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Dictionary learning for VQ feature extraction in ECG beats classification

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ABSTRACT

Vector quantization(VQ) can perform efficient feature extraction from electrocardiogram (ECG) with the advantages of dimensionality reduction and accuracy increase. However, the existing dictionary learning algorithms for vector quantization are sensitive to dirty data, which compromises the classification accuracy. To tackle the problem, we propose a novel dictionary learning algorithm that employs *k*-medoids cluster optimized by *k*-means++ and builds dictionaries by searching and using representative samples, which can avoid the interference of dirty data, and thus boost the classification performance of ECG systems based on vector quantization features. We apply our algorithm to vector quantization feature extraction for ECG beats classification, and compare it with popular features such as sampling point feature, fast Fourier transform feature, discrete wavelet transform feature, and with our previous beats vector quantization feature. The results show that the proposed method yields the highest accuracy and is capable of reducing the computational complexity of ECG beats classification system. The proposed dictionary learning algorithm provides more efficient encoding for ECG beats, and can improve ECG classification systems based on encoded feature.

1. Introduction

Electrocardiogram (ECG) is the record of cardiac electrical activity signal. Categories of heart beats (normal or different types of disorder) are important signs for diagnosing cardiovascular diseases. As manual analysis of beats is very laborious, automatic ECG classification has been studied and applied in practice.

Artificial intelligence and machine learning have been widely used in this domain, where features are extracted from ECG and used in both classifier training and classification. While many classifiers such as PSO-RBF classifier (Korürek & Doğan, 2010), PSO-SVM classifier (Melgani & Bazi, 2008), SVM classifier (Ye, Coimbra, & Kumar, 2010), LS-SVM classifier (Dutta, Chatterjee, & Munshi, 2010), have been adopted in the studies, the choice and extraction of proper features become very important for achieving satisfied classification performance.

At present, there are three most popular types of features representing different aspects of ECG: temporal features, statistical features and morphological features. Among them, morphological information is the most difficult to be quantified, whether in manual analysis or automatic classification. For example, the duration of the QRS wave can be easily computed by $time_{end} - time_{start}$, but representing the morphological information of the wave is much harder. In the context of classification, features are regarded as observation, and they should express useful information as much as possible for an effective classification.

On the other hand, dimensionality serves as another important performance of a feature. Generally speaking, the feature dimensionality dominates the amount of computation in classifier learning because most classification algorithms have a time complexity $\geq O(d_L^n)$, where $n \geq 1$ and d_L is the feature dimensionality. Reducing the feature dimensionality can effectively reduce the amount of computation.

Therefore, we focus on the study of morphological feature that can both increase classification accuracy and reduce the computational complexity in classifier learning. Some recently reports about time series feature extraction have attracted our attention (Baydogan, Runger, & Tuv, 2013;

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Kim, Yazicioglu, Merken, Van Hoof, & Yoo, 2010; Wang, Liu, FH She, Nahavandi, & Kouzani, 2013a; Wang, Liu, She, Nahavandi, & Kouzani, 2013b; Wang, Sun, She, Kouzani, & Nahavandi, 2013c). They first divided beats into some local parts, and then encoded these local parts as feature, which achieved state-of-the-art classification performances. The encoding process has two main steps, i.e., firstly learning a dictionary from a local part of the dataset, and then encoding the local beats as feature by similarity measure between the dictionary and the local part.

The dictionary plays an important role in feature extraction because it directly decides which code is matched. In such encoding methods (Baydogan et al., 2013; Kim et al., 2010; Liu et al., 2014; Wang et al., 2013a,b,c), *k*-means clustering and its extensional algorithms, sparse coding, have been widely used to learn the dictionary. However, dictionaries generated by above learning methods are very sensitive to dirty data, because their cluster centers are combination of all training samples containing both favorable and dirty data.

For solving this problem, we propose a novel dictionary learning algorithm that employs *k*-medoids cluster optimized by *k*-means++ and builds dictionaries by searching and using representative samples. Furthermore, we implement a classification system that performs the proposed dictionary learning algorithm in feature extraction.

The rest of the paper is organized as follows. In Section 2, we introduce the related works. In Section 3, we describe the existing vector quantization ECG and the difference between our method and the existing ones. In Section 4, we propose our dictionary learning algorithm for vector quantization feature extraction. In Section 5, we present the classification framework based on the proposed method. We present experiments and results in Section 6. Finally we conclude the paper in Section 7.

2. Related work

At present, there are many studies concerning about automatic ECG classification. The classification system needs certain features extracted from ECG signals first and then classifies them by a classifier. Lots of classifiers have been widely used for this purpose, such as neural network (Korürek & Doğan, 2010; Özbay & Tezel, 2010; Zidelmal, Amirou, Ould-Abdeslam, & Merckle, 2013) and SVM (Dutta et al., 2010; Melgani & Bazi, 2008; Moavenian & Khorrami, 2010; Ye et al., 2010). While the existing classifiers may work well in the systems interchangeably, different kinds of features have been proposed to represent different aspects of ECG signals. Generally speaking, there are three most popular types of features reflecting different aspects of ECG: temporal features, statistical features and morphological features.

