A Neural Based Comparative Analysis for Feature Extraction from ECG Signals

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Abstract. Automated ECG analysis and classification are nowadays a fundamental tool for monitoring patient heart activity properly. The most important features used in literature are the raw data of a time window, the temporal attributes and the frequency information from the eigenvector techniques. This paper compares these approaches from a topological point of view, by using linear and non-linear projections and a neural network for assessing the corresponding classification quality.
The non-linearity of the feature data manifold carries most of the QRS-complex information. Indeed, it yields high rates of classification with the smallest number of features. This is most evident if temporal features are used: non-linear dimensionality reduction techniques allow a very large data compression at the expense of a slight loss of accuracy. It can be an advantage in applications where the computing time is a critical factor. If, instead, the classification is performed offline, the raw data technique is the best one.

Keywords: CCA, ECG, EKG, electrocardiogram, eigenvectors, feature extraction, multilayer perceptron, MUSIC, PCA, QRS-complex, supervised learning.

1 Introduction

The standard procedure used by physicians to monitor heart is to measure and record its electrical activity through an electrocardiogram (ECG). A healthy ECG, shown in Fig. 1, presents six fiducial points (P, Q, R, S, T, U) which are correlated to the four principal stages of activity of a cardiac cycle: isovolumic relaxation, inflow, isovolumic contraction, ejection.
This path should repeat itself constantly over the time; otherwise, a person suffers from arrhythmias.

ECG recording is usually performed with the use of ten electrodes attached to a human body to analyze, at the same time, twelve leads, both peripherals (I, II, III, aVR, aVL, aVF) and precordials (V1, V2, V4, V5, V6). The recordings are, then, visually inspected by an expert, e.g. a cardiologist, looking for anomalies, i.e. diseases.

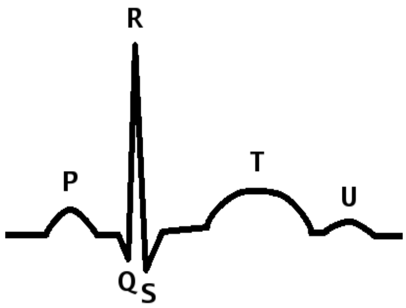

Fig. 1. Healthy ECG

Several techniques for an automated ECG analysis have been proposed in literature. Adaptive filtering for noise cancelling and arrhythmia detection is suggested in [1]. A fuzzy K-nearest neighbor classifier is used in [2]. Finally, ECG classification based on artificial neural networks has been adopted in [3-5]; an extensive review can be found in [6].

A fundamental phase prior to classification is the feature extraction. Indeed, high percentages of misclassifications are often due to an inappropriate feature selection [7-9]. Depending on the algorithm used for their extraction, features can be classified into two primary areas: temporal-based and eigenvectors-based. The former aims at exploiting the temporal evolution of the ECG signal (e.g. R-R variance); some examples can be found in [10, 11]. The latter, i.e. the Eigenvector method, is used for estimating frequencies of signals from noise-corrupted measurements; it is based on an eigen-decomposition of the correlation matrix of the signal. The two most used methods within this class are: Pisarenko [12] and MUSIC [13]. An application of these two to ECG classification can be found in [14-16].

This paper presents a comparative analysis about the classification performances of a multilayer perceptron (MLP) trained on six different datasets: ECG raw data, temporal features, eigenvector features and their projections using the curvilinear component analysis (CCA) [17]. First, Sec. 2 describes the proposed approach. Then, the results of the experiments are presented and discussed in Sec. 3.

2 The Proposed Approach

Unlike the traditional approach to ECG, which aims to improve the classification quality, and by considering that, in general, the results are very good, here the characteristics of the most important feature extraction techniques are analyzed in itself, for having a deeper insight in how they represent the QRS complex. At this aim, neural networks are used as tools for assessing the quality of the representation in order to evaluate the validity and properties of each technique. Here, the MLP network is used because it is well-suited for pattern recognition [18]. At this purpose, it has a single hidden layer and five output units equipped with the soft-max activation function [18]. Because of the use of the cross-entropy error function [18], they yield the probability of membership for the following classes: normal beat, right bundle branch block beat, premature ventricular contraction, atrial premature contraction, other anomalies.

