AUTOMATIC CLASSIFICATION OF HEARTBEATS

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ABSTRACT

We report improvement in the detection of a class of heart arrhythmias based on electrocardiogram signals (ECG). The detection is performed using a 4 dimensional feature vector obtained by applying an iterative feature selection method used in conjunction with artificial neural networks. The feature set includes the pre-RR interval, which is a primary measure that cardiologists use in a clinical setting. A transformation applied to the pre-RR interval reduced the false positive rate. Our solution as opposed to existing literature does not rely on high-dimensional features such as wavelets, signal amplitudes which do not have direct relationship to heart function and difficult to interpret. Also we avoid obtaining patient specific labeled recordings. Furthermore, we propose semi-parametric classifiers as opposed to restrictive parametric linear discriminant analysis and its variants, which are a mainstay in ECG classification. Extensive experiments from the MIT-BIH databases demonstrate superior performance by our methods.

Index Terms— ECG, Classification, False positives, Discriminant analysis, Artificial neural networks

1. INTRODUCTION

Cardiovascular diseases (CVD) are a leading cause of fatalities representing 30% of all global deaths [1]. Due to inadequate preventive measures, CVD related fatalities continue to rise. Electrocardiogram (ECG) is widely used to monitor heart function. At present, an expert cardiologist analyzes short-duration ECG plots to detect abnormalities. Since certain kinds of heartbeat arrhythmias occur sporadically over an extended period, patients require long term monitoring. Towards that end, automated classification of heartbeats is vital as manual examinations are tedious. In this paper, we propose techniques to detect two types of heartbeat arrhythmias – Ventricular Ectopic Beats (VEB) and Supra Ventricular Ectopic Beats (SVEB). Existing techniques for detecting SVEB are prone to high false positive rates which have negative consequences in the form of stress, follow-up testing and monetary loss [2]. The feature set is the cornerstone of statistical classification and therefore a judicious selection of a small set of meaningful features is important. However, feature selection for arrhythmia detection in contemporary literature is based on trial and error. In our approach, we begin with a base set of features (32 features) and apply the incremental wrapper algorithm [3] for determining an optimal feature set using misclassification rate as the objective function. Also, we introduce a reliable feature that cardiologists rely on, known as pre-RR interval. We apply a normalization technique to the pre-RR interval to reduce inter (intra) - patient variations in heartbeat cycles. The normalization disambiguates overlap in the patterns of normal and problematic ectopic heartbeats. In a clinical setting, cardiologists use a small set of features to identify arrhythmias. Consulting with cardiologists and in conjunction with the incremental wrapper approach, we identified a four dimensional feature set effective for arrhythmia detection.

As noted earlier, linear discriminant analysis (LDA) classifier is the de-facto standard in heartbeat detection, barring a few exceptions; Weins et al [4], Ince et al [5]. To determine the effect of classifiers on heartbeat detection rates, we tested using the LDA, the quadratic discriminant analysis (QDA), and the artificial neural network (ANN) classifiers. Results unequivocally demonstrate that the ANN together with a four feature-set combination delivers improved performance.

2. RELATED WORK

Needless to say, classification of heartbeats is a challenging problem. This is due to near chaotic behaviors observed in heart abnormalities. Typical features used to classify heartbeats are based on a combination of heart physiology and mathematical constructs such as wavelet coefficients, and signal amplitudes. A substantial number of these features are required for acceptable rates of detection. However, due to large variations *within* and *between* patients, these features are unstable and in many cases, induce additional noise. Therefore a careful selection of a small set of features related to heart function is essential. Several classifiers have been explored; chiefly the LDA. Chazal et al [6] used a classifier based on linear discriminants trained on a large set of labeled training data of heartbeats. The labeled training and testing sets were

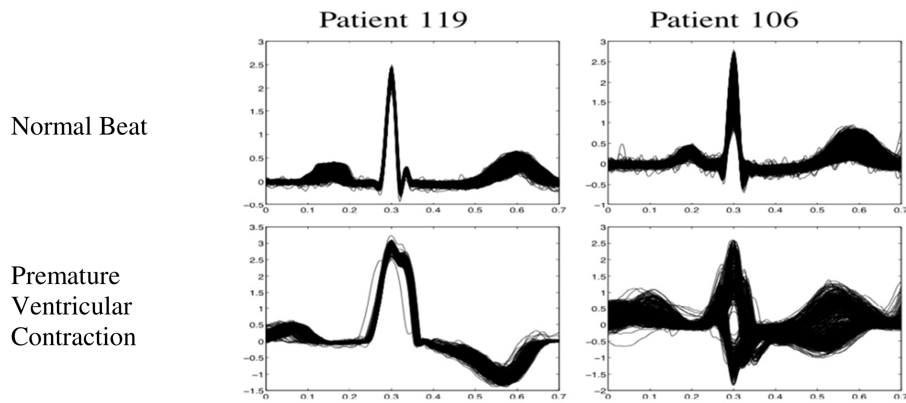

Fig. 1. Example of heartbeat shapes from the MIT-BIH data set. Each column represents a patient and each row the beats for that specific class. Note the variations in the beat morphology across patients as well as within a patient (Source Alvarado et al [10])

