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Syntactic Recognition of Common Cardiac Arrhythmias

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Abstract

This paper outlines a syntactic approach to the recognition of common cardiac arrhythmias within a single ambulatory ECG trace. This methodology essentially involves the annotation of an electrocardiogram trace in terms of the syntax primitives and the subsequent parsing of these annotations into various syntactic forms that describe their appropriate arrhythmia. The syntax primitives, which we collectively term *arlets*, are a set of curves, which are modelled as a series expansion of orthonormal hermite basis functions. By using as features the parameters of this model, a probabilistic neural network is then employed to detect the occurrences of arlets within an ECG trace. The approach was evaluated using data from the MIT-BIH arrhythmia database.

Introduction

Cardiac arrhythmias are dysfunctions or disturbances in the behaviour of the heart. These disturbances produce abnormalities in rate, rhythm and the site of impulse formation; factors that may in turn alter the normal sequence of atrial and ventricular activation. In electrocardiograms, such arrhythmias manifest themselves as deformations in the observed waveform. Such deformations, as associated with a diagnosed arrhythmia, occur with a consistency and morphological similarity that they may be look upon as a "waveform pattern" in the temporal domain. In general, ECG arrhythmia waveforms can be subdivided into two type classes; (i) events : which are single ectopic occurrences and, (ii) rhythms : which are a continuous series of one or more event types.

Some common cardiac arrhythmias that are identifiable by the methodology outlined in this paper are shown in figure-2 and a clinical overview of them can be found in [1]. If one looks at the morphological characteristics of cardiac arrhythmias, one will find that there are large number of them that are defined in terms of others arrhythmias. This is especially so for the rhythms. Therefore, given the "language" of arrhythmias is well structured, it seems only appropriate that a syntactic approach to the recognition of arrhythmias be used. But like all syntactic methodologies, the performance of the process is largely dictated by the ability of the process to identify those primitives that form the syntax or "alphabet" of the system. In this paper, an artificial neural network approach to recognising the syntax primitives is adopted, using a series expansion of orthonormal basis functions to model the various syntax primitives, together with a

probabilistic neural network to classify the coefficients of the series expansion.

What are arlets?

The syntactic recognition process presented in this paper is essentially based on the recognition of a series of five primitives, which we call *arlets*. They represent the syntax primitives of this syntactic recognition process - see figures-1. Using these arlets, the morphology of the more common cardiac arrhythmias can quite easily be described as a string of primitives; see figure-2. With this in mind, the identification of such arrhythmias from an ECG trace now becomes a procedure that involves just the annotation of the ECG trace in terms of arlets and, the subsequent parsing of these annotations into the various syntax structures or "words" that describe these arrhythmias. Because, the parsing of such annotations in this application is greatly simplified by the relatively small size of the syntax set ie. five (four for the experiment evaluation), this paper shall concern itself with the detection of arlets only.

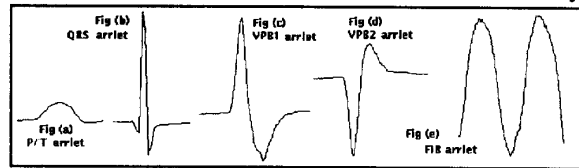


Figure 1 : Syntax primitives or arlets.

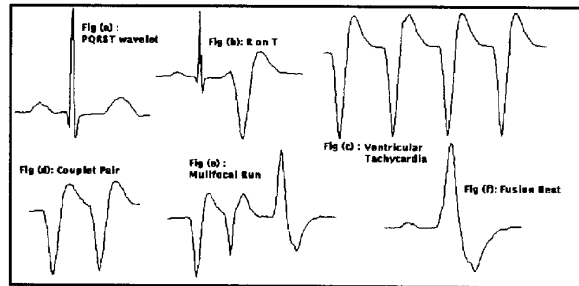


Figure 2 : Typical cardiac arrhythmias. (a) (NORMAL) = (P-T)+(QRS)+(P-T); (b) (RONT) = (P-T)+(QRS)+(VPB2); (c) (VTACHY) = (VPB2)+(VPB2)+(VPB2)+(VPB2); (d) (COUP) = (VPB2)+(VPB2); (e) (MFOCAL) = (VPB2)+(VPB2)+(VPB1); (f) (FUSION) = (P-T)+(VPB1)

Sornmo et al. [2] demonstrated that by using just the first three hermite basis functions, one could adequately model the shape of a QRS complex. However, since arlets VPB1 and VPB2 have more complex morphologies than the QRS complex, we would expect $N > 3$. In the experiment evaluation of the recognition process outlined in this paper,

$N=11$ was used. Also, in ambulatory ECG traces, it is not unusual to find the P wave and/or T wave absent because of their comparatively small amplitudes. Therefore, the P/T primitive was excluded from the arlet set during experimentation.