Most studies used two or all three types of features (De Chazal, O'Dwyer, & Reilly, 2004; Dutta et al., 2010; Mar, Zaunseder, Martinez, Llamedo, & Poll, 2011; Melgani & Bazi, 2008; Ye et al., 2010). Compared with the others, morphological features are more difficult to be quantified, whether in manual analysis or automatic classification. One popular method is directly using the sampling points to represent the morphological information (Melgani & Bazi, 2008). This solution contains all the details of ECG signals, but the dimensionality is too high. Function-fitting is another method that has lower dimensionality, but it will lose much detailed information (Karpagachelvi, Arthanari, & Sivakumar, 2010). These methods can be regarded as using time-domain morphological features. Yet quite a lot of methods (Khorrami & Moavenian, 2010; Ye et al., 2010) used the frequency-domain morphological features such as FFT (Fast Fourier Transformation) and DWT (Discrete Wavelet Transform) features, which offer some degree of compromise between dimensionality of feature and amount of information, and are also widely used in ECG beats classification. If feature dimensionality is the only concern, one can use some a dimensionality reduction algorithm such as PCA (Principal Component Analysis) and ICA (Independent Component Analysis) (De Chazal et al., 2004; Melgani & Bazi, 2008; Wei, Chang, Chou, & Jan, 2001) to reduce it. Even though the dimensionality reduction is effective, the features extracted before dimensionality reduction are still important because they provide the information for dimensionality reduction.

Some recent reports (Baydogan et al., 2013; Kim et al., 2010; Wang et al., 2013a,b,c) have employed encoded features that have very low dimensionality and can achieve state-of-the-art classification performance. An encoder is a system for mapping a sequence of continuous or discrete vectors into a digital sequence suitable for communication over or storage in a digital channel. In computer vision, the sequences produced by encoders, also known as encoded features, have been widely extended to represent images and videos (Zang, Wen, Wang, Liu, & Song, 2015). Over the years many works have adopted encoding method for representing ECG in classification systems, such as Bag of Words (Baydogan et al., 2013; Liu et al., 2014; Wang et al., 2013b), Bag of Pattern (Wang et al., 2013c), and Sparse Codes (Wang et al., 2013a). In these studies, signal is divided into some local segments, and clustering algorithms are employed to train the dictionary, where each cluster center is a codeword of the dictionary, finally beats are encoded by similarity measure between theirs local segments and the dictionary.

Our method aims to boost the performance of the dictionary under Bag of Words frameworks. In order to construct codeword of dictionary, we try to find representative samples, rather than *k*-means methods (Baydogan et al., 2013; Liu et al., 2014; Wang et al., 2013b) that use means of samples as codewords of dictionary or Sparse Codes methods (Wang et al., 2013a) that adopts a linear combination of a few elements. So, the proposed method can avoid the influence of dirty data and thus increase the classification accuracy.

3. Vector quantization

Vector quantization learns a set of dictionaries to encode ECG local segments, which can be directly utilized in feature extraction for ECG classification. Existing vector quantization methods widely use *k*-means dictionary learning algorithm.

In ECG classification system, let $\mathbf{X}$ be a set of ECG local segments, one can simply split an object (a local segment of ECG signal) and represent it as $\mathbf{X} = [x_1, x_2, \ldots, x_n]$. The Bag of Words (BoW) method (Baydogan et al., 2013; Wang et al., 2013b) applies the *k*-means clustering algorithm to solve the following problem

$$\min_{\mathbf{D}\in R^{(d\times K)},\mathbf{W}\in R^{(K\times n)}} \sum_{i=1}^{n} ||x_i - \mathbf{D}w_i||_2 \tag{1}$$

where dictionary $\mathbf{D} \in R^K$ includes the K cluster centers that need to be found. w is a binary vector and $|w| = 1$. When a local segment is assigned a codeword w_i, each local segment x_i is approximated by d_{w_i}. Therefore the codeword w_i represents x_i, and the low dimensional feature is obtained.

Let a set of ECG $\mathbf{E} = (e_1, e_2, \ldots, e_m)$ be a dictionary training set for dictionary learning, where e_j is the jth ECG in the set that has segments $\mathbf{E}_j = (s_{1,j}, s_{2,j}, \ldots, s_{n,j})$. For each segment of the whole dictionary training set, a clustering algorithm *k*-means can be utilized in vector quantization to build the ith dictionary as in (Baydogan et al., 2013; Wang et al., 2013b):

Assignment step

$$w_{i,j} = arg\min_k ||s_{i,j} - d_i^{(k)}|| \tag{2}$$