obtained from the MIT-BIH [7] arrhythmia database consisting of 48 real world patient recordings, each of 30 minute duration. A 22 patient subset consisting of 51020 heartbeats was chosen as the *training* set, while another subset of 22 patients consisting of 49711 heartbeats was chosen as the *testing* set. The remaining 4 patient recordings were not considered as they were on pacemakers and consist of only "paced," (*unknown* type) heartbeats. With training set and testing set clearly defined, a set of carefully chosen features were extracted from each heartbeat present in the two subsets.

However, due to inter (intra) - patient variations in ECG patterns in Fig.1, the time domain, frequency domain and ECG morphology features are unstable over time. The variation and instability in the features cause classifiers to fail when applied to a signal from a new patient. Hu et al [8] used a "*mixture of experts*" model in which a global classifier and a local classifier are combined to make the classification decision. The local classifier is trained on patient specific labeled data and the global classifier uses the entire patient data set. A gating function is used to weight the classification decision from the global and local classifiers and combines them to make the final decision. Chazal et al [9] builds on [6] to incorporate a similar local-global classifier mixture approach. However, Chazal et al [9] differs from Hu et al [8] in features extraction, and the number of patient specific heartbeats used for training local classifier. Wiens et al [4] proposed an active learning technique that reduces the number of patient-specific labeled data required to train a support vector machine classifier (SVM). Ince et al [5] proposed classification based on the ANN, and Alvarado et al [10] in a departure from traditional approaches used pulse based representations of signals for heartbeat classification using time based samplers such as Integrate and Fire (IF) model [10]. In [11], we compared the performance of LDA, QDA and artificial neural networks (ANN) in detecting Ventricular Ectopic Beats (VEB). In [12], we focused on detecting Supra Ventricular Ectopic Beats (SVEB) and proposed a classification technique based on the variations in the ECG morphology of SVEB's. In this paper, we propose new features and techniques to detect VEBs and SVEBs. We extracted 32 time domain, frequency domain and ECG morphological features and using incremental wrapper approach [3], selected small subset of four features that best capture heart function dynamics. Furthermore, upon consulting with practicing cardiologists, we focused on a time domain feature known as pre RR Interval (The time duration between the current heartbeat and the previous heartbeat. We use a normalization technique to reduce its sensitivity to variation. The pre RR interval normalization yields a significant benefit in that it eliminates the necessity of a local classifier on patient-specific data as required by the local classifier in a "*mixture of experts*" framework. The ANN classifier is a suitable choice as it can model highly non-linear behaviors and it improved classification results.

3. ECG FILTERING

The benchmark database for heart arrhythmia detection is the MIT/Beth Israel Hospital (BIH) Arrhythmia Database available in PhysioBank archives [7]. To minimize the noise in the ECG signal, we preprocessed the ECG signal by removing baseline wander and the 60 Hz power line interference. We passed the signal through median filters of window sizes 200ms and 600ms to extract the baseline wander, which is then subtracted from the original signal to obtain the filtered signal. Furthermore, power line interference was removed by using a notch filter centered at 60Hz.

4. CLASSIFIERS

In the mainstream literature on arrhythmia detection, the LDA is a *de facto* standard. However due to the complexity of irregular heartbeat patterns, we believe a semi-parametric model that assumes no stochastic structure *a priori* is desirable and chose the ANN classifier. LDA assumes that the underlying probability density function of the data is

Gaussian. By calculating the posterior probability of class membership of a new example, LDA classifies the example into one of the *k* classes. The classifier chooses the class with highest posterior probability [6]. Artificial Neural networks (ANN) with Back propagation algorithm is chosen often when it is difficult to mathematically express a relationship between the inputs (feature vector) and the outputs (classes). Our implementation consists of an input layer where the number of nodes equals the dimension of the feature vector, 7 hidden layer nodes and 5 output layer nodes, with each node representing one of 5 heartbeat classes [13]. The learning rate was fixed at 0.2 and weights were randomly drawn from a uniform distribution of variance 0.2. A common heuristic for the number of hidden layer nodes in the ANN literature is the sum of input and output layer nodes divided by 2, see [14] for details about ANN.