Each approach results in a different data manifold, which is here studied both by means of its intrinsic dimensionality and its level of non-linearity by using CCA and the corresponding projected space visualization through the *dy-dx* diagram. CCA is a neural network which is able to project its input into a space of reduced dimensionality while preserving the manifold topology by means of local distance preservation. In this sense, it can be used to reduce the number of features without altering the original manifold. This is validated by the *dy-dx* plot, which is the plot of the distances of samples in the latent space (*dy*) versus the distances of corresponding samples in the data space (*dx*). In this scenario, it acts as a tool for the detection and analysis of non-linearities. Generally, the more the deviation of data cloud with respect to the bisector, the more nonlinear the manifold is. Therefore, the input space can be reduced without losing information about the data.

The three main techniques, i.e. ECG raw data, temporal and eigenvector features, are then analyzed according to the number of features they require, the geometry of the representation (linear or non-linear), the accuracy of the classification and the validity of their possible reductions (feature extraction).

3 Feature Analysis and Comparison

To test the proposed approach and its classification performance, several experiments have been conducted on the MIT-BIH Arrhythmia dataset [19-21]. First of all, it has been chosen because of its widespread use in research and the wide range of diseases covered. Moreover, each QRS complex within each record is labeled; hence, a supervised learning approach is quite straightforward. Also, the entire dataset is very well documented.

The chosen records are [22]: 106, 119, 200, 203, 207, 208, 209, 212, 231, 232, 233. For sake of simplicity, only the first 250.000 samples of the L2 lead of these records have been used for training and testing purposes. This should be not considered, at all, as a limitation of the proposed approach; indeed, L2 is, typically, the lead which carries most of information and is, in general, used as a reference for the interpretation of the others.

Six different datasets have been used to train and test the MLP: ECG raw data, temporal features, eigenvector features and their projections using CCA. The goal is the analysis of the dataset manifolds and the study of the most relevant subset of features for classification. Finally, in all the above cases, two-thirds of data have been used to train the network, while the remaining one-third has been used to test it.

3.1 ECG Raw Data

The first experiment deals with data extracted directly, i.e. without the feature extraction phase, from the MIT-BIH database. Each one of the above cited records has been parsed in order to extract its QRS complexes. At this purpose, labels, which point to R-peaks time instants, have been used as the center of a 41-time instants window (twenty time instants before the one pointed by the label and twenty after it). In addition, the R-R time, i.e. the time between two consecutive R-peaks, has been added as last feature of this initial set. Consequently, the resulting training set is a matrix made of forty-two columns and as many rows as the number of QRS complexes. Then, two-thirds of this set, i.e. the training set, has been fed to the MLP with an input layer composed of 42 neurons and a hidden layer composed of 100 neurons. The confusion matrix resulting from the testing is shown in Fig. 2a. An overall accuracy of 99.1% is reached (see Table 1). This classification is very accurate. However, this method requires a lot of attributes, which are the raw sampled data of the temporal window. In this sense, there is no feature creation, which implies a very time-consuming algorithm.