Outline of methodology

The recognition process is subdivided into five stages, namely (i) preprocessing, (ii) feature extraction, (iii) the classification of arlets, (iv) post-processing and, (v) the classification of arrhythmias. Stages (i) to (iv) represent the detection of arlets ie. the annotation process. At the front end of this process, is a sliding window, whose contents, $s(x)$, are passed to the recognition system for identification.

Pre-Processing

Pre-processing of the sliding window data, $s(x)$, entails a normalisation procedure followed by the removal of the data's linearity. Normalising the data involves dividing each sample of the signal, $s(x)$, by the resolution of the digitisation process. Once normalised, the linearity of the signal is removed. This is done by fitting a linear equation, $y(x)$, through the evenly sampled points of $s(x)$ and subsequently taking the difference between $s(x)$ and $y(x)$. The fitting is done using linear regression.

Feature extraction

Once the signal $s(x)$ has been preprocessed the resulting signal, $u(x)$, is modelled as a series expansion of N hermite basis functions; see eqn(1). Since the hermite set of functions is an orthonormal one, the series expansion coefficients of signal $u(x)$, $\{a_{0,\sigma}, a_{1,\sigma}, \dots, a_{N-1,\sigma}\}$, are computed by evaluating the integral of eqn(3) using numerical gaussian quadrature techniques [3].

$$u(x) \approx u_{N,\sigma}(x) = \sum_{i=0}^{N-1} a_i h_{i,\sigma}(x) \quad (1)$$

$$h_{n,\sigma}(x) = \frac{1}{\sqrt{\sigma}} \exp\left(-\frac{x^2}{2\sigma^2}\right) \hat{H}_n\left(\frac{x}{\sigma}\right) \quad (2)$$

$$a_{n,\sigma} = \int_{-\infty}^{\infty} u(t) h_{n,\sigma}(t) dt \quad (3)$$

In addition, the spread value, σ , is estimated using gradient-descent techniques such that the squared error between the synthesised signal, $u_{N,\sigma}(x)$ and the original signal, $u(x)$, is minimised.

Classification of arlets

Once the series expansion coefficients, $\{a_{0,\sigma}, a_{1,\sigma}, \dots, a_{N-1,\sigma}\}$, and spread value, σ , have been computed, they are passed to a probabilistic neural network, PNN [4] as a $N+1$ dimensional feature vector for classification.

Training samples for the probabilistic neural network were derived from the annotated ECG traces of the

MIT-BIH arrhythmia database. The probabilistic neural network has five classes, namely, QRS, VPB1, VPB2, FIB and UCLASS ie. an unknown or non-arlet class. Sample vectors for the unknown class were selected randomly for each ECG trace in the MIT-BIH database such that no annotated arrhythmia belonging to any of the other four classes were within 0.1sec of it.

A feature vector is said to belong to the i th class if and only if, the i th class has the largest posteriori probability estimate and, its probability density estimate exceeds a specified minimum threshold value; otherwise, it is unclassified.

Post-Processing

Using the PNN to classify the signal within the sliding window with each time shift, leaves us with a classification result at each point in time. Therefore, as the i th arlet enters the sliding window with each shift in time, the probability density function estimate of the i th class, as given by the PNN, will rise to a maximum when the arlet is centred in the window and falls when the arlet moves away from the window's centre. This characteristic behaviour is used to detect the location of an arlet in time.

To reach a decision, the post-processing stage uses a detection algorithm that makes use of each class's p.d.f. estimate, the *posteriori* probability estimate and the time in which the PNN remains classified.

Conclusion

The syntactic recognition process outlined in this paper was evaluated against twenty-six selected 10-sec segments of ECG traces from the MIT-BIH database. These segments were chosen from records which had a good content of varied arrhythmia occurrences including some noise jitter and baseline wander. Some of the arrhythmias detected include PVC, multifocal, couplet, trigeminy, ventricular fibrillation and ventricular tachycardiac. Of the 341 actual annotations, the process identified 311 with 18 false annotations and 17 missed annotations, although some "tuning" of the post-processing stage was required to achieve these results. Improvements to the process are still required to reduce its computational expense.

References :

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