HIGH-DIMENSIONAL DISCRIMINANT ANALYSIS OF HUMAN CARDIAC ARRHYTHMIAS

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ABSTRACT

Sudden ventricular arrhythmia is a leading cause of death. It is important to be able to distinguish between different arrhythmias in order to deliver proper treatment. This study presents results of linear and quadratic discriminant analysis of normal sinus rhythm, ventricular fibrillation and ventricular tachycardia in different representation spaces, using different observation lengths. In particular, 0.5 s, 1 s, 2 s and 4 s segments of electrocardiogram waveforms are considered, along with their magnitude spectra, and lower dimensional projections of magnitude spectra onto principal components. All considered representations are of much higher dimension than in prior art. Results suggest that Fourier magnitude spectra of 2 s windows, or low dimensional projections, are sufficient for achieving best classification results. Results also suggest that additional improvements could be obtained by considering more sophisticated non-linear decision boundaries.

Index Terms— Cardiac arrhythmia, ventricular fibrillation, ventricular tachycardia, classification.

1. INTRODUCTION

According to the World Health Organisation data, cardiovascular disease (CVD) is the leading cause of death in middle and high income countries, and among the top ten causes of death in low income countries [1]. Development of effective drug treatments that may prevent cardiac arrhythmia is therefore a high-priority challenge for modern pharmacology. For the development of such treatments it is crucial to have a clear understanding of what distinguishes different forms of arrhythmia, and based on that, establish their precise definitions. Additionally, this is necessary for assisting the design of better automated external defibrillator (AED) and implantable cardioverter-defibrillator devices. In 1988 an attempt was made to provide standardised objective definitions of ventricular tachycardia (VT), ventricular fibrillation (VF) and other arrhythmias, but it was recognised that their discrimination typically involves a significant degree of subjective judgement [2]. Current methodology for detection of ventricular arrhythmia focuses on classification without any regard for interpretation. Most classification schemes make use of heuristic low dimensional representations of the electrocardiogram (ECG), and use arbitrary parameter choices. By performing classification using more natural higher-dimensional representations and standard, well understood tools, it is hoped that an improvement in classification accuracy is achieved. Thus, this study has its focus on achieving the best possible classification accuracy between sinus rhythm (SR), VT and VF using simple, and well understood tools. Then, in future work (given good classification performance), interpretation of generated models will be addressed, hopefully leading to more objective criteria for ventricular arrhythmia definitions.

From a therapeutic point of view being able to differentiate between VF and VT is very important since they respond to interventions differently and VF is lethal, while VT is not. There have been many studies into the topic of differentiating SR from VF, however few studies attempt to differentiate VT from VF. For VF and VT detection, Thakor *et al.* proposed an algorithm which first applies a hard threshold to transform an ECG segment into a binary sequence, and then performs a sequential hypothesis test on the average number of zero crossings until a decision is made [3]. In [4], the authors proposed an algorithm which uses the energy distribution information in a wavelet transform domain to differentiate between VF, VT, and a VT-VF class which contains realisations that are difficult to categorise as either VT or VF. An algorithm for VF detection based on empirical mode decomposition (EMD), was proposed in [5]. Counting the time between turning points was proposed in [6] to differentiate fast-VT, slow-VT and VF. A comparison of ten methods for differentiating between non-VF and VF, for use in an AED, was presented in [7]. The same authors later proposed a phase space method [8] and demonstrate that it outperforms all methods studied in [7] in its capability to discriminate VF from non-VF segments. While all these previous works have been yielding gradual improvements, the problem of differentiating between SR, VT and VF is still not solved sufficiently accurately, the main difficulty being in differentiating between VT and VF. Some of these studies even resort to creating a category specifically for the examples which are difficult to distinguish [4, 6], but this is not physiologically acceptable, and does little to assist understanding of the problem. In addition, all existing classification algorithms use heuristics to derive some low-dimensional representations of ECG signals.

The goal of this study is a systematic investigation of discrimination between SR, VT, and VF, using as few heuristics as possible, and for that purpose the simple, but often effective classifiers, linear discriminant analysis (LDA) and quadratic discriminant analysis (QDA), are considered. Results from these simple classifiers are then used to motivate investigation of non-linear boundaries for future research direction. Another issue of interest is the selection of observation length which is most suitable for discrimination, whilst simultaneously trying to minimise detection time. For this purpose, 0.5 s, 1 s, 2 s and 4 s segments of ECG waveforms are considered. The considered representation spaces for classification are all high dimensional spaces compared to prior art.

2. ARRHYTHMIA CLASSIFICATION

2.1. Reference Prior Art

Given an ECG segment $\mathbf{x} = \{x[n], n_1 \leq n \leq n_2\}$, it is desired to be able to label it as being SR, VT or VF. Often, discrimination is only required between two classes, one of which may be a combination of classes; e.g non-VF vs VF or SR vs arrhythmia or VT vs VF, as these might be most relevant. For comparison, in this paper the phase space feature representation proposed in [8] is considered, since the authors demonstrated its superior performance in terms of accuracy and numerical complexity compared to previously published algorithms.

