Automated Prediction of Spontaneous Termination of Atrial Fibrillation from Electrocardiograms

D Hayn[1], K Edegger[1], D Scherr[2], P Lercher[2],
B Rotman[2], W Klein[2], G Schreier[1]

[1]ARC Seibersdorf research GmbH, Biosignal Processing and Telemedicine, Graz, Austria
[2]Medical University of Graz, Department of Internal Medicine, Division of Cardiology, Austria

Abstract

An algorithm for differentiating ECGs with atrial fibrillation (AF) that will spontaneously terminate within 60 seconds from signals, where it won't, has been developed using the AF Termination Challenge Database from PhysioNet. The algorithm was based on the calculation of the major AF frequency by canceling out the QRS complexes and T waves from the original ECGs and then applying short time Fourier transform techniques to the remaining signals. The major AF frequency and the mean RR interval were considered for classification.

Validation of the algorithm was done by sending the algorithm's results for test-set-a of the AF Termination Challenge Database to PhysioNet. We found, that for ECGs with a low AF frequency it was more likely, that AF would terminate spontaneously than for ECGs with higher frequencies. Our algorithm was able to correctly classify 93.3% (28/30) of the signals of the test-set-a.

1. Introduction

Atrial fibrillation (AF) is the most common cardiac arrhythmia, affecting more than two million people in the US [1]. During AF the excitation process and subsequently the mechanical activity of the atria is uncoordinated, leading to a loss of their pumping function. AF itself does not present a life threatening condition and – since it can even occur without symptoms – it may stay unnoticed for quite some time [2]. Nevertheless, AF increases the risk for stroke about 5-fold, it is responsible for about 15-20 percent of all strokes [1] and it is associated with a high risk of cardiovascular morbidity and mortality.

AF termination can be accomplished by direct cardioversion or drug administration and – in case of paroxysmal AF – it may also appear spontaneously. Determination of the AF frequency during catheter ablation showed, that the magnitude of AF frequency decline correlates with the AF termination probability [3]. It has also been shown, that drug-induced termination of AF is preceded by a decreasing AF frequency [4]. Prior studies that tried to detect similar effects right before spontaneous termination of AF found no increase in AF frequency in the final part of AF [5].

The mechanisms forcing spontaneous termination of AF are still unclear. Their knowledge may be useful in the individual selection of the optimal intervention for AF patients. It was the aim of this study to detect properties of the surface ECG and to develop methods that enable the prediction of spontaneous termination of AF.

2. Methods

2.1. Datasets

The algorithm described has been developed using the AF Termination Challenge Database from PhysioNet [6]. The database consists of three datasets (learning-set, test-set-a and test-set-b) containing three types of ECGs, all of which feature AF:

- Type N: ECG with AF that did not terminate within at least one hour after the end of the signal
- Type S: ECG with AF that did terminate exactly one minute after the end of the signal
- Type T: ECG with AF that did terminate within one second after the end of the signal

The signals consist of one minute ECGs that have been extracted from Holter ECG recordings and feature a sampling rate of 128Hz. Two channels according to two different leads are available for each signal.

The learning-set contains ten signals of each of the three types N, S and T, respectively. The type of each signal of the learning-set can be determined from the filename. Test-set-a contains 30 signals of either type N or T. Test-set-b contains 20 signals of type S or T.

Our algorithm was designed in order to separate all these signals into two groups:

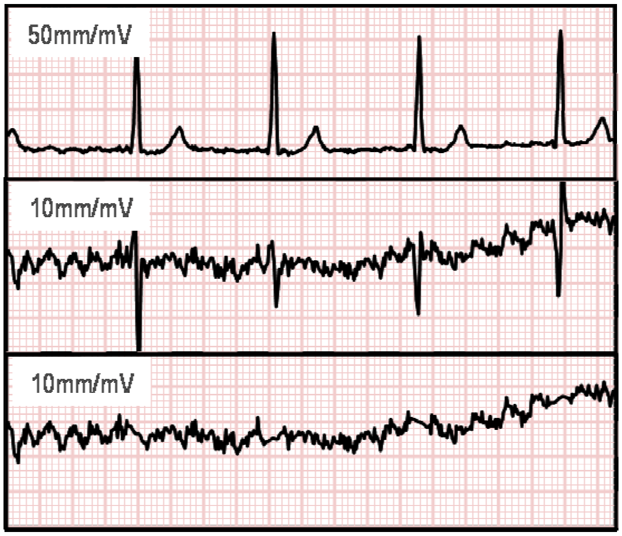

Figure 1: Original ECG (upper track), signal after QRST cancellation (middle track) and final signal after blanking the QRS complexes (lower track) as achieved for signal *n01.dat* from the AF Termination Challenge Database. The time resolution is 25mm/s.