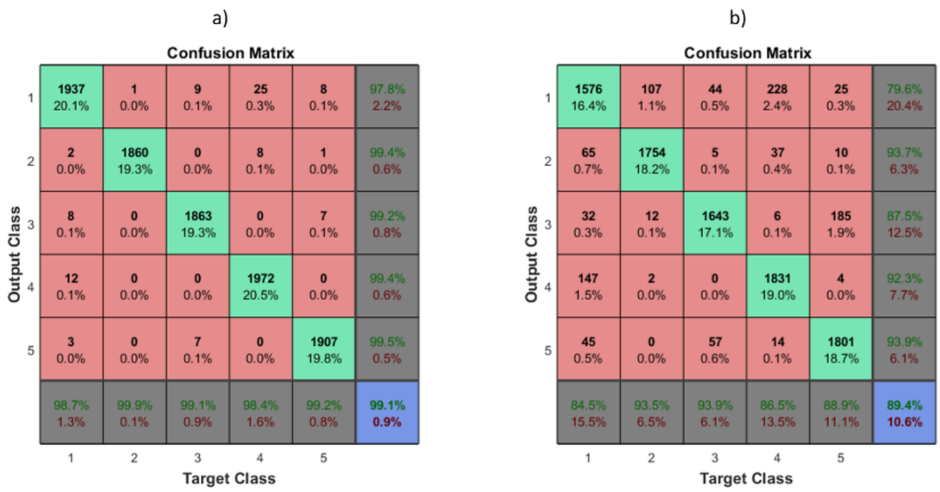

Fig. 2. ECG raw data confusion matrix: original (a) and reduced (b) space cases

The analysis of the data manifold by means of the principal component analysis (PCA) [18] suggests the intrinsic dimensionality is probably four (96.42% explained), as seen in Fig. 3. However, the non-linearity of data has to be considered. At this aim, CCA is performed (λ = 70, epochs = 10), in order to project to a four-dimensional space. The corresponding *dy-dx* diagram, see Fig. 8 left, is concentrated around the bisector, which proves the manifold is nearly a hyperplane. If the projected data are fed to an MLP with one hidden layer of 20 neurons, the overall test performance is decreased to 89.4% (see Table 1 and Fig. 2b), that is 9.78% loss of accuracy.

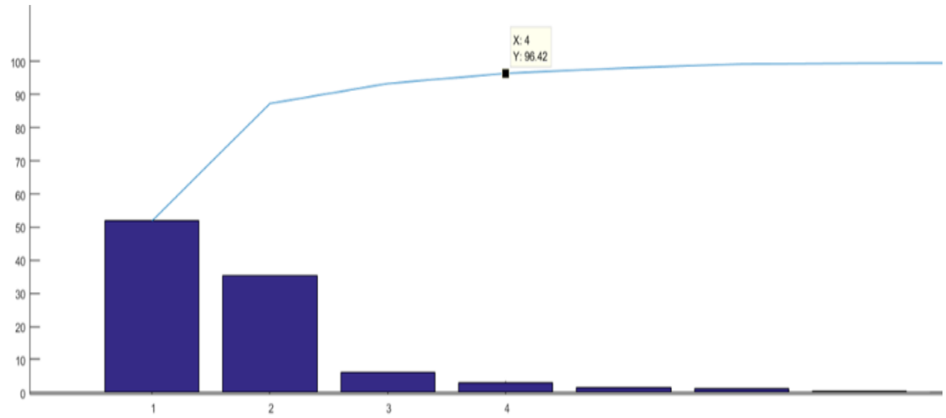

Fig. 3. ECG raw data PCA analysis

3.2 Temporal Features

The second dataset used to test the proposed approach is made of fifteen statistical features extracted from each record of the ECG raw data dataset. The selected features are the following: mean, max value, root mean square, square root mean, standard deviation, variance, shape factor (with RMS), shape factor (with SRM), crest factor, latitude factor, impulse factor, skewness, kurtosis, normalized 5^{th} central moment, normalized 6^{th} central moment. As before, the R-R time, i.e. the time between two consecutive R-peaks, has been added as last feature of this set. Data are statistically normalized (z-score). Two-thirds of this set, i.e. the training set, has been fed to the MLP. Here, the input layer is composed of 16 neurons and the hidden layer by 40.

The confusion matrix resulting from the testing is shown in Fig. 3a. An overall accuracy of 96.0% is reached (see Table 1). The classification is worsened with regard to previous method. However, this method requires fewer attributes: from 42 to 16, that is a nearly 61.9% reduction.

Fig. 5 shows the result of the PCA analysis: the intrinsic dimensionality is probably six (96.68% explained). In order to check the non-linearity of the manifold, CCA is again performed (λ = 70, epochs = 10), by projecting to a six-dimensional space. The corresponding *dy-dx* diagram, see Fig. 8 middle, is less concentrated around the bisector. However, it is thicker for larger distances. The manifold is non-linear, but locally linear (short distances are well preserved in the projection). If the six projected features are the inputs of an MLP with one hidden layer of 20 neurons, the overall test performance is decreased to 93.5% (see Table 1 and Fig. 4b), that is 2.6% loss of accuracy.