The Phase Space Algorithm (PSA) [8] aims at diagnosing whether a defibrillation shock should be delivered, which amounts to classifying ECG segments as VF or non-VF. The phase space representation is formed by taking discretised values of samples $x_1[n] = x[n]$ and $x_2[n] = x[n-k]$ of $\mathbf{x}$ as pairs in $\mathbb{R}^2$, where k is selected to correspond to 0.5 s[1]. The discretisation step is chosen such that the complete range of $x_1[n]$ and $x_2[n]$ takes up to 40[1] unique values. The number $N(\mathbf{x})$ of visited boxes in this phase space is then found, and finally, the ratio between the number of visited boxes and the total number of boxes $\eta(\mathbf{x}) = \frac{N(\mathbf{x})}{N_{\max}}$, $N_{\max} = 40 \times 40$ is compared to an empirically determined threshold $\eta_{\text{thresh}} = 0.15$[1]. If this threshold is exceeded, VF is decided, otherwise non-VF is decided. Classification using this empirical threshold is referred to as the Original Phase Space Algorithm (OPS). Also considered in this study are maximum likelihood (ML) decision boundaries determined from distributions estimated using available training data. In particular, probability distributions $\mathcal{P}_k(N(\mathbf{x}))$ of $N(\mathbf{x})$ are estimated for the three classes of interest, $k \in \{\text{SR}, \text{VT}, \text{VF}\}$, and the class of an observed vector $\mathbf{x}$ is predicted according to

$$\mathcal{C}(\mathbf{x}) = \arg\max_k \mathcal{P}_k(N(\mathbf{x})) \tag{1}$$

This approach allows classification in the feature space $N(\mathbf{x})$ between VT and VF, or three way classification. Also introduced is a modification where the phase space is formed by pairs $x_1[n] = x[n]$ and $x_2[n] = x[n] - x[n-1]$, again discretised so that each take up to 40 unique values. This corresponds to the standard notion of a phase space, and it may be more robust to variations in heart rate. This modification is referred to as Phase Space Modified (PSM).

2.2. Discriminant Analysis

In order to avoid heuristic feature selection, classification directly in the domain of ECG waveforms is considered. VT is considered to occur if 4 or more consecutive ventricular premature beats (QRS complexes) precede their corresponding P-wave, independent of the rate[2]. In many cases, but not all, a 2 s window of ECG is sufficient to capture 4 premature beats. Thus, a 4 s window is considered. For VF, QRS complexes are no longer discernible [2], which suggests the rate of cardiac deflections (not heart rate, since the notion is not applicable) is even higher than that of VT, a 4 s window should be plenty to capture the disorder. Thus, segments longer than 4 s are not considered. In addition to time waveforms, their Fourier magnitude spectra are considered, as they abstract the variability caused by different time alignments which are irrelevant for class identity.

At 100 Hz sampling, which is close to the minimal sampling frequency which would result in an apparently distortion free ECG signal, 4 s observation length results in 400-dimensional feature space, which can make statistical inference challenging. The problem is dealt with by employing:

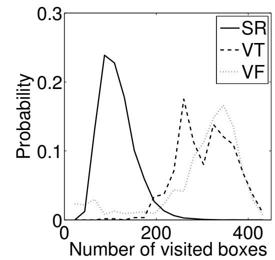
(i) Shorter time segments. In addition to 4 s segments, 2 s, 1 s and 0.5 s segments are considered. This achieves a progressive dimension reduction and also enables assessment of the effect the observation length on discrimination capabilities.

(ii) Simple classification algorithms. For classification, first LDA is considered, as in many practical tasks it gives better results than more sophisticated methods [9], and also because the linear class boundaries it imposes require a relatively small number of parameters to be estimated; an issue which could be critical in high dimensional feature spaces, particularly in the absence of sufficient training data. Finally, to allow for some flexibility in classification boundaries QDA is considered.