5. RESULTS AND DISCUSSION

In this section, we document the results from prior research as well as our findings. The task is designed as a two-class classification. The five heart arrhythmia groups determined by the association for the advancement of medical instrumentation (AAMI) are bundled into two binary classes:{SVEB} versus {Normal, VEB, Fusion, and Q} for SVEB detection, and {VEB} versus {Normal, SVEB, Fusion, and Q}. The symbol, Q stands for a class of beats labeled as "unknown," also known as "paced" beats. We note that while the results are reported as if it is a two-class classification as per AAMI guidelines, the architecture of the algorithms consisted of 5 output classes. Upon classification, using the testing set, the five classes were bundled into two as outlined above. The performance of the algorithms were measured in terms of Sensitivity (proportion of actual positives which were correctly identified [6]), Positive Predictive Value (proportion of positive test results that are true positives), and the F - Score (An overall measure of performance as a function of sensitivity and PPV, See equation 3 in Wiens et al [4]).

5.1. Feature Selection

In the literature, several features based on ECG signals have been proposed. Chazal introduces time duration and morphology features; see Table 3 in [6], Wiens et al [4] proposed wavelet features based on multi-resolution analysis, see Table 1 in [4], and in this paper we introduce features based on the Fourier transform in the frequency domain. Our feature selection is based on an initial set of 32 features (See Table 1 for the list of 32 features) that consists of time domain, frequency domain and heartbeat morphology. Using the base set of 32 features, we applied a well-known technique called incremental wrapper approach [3] to determine a subset of features for upstream heartbeat detection. The incremental wrapper approach is very similar to stepwise regression techniques [15] wherein the independent variables are added and deleted incrementally to determine the optimal number of features that are highly correlated with the output variable. Using the LDA in conjunction with Incremental wrapper approach, a 11 dimensional feature vector was identified (See Subset 1

Features	
• Pre RR Interval	• RS duration
• Post RR Interval	• **T wave duration**
• Average RR Interval	• Energy of QRS complex
• Local Average RR Interval	• Energy of QR segment
• QRS duration	• Energy of RS segment
• QR duration	• Energy of T wave
• ECG Morphology of QRS complex (5 features)	• Maximum Fourier coefficient of QR segment
• ECG Morphology of T wave (9 features)	• Maximum Fourier coefficient of RS segment
• P wave flag	• **Maximum Fourer Coefficient of QRS complex**
• **Normalized pre RR Interval**	• **Amplitude of R Peak**

Table 1. List of features extracted from the ECG signal

Subset 1 (11 dimensions)	**Subset 2 (4 dimensions)**
• Normalized Pre RR Interval	• T wave duration
• Post RR Interval	• Amplitude of R Peak
• T wave duration	• Maximum Fourer Coefficient of QRS complex
• Energy of T wave	• Normalized Pre RR Interval
• ECG Morphology of QRS complex (5 features)	
• Maximum Fourier coefficient of RS segment	
• QRS duration	

Table 2. List of features selected using Incremented Wrapper Approach

Methods	SVEB			VEB		
	Se	PPV	F-Score	Se	PPV	F-Score
Chazal et al [6]	75.9	38.5	51.08	77.7	81.9	79.74
Chazal et al [9]	87.7	47	61.20	94.3	96.2	95.24
Alvarado et al [10]	86.19	56.68	68.38	92.43	94.82	93.60
Ince et al [5]	63.5	53.7	58.19	84.6	87.4	85.97
Wiens et al [4]	92	99.5	95.60	99.6	99.3	99.44
Proposed LDA (11 dimensional feature vector)	**91.94**	**67.52**	**77.86**	**81.98**	**96.63**	**88.70**
Proposed ANN (11 dimensional feature vector)	**75.15**	**78.85**	**76.95**	**92.45**	**79.85**	**85.68**
Proposed LDA (4 dimensional feature vector)	**92.59**	**55.68**	**69.54**	**69.83**	**97.91**	**81.51**
Proposed QDA (4 dimensional feature vector)	**92.92**	**57.26**	**70.85**	**69.34**	**93.94**	**79.78**
Proposed ANN (4 dimensional feature vector)	**87.19**	**83.78**	**85.45**	**89.78**	**92.56**	**91.14**

Table 3. Comparison with state of the art classification techniques

in Table 2). Similarly, using ANN, the incremental wrapper algorithm produced a 4 dimensional feature vector (See Subset 2 in Table 2). The features comprising the four dimensional feature vector also appear in bold in Table 1. Consultations with cardiologists have revealed that these are indeed the first order features they use in clinical settings.