- "Terminating": AF did terminate within one minute (i.e. type S or type T)
- "Not terminating": AF did not terminate within one hour (i.e. type N).

According to these two types of signals we used an extended learning-set-2 to develop our algorithm. This data set contains the 30 signals of the learning-set (10xN, 10xS, 10xT) as well the 20 signals of the test-set-b (10xS, 10xT).

Evaluation of the algorithm was done using PhysioNet's auto scorer for test-set-a of the AF Termination Challenge Database.

2.2. Signal inspection

Several tools for parameter extraction and comparison of such parameters from different signals have been developed. Parameter calculation was done in the time as well as in the frequency domain. We also implemented visualization tools for easily inspecting and comparing the parameters calculated for the different signals.

Furthermore, several tools of the biosignal analysis system g.BSanalyze 2.0 (Guger Technologies, Graz, Austria) were used for signal inspection and parameter extraction.

2.3. Signal processing

The signals were downloaded from the Internet and included into our biosignal database that contained not only information about the signals themselves, but also several different sets of processing parameters and selected results. In addition, the database provided parallel signal processing and the basis for comparison of the algorithm's results with expert annotations.

Signal processing itself was done in Matlab (The MathWorks, Inc., Natick, MA, USA). We used our existing biosignal processing system which had been developed in the course of previous ECG processing projects [7, 8] for preprocessing the signals and detecting the QRS complexes. QRS detection was based on an adaptive threshold based algorithm that was applied to the first derivative of one of the two channels of the original signal. Selection of the channel featuring better properties for QRS detection was done automatically. Then, each single heart beat was classified according to its QRS morphology. Thereafter, for each class of heart beats an averaged beat morphology was calculated for both channels, containing the QRS complex plus the T wave.

In order to analyze the atrial portions of the signal, it was our aim to eliminate those parts of the ECG, whose origin was in the ventricles. Therefore we subtracted the averaged heart beats from the signal within a predefined time window right around each QRS complex, containing the QRS complex itself plus the T wave. We then blanked the QRS complexes completely by interpolating the signal over the QRS part of each detected heart beat. ECGs after averaged beat subtraction with and without QRS blanking can be seen in Fig. 1.

Subsequently, we filtered the remaining signal using a Butterworth band pass filter. Finally we applied different

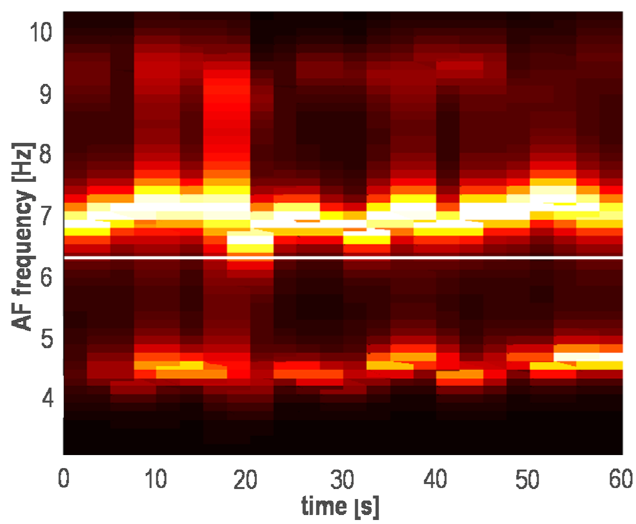

Figure 2: Frequency distribution over time for signal *n01.dat* of the learning set. The light regions show components with high spectral density, while dark regions are according to low spectral density. The white line represents the frequency threshold that was used for our initial entry to the Computers in Cardiology Challenge.