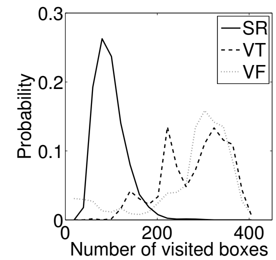
(iii) Data-driven dimension reduction. Since even with 0.5 s observations QDA requires estimation of a relatively large number of parameters ($50 \times (50+3)/2+1 = 1326$ [9]) for estimation of the corresponding quadratic boundaries it is

[1] These parameters are all selected by the original work, [8]

advantageous to consider some systematic dimension reduction. To achieve this, principal component analysis (PCA) is performed on magnitude spectra feature vectors of each individual class, and $3N$-dimensional subspaces spanned by the union of the first N principal components of each class are formed. All data are then projected onto these subspaces. Values of N considered are 5, 10, and 15, referred to as 5, 10 and 15 principal components (PCs). Preliminary analysis showed that at least 60% cumulative energy was contained by the first 5 principal directions in all three classes, so further dimension reduction is not considered. The upper limit on the number of principal directions considered is set to 15 (45 dimensions), which exceeds the dimension of 0.5 s magnitude spectra (25).



a)



b)

Fig. 1: Probability distributions of the number of visited boxes variable $N(\mathbf{x})$, for SR, VT and VF at 8 s observation window. a) PSA feature. b) PSM feature.

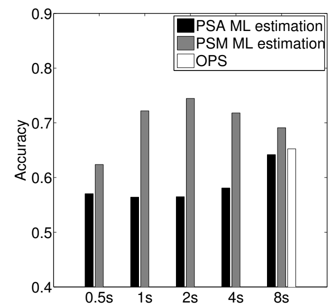


Fig. 2: Results of OPS, PSA and PSM classification of non-VF vs VF with 0.5, 1, 2, 4 and 8 second segments

3. EXPERIMENTAL PROCEDURE AND RESULTS

3.1. Data and Preprocessing

Databases used from Physiobank [10] were the European ST-T Database (EDB) [11], the Creighton University Ventricular Tachyarrhythmia Database (CUDB) [12], the MIT-BIH Arrhythmia Database (MITDB) [13] and the MIT-BIH Malignant Ventricular Arrhythmia Database (VFDB) [14]. Only data that were explicitly labelled as SR, VT or VF were used. Due to the fact that the databases EDB and MITDB do not contain many realisations of VT or VF, additional realisations of VT and VF are taken from VFDB, and further VF realisations from CUDB. Neither of these databases contain annotations that have been audited thoroughly, so SR was not extracted from them. SR was randomly subsampled to the same amount as VT and VF, which were roughly equal in amount. This gave approx 6000s pools of each class to draw observations from.

It is considered that most of the relevant information is contained in the 40Hz baseband [15] and that preprocessing with a 30Hz low pass filter does not affect experimental results [4, 5, 8, 7]. However, based on visual inspection of low-pass filtered data it was decided that 30Hz cut-off frequency was too low, so 49Hz low-pass filtering was used, followed by downsampling to 100Hz. In addition to this, a 0.5Hz high pass filter was applied to remove wandering baseline [15]. All ECG records are then normalised so that the squared sum of each record is equal to the number of samples in the record, thus making the variance of individual time samples equal to 1.

3.2. Preliminary Results

3.2.1. The Phase Space Algorithm

Empirical probability distribution functions of the filled-boxes variable $N(\mathbf{x})$ for the PSA and PSM features are shown in Figure 1a and Figure 1b, respectively. These distributions correspond to 8 s observations, as originally considered in [8]. It can be observed from these distributions that both representations achieve a relatively good separation of SR from VT and VF, and lesser separation of VT from VF, which could be a source of confusion in classifying non-VF vs VF. Such probability distributions are then estimated for other observation lengths and used for classification.

Figure 2 shows the accuracy of classification of SR and VT (non-VF) vs VF with the PSA and PSM features using ML classification and OPS classification. Classification with ML estimation was performed as a three way classification, and confusions between SR and VT were not treated as misclassification. Equal amounts of non-VF and VF were used for testing, according to the 1:1:2 ratio for SR:VT:VF, while the remainder of data was used for estimating the distributions. The merit of classification in the PSM representation is apparent from the results. The generalisation accuracy is estimated using 5-fold cross validation – the OPS method does not have a training phase and is exposed to exactly the same testing samples as the other methods.

Results for OPS classification are only presented for 8 s observations in agreement with the original work. In contrast with [8], where no pre-selection of test data is made, test samples are balanced across classes, and different databases are used for testing and training, which accounts for the difference in the results of this study and [8].

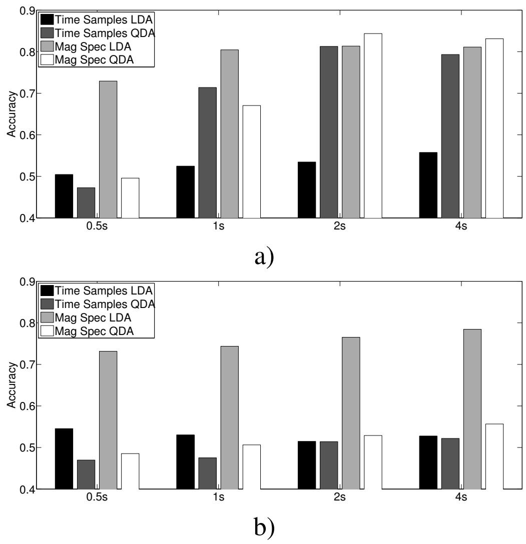


Fig. 3: Results of classification in time and magnitude spectrum domains with varying observation lengths. a) non-VF versus VF. b) VT versus VF