5.2. Results

The classification performance of the various algorithms is summarized in Table 3. First five rows of the table represent the results obtained using the existing classification techniques, while the last five rows (in bold) represent results obtained using LDA, QDA, and ANN based on our proposed modifications. Column 1 identifies prior techniques and our proposed method(s), Columns 2, 3 and 4 represent sensitivity (Se), positive predictive value (PPV) and F-Measure for SVEB respectively; and Columns 5, 6, and 7, represent sensitivity (Se) and positive predictive value (PPV), and F-Measure for VEB respectively. We call attention to classification of SVEB type arrhythmia. Notice that ANN with a 4 dimensional feature vector achieves significant reduction is the false positive rate, which is captured by the metric PPV. This is significant in that the features are not only meaningful to the cardiologist, but also capture the heart function succinctly. It achieves the dual purpose of compression and accuracy. The performance relative to VEB is comparable to prior results reported. It is noted that detection methods in a real-world setting are not intended to replace the cardiologist, but to assist him (her). It is well known that anomaly detection algorithms that produce false alarms are undesirable in applications. Thus a procedure with a high PPV and high sensitivity (Se) is desirable.

Chazal et al [6, 9] used a 26 dimensional feature vector consisting of time domain and ECG morphological features. Alvarado et al [10] used time domain features based on bin counts obtained using Integrate and Fire [10] algorithm. However for a cardiologist, transformation of ECG signal to bin count is hard to interpret. Wiens et al [4], in addition to using typical time domain features, used wavelet coefficients to form a feature vector of 67 dimensions. Wavelet coefficients are known to be unstable and are not easily understandable to a cardiologist. Any ECG detection algorithm must be useful and its features meaningful to the cardiologist.

We extracted 32 features (See Table 1) and using incremental wrapper approach [3], selected two subsets that best represent the heartbeat cycles. Subset 1 (Table 2) was obtained using the incremental wrapper method in conjunction with LDA yielding 11 features. We applied the same 11 dimensional feature set to ANN as well and the difference in performance summarized in Table 3. Clearly, the overall measure of classification; the F-score is marginal between LDA and ANN.

Similarly, subset 2 (Table 2, column 2) was obtained by applying the incremental wrapper method in conjunction with ANN. The Normalized pre RR Interval was computed by dividing the pre RR Interval of a heartbeat using the average pre RR Interval of normal beats (Any heartbeat other than SVEB or VEB) in the neighborhood of that heartbeat. Since the Normal beats surrounding a heartbeat is not known *a priori*, the technique involves the detection of the Normal beats before computing the average pre RR Interval. Recall that the normalization is needed to disambiguate the normal beats from the problematic heartbeats. The ANN with the 4 dimensional feature set outperforms LDA, QDA, and other methods relative to the F-Measure statistic. Strikingly, the results from LDA and QDA are very similar as they both rely on the mean vector and the covariance matrix. The QDA could not be evaluated using the 11 dimensional vector because of near singularities (multicollinearity) among the features. Multicollinearity (highly correlated features) may be addressed using principal component analysis which adds an additional degree of complexity. See Table 3 for comparisons. Examining Table 3, the reader may be tempted to believe that Chazal, Alvarado, and Wiens report better results in the detection of VEB. It is to be noted that they use high dimensional feature vectors, which are arcane to the practitioner as opposed to our succinct 4 features and we eliminate the necessity to obtain patient specific data. Lastly, we could not comment on all the experimental results due to space limitations. We encourage the reader to visit https://sourceforge.net/projects/ecganalysis/ for details, experimental results, MATLAB code, and references.

6. CONCLUSION

In conclusion, a judicious choice of the features meaningful to the cardiologist shows a measurable impact on the detection of some common types of heart arrhythmia (VEB, SVEB). The usage of the incremental wrapper approach helped to identify important features that are related to heart function while controlling for the dimensionality of the feature vector and eliminating the requirement of patient-specific labeled data. The application of the ANN classifier appears to have captured the non-linear behavior inherent in heart function. It is envisioned that these algorithms can be used in clinical settings as an assistive aid to cardiologists to accelerate the tedious process of examination and analyses of electronic cardiograms (ECG) charts. As next steps, we are exploring enhancements to the *Mixture of Experts* approach that utilizes different sets of features for each type of arrhythmia and consists of a competitive network of different types of algorithms (experts) in a departure from the others to enhance detection and classification.

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