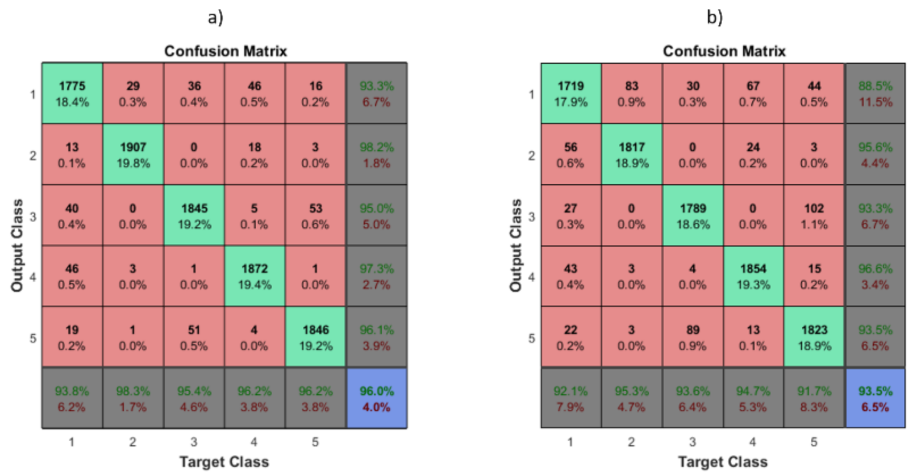

Fig. 4. Temporal features confusion matrix: original (a) and reduced (b) space cases

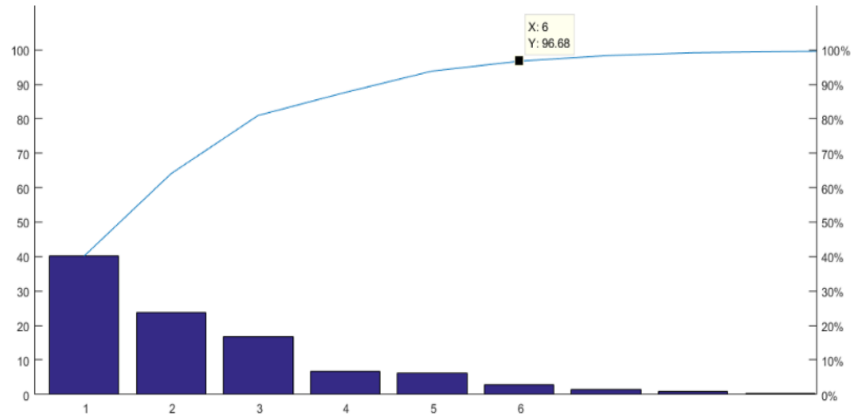

Fig. 5. Temporal features PCA analysis

3.3 Eigenvector Features

The third dataset, normalized with z-score, is made of eight features extracted from each record of the ECG raw data dataset using the MUSIC algorithm. Different sub-space dimensions for the algorithm have been tried and compared in order to check how the classification performance varies versus this parameter. The best results have been obtained with a subspace of dimensionality equal to five. As before, the R-R time has been added as last feature of this set. Two-thirds of this set, i.e. the training set, has been fed to the MLP. Here, the input layer is composed of 9 neurons and the hidden layer of 40. The confusion matrix resulting from the testing is shown in Fig. 6a. An overall accuracy of 90.3% is reached (see Table 1). The classification is the worst, but still accurate. However, this method requires the smallest number of attributes: from 42 to 9, that is a nearly 78.6% reduction.

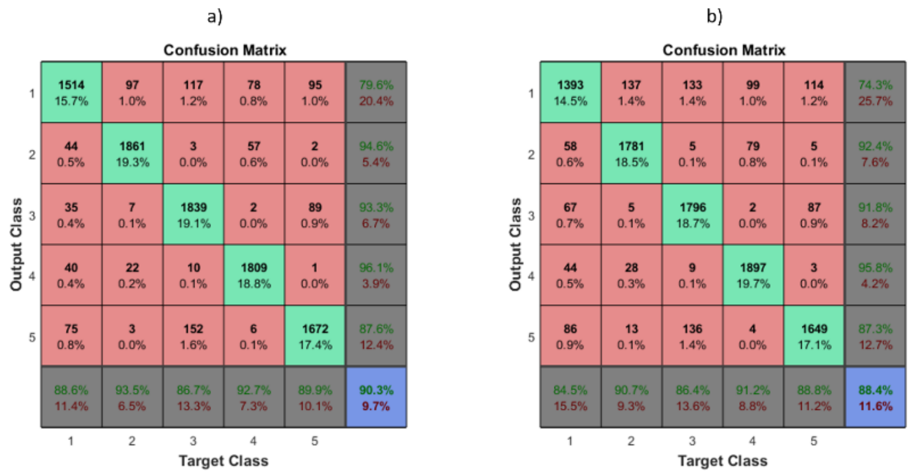

Fig. 6. Eigenvector features confusion matrix: original (a) and reduced (b) space cases