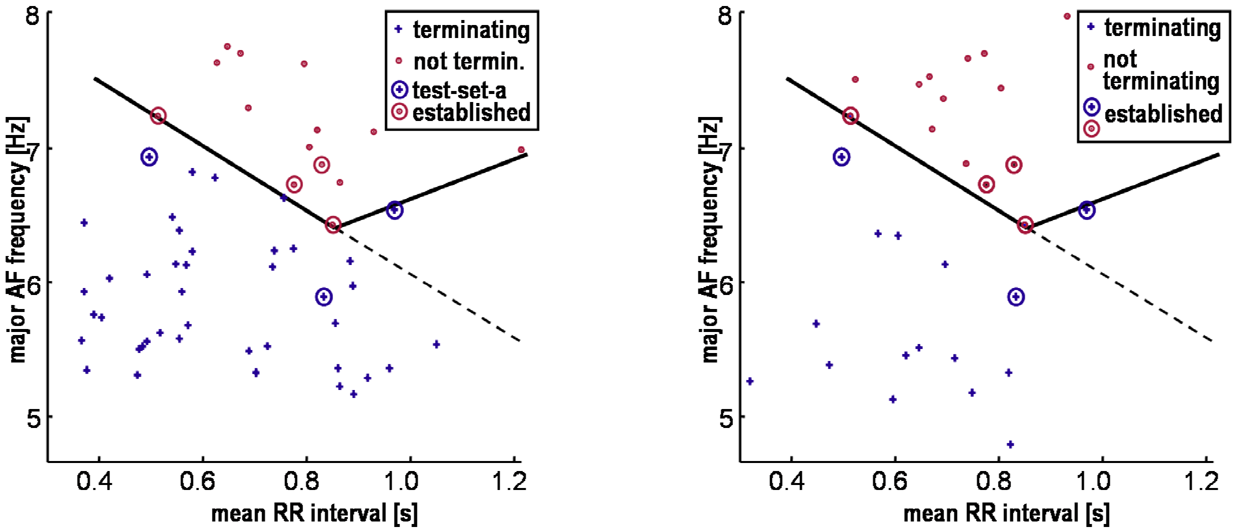

Figure 3: Mean RR interval versus major AF frequency plots. Each signal is represented by one point within the plots. The solid line represents the separator used for our final entry to the challenge. The dashed line corresponds to a simpler but probably more robust separator. The diagram on the left hand side displays the results as achieved for the extended learning-set-2 plus those signals with already established type (because of prior entries to the Computers in Cardiology Challenge). The diagram on the right hand side shows the corresponding plot for test-set-a, which was used for our final entry.

methods for frequency analysis to the resulting signal. By filtering the signal prior to frequency analysis we forced the parametric and model based methods of spectrum calculation to focus on a certain frequency region (i.e. the pass band of the filter). This was useful especially when using low order systems.

Frequency analysis was applied to short consecutive parts of the signal in order to analyze the variations of AF properties over time. Fig. 2 shows the frequency distribution over time as achieved by this method, using time windows of 5s with an overlap of 50%. The spectrum amplitude of each time window has been normalized. Light regions correspond to spectral maxima components; components with relative low spectral densities are dark.

2.4. Signal classification

We chose the channel that was not used for QRS detection for frequency analysis, since this channel usually exhibited a better ratio of atrial to ventricular components. The best results were achieved using a first order Butterworth filter with a bandwidth of 4 to 10Hz and the MUSIC method of order 12 for calculation of the pseudo-periodogram. The signal was split into time windows of five seconds (without overlap) and frequency analysis was done separately for each segment. For each segment the frequency with the maximum spectral component was calculated. Classification of the signals was based on the mean value of all these frequencies of all segments (major AF frequency).

Our first entry to the Computers in Cardiology Challenge was done using this major AF frequency only. Signals with a major AF frequency above 6.3Hz were classified as “not terminating”, others as “terminating”.

In order to further improve the initial result we also used the mean RR interval of the signal in our consecutive entries to the challenge. The final version of our algorithm that was used for our fifth entry to the Computers in Cardiology Challenge classified all signals according to the prediction factor p:

$$p = f_{AF} - k1 * RR \quad \text{if RR} < 0.85\text{s}$$

and (1)

$$p = f_{AF} + k2 * RR \quad \text{if RR} > 0.85\text{s}$$

where f_{AF} was the major AF frequency in Hz, and RR the mean RR interval in seconds, k1 and k2 were empiric coefficients that were set to $k1 = 2.6787s^{-2}$ and $k2 = 1.4956s^{-2}$. Signals with p>4.15Hz were classified as “terminating” others as “not terminating”.

3. Results

Our algorithm was able to classify 100% of the not-terminating signals from the terminating signals when applied to the extended learning-set-2 containing the learning-set plus the test-set-b of the AF Termination Challenge Database.

When applied to test-set-a we initially achieved a score of 90% correctly classified signals (27/30), using only the major AF frequency to separate in between terminating and not-terminating signals. This score could be slightly improved to 93.3% (28/30) by optimizing the QRST cancellation and the frequency analysis units and by using the prediction factor p that also considers the mean RR interval instead of the major AF frequency only.

4. Discussion and conclusions

When eliminating the ventricular portions of the ECGs by averaged beat subtraction, we found, that even though T wave elimination worked well, subtraction of the averaged beats did not accurately remove the ventricular portions of the signal in the regions of QRS complexes: Due to the low sampling frequency, a low amplitude resolution and due to the unstable state of the heart during AF, the QRS