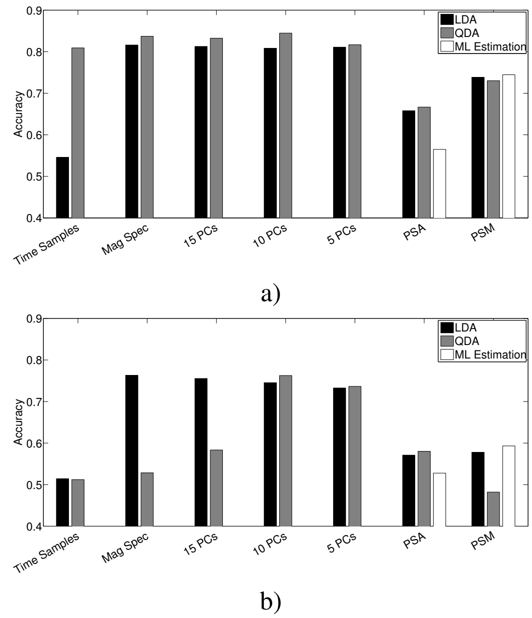


Fig. 4: Results of classification using 2 second observation length and time, magnitude spectra, principal components, PSA and PSM representation spaces. a) non-VF versus VF. b) VT versus VF

3.2.2. Classification in ECG and magnitude spectra spaces

Figures 3a and 3b shows classification of non-VF versus VF and VT versus VF respectively in the ECG and magnitude spectra representations. The observation length is varied from 0.5 s to 4 s. It can be seen that a 2 s window provides best classification results for non-VF vs VF, and that 4 s windows achieve some further improvement in the case of VT vs VF classification. In presenting the main findings in only results obtained with 2 s windows are shown, as the best compromise between accuracy and required time for detection.

3.3. Main Experimental Procedure and Results

Figures 4a and 4b respectively show the accuracy of binary classifications tasks non-VF vs VF and VT vs VF. Classification using 2 s observation lengths is considered in the time domain, magnitude spectrum domain, and in the reduced representation spaces described in Section 2.2. Classification is also considered in the PSA and PSM feature spaces. In all feature spaces, classification is performed using LDA and QDA, and additionally using ML estimator in the case of PSA and PSM features. For LDA and QDA classifiers, the class data for training and testing are balanced, and 5-fold cross validation is employed in order to obtain a better estimate of generalisation error. Since the testing datasets are balanced, only the average classification accuracy is presented, rather than sensitivity and specificity values since they depend on the proportion of SR, VT and VF in the test data.

Figure 4a demonstrates that classification in magnitude spectra performs better than classification directly in the time domain. Additionally QDA achieves small, consistent improvement over LDA. Dimension reduction appears to have little impact on classification accuracy. Classification of non-VF vs VF is better in all high dimensional representation spaces than in the PSA and PSM representation spaces.

Figure 4b shows that for classification of VT vs VF magnitude spectra representations achieves better performance than classification directly in the time-domain. Here, QDA does not perform well at classification unless dimension reduction is applied. For QDA classification, the error rate on the training set is similar to the error rates on the testing sets, suggesting that overfitting is not occurring, but more likely that quadratic boundaries are not the proper boundaries to fit for this classification task. With dimension reduction QDA classification improves, suggesting that non-linear boundaries have potential to improve classification accuracy, and hence that methods more sophisticated than QDA are required. Again, classification in the PSA and PSM representation spaces is poor.

4. CONCLUSION

Non-VF vs VF and VT vs VF classification was investigated using time-domain ECG waveforms, their magnitude spectra, and projections of magnitude spectra onto lower-dimensional principal component spaces. The effect of observation length on classification accuracy was also investigated, and for that purpose classification was performed using 0.5 s, 1 s, 2 s and 4 s segments of ECG signals. It was observed that a 2 second observation length is sufficient for obtaining best or close to best classification accuracy. This is a new insight considering that in prior classification methods, windows as long as 8 seconds are considered [7, 8]. All new representations considered in this study are of much higher dimension than representations used in previous studies, with the minimum dimension used being 15. Experiments showed that significant gains in classification accuracy can be achieved by posing the problem in high-dimensional representation spaces. It was also observed that classification using magnitude spectra achieves higher accuracy than classification using time-domain waveforms. Finally, experiments suggest that additional gains in classification accuracy could be achieved by employing non-linear decision boundaries, but for that purpose, methods more sophisticated than QDA should be considered. Interpretation of decision boundaries in terms of physical features which distinguish VT from VF was not addressed in this study, as further improvements in their classification accuracy are expected as a result of future work.

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