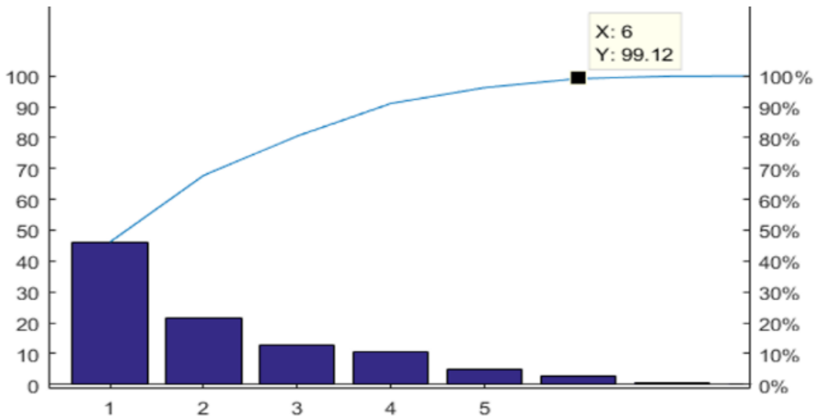

Fig. 7. Eigenvector features PCA analysis

Fig. 7 shows the result of the PCA analysis: the intrinsic dimensionality is probably six (99.12% explained). In order to check the non-linearity of the manifold, CCA is again performed (λ = 30, epochs = 10), by projecting to a six-dimensional space. The corresponding *dy-dx* diagram, see Fig. 8 right, is similar to the corresponding temporal feature case. However, it is thicker for smaller distances. The manifold is still non-linear, but locally less linear. If the six projected features are the inputs of an MLP with one hidden layer of 20 neurons, the overall test performance is decreased to 88.4% (see Table 1 and Fig. 6b), that is 2.1% loss of accuracy.

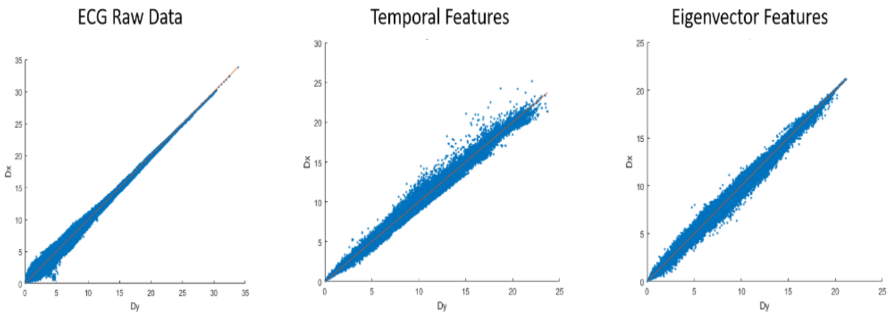

Fig. 8. CCA dy-dx diagrams

Table 1. MLP classification results

	Original Space (# Features)	Reduced Space (# Features)
ECG Raw Data	99.1 (42)	89.4 (4)
Temporal Features	96.0 (16)	**93.5 (6)**
Eigenvector Features	90.3 (9)	88.4 (6)

3.4 Discussion

All the experiments have shown a trade-off between smallest number of features and linearity. This is also more obvious in the case of dimensionality reduction. The raw data (no feature extraction) belong to a quasi-linear manifold in a four dimensional space. Despite this simple geometry, the largest number of features (data in a time window) is required (forty-two values). Also, it is more evident when a non-linear reduction to a space with the intrinsic dimensionality of data is performed: indeed, the worst decrease in accuracy (9.78%) is observed.

The choice of feature extraction techniques, as the temporal and the eigenvector ones, implies an important economy in the number of attributes, but at the expense of a loss of linearity. The temporal features lie on a non-linear manifold with local linearity. The MUSIC features also lie on the same kind of manifold, but the linearity exists only for smaller neighborhoods. The accuracy of the temporal method is close to the raw data one but requires only sixteen features (61.9% for a loss of only 2.9% of overall accuracy) and the minimum number of features (six) w.r.t. the classification performance (loss of 5.6%). The same observations can be repeated for the eigenvector technique. However, the classification is slightly worse.

This paper has shown a correlation between non-linearity, number of features and accuracy. It can be concluded that the best representation of the QRS-complexes is determined by the non-linearity of the temporal features: 93.5% precision for only six features (extracted from sixteen attributes by means of CCA dimensionality reduction). On the other end, the large number of features of the raw data representation yields the best accuracy, but the simplicity of the manifold does not allow any good dimensionality reduction.

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