectures (i.e., handcrafted features fed as input to a kernel classifier), deep learning has shown outstanding results in many applications such as image classification [23], object recognition [6], face recognition [29], medical image analysis [10], and time series data [16,24,36]. For the particular case of physiological data, Mirowski et al. [45] used convolutional networks for epileptic seizure prediction from intracranial EEG signals. Längkvist et al. [41] proposed an RBM-based method for sleep stage classification from 4-channel polysomnography data. Wang and Shang [57] used DBN to automatically extract features from raw unlabeled physiological data. For the automatic classification ECG signals, one can find the solution proposed in [30] based on the combination DBN and SVM. In particular, DBN was used for feature learning and the obtained features are fed to SVM for training and classification.

In our context, we use deep learning to achieve two main objectives: (i) learn a suitable feature representation of the ECG signals in an automatic way unlike state-of-the-art methods which rely on handcrafted features; and (ii) use active learning (AL) techniques to reduce the expert effort in labeling data instances for inducing the classifier. Given the training data available at hand, we first learn an appropriate feature representation in an unsupervised way using a denoising autoencoder (DAE) with sparsity constraint. After this feature learning phase, we build an initial DNN tailored to the classification of AAMI classes by adding on the top of the resulting hidden representation layer a *softmax* regression layer. During the interaction phase, unlike the available methods, we do not make the user label the first few minutes but instead we use AL techniques.

The aim of AL is to rank the unlabeled set according to a criterion that allows us to select the most useful samples that can improve the model, thus minimizing the number of training samples necessary to maintain discrimination capabilities as high as possible. When faced with large amounts of unlabeled data, such algorithms automatically identify the exemplar beats for manual annotation [11,20–22,28,39,48,49]. The most ambiguous samples are given to the expert for labeling and then they are used to retrain the classifier. It is expected that the AL process will increase the generalization ability of the classification system on the difficult samples for the next iterations. As ranking criteria, the method relies on the DNN posterior probabilities to associate confidence measures such as entropy [21,28,48] and Breaking-Ties (BT) [11,39,49]. In the first criterion, we calculate for each ECG test beat the entropy value, and then the beats with the highest entropy values are selected for labeling. High values of entropy mean that the ECG beats are classified with low confidence, and thus adding them to the training set can be useful to improve the classifier decision regions in the feature space. In the second criterion called BT, the difference between the two highest DNN posterior probabilities is indicative of the way a sample is handled by the classifier. When the two highest values are close, the classifier confidence is low. Thus, the beats having low difference between the two highest support values are selected for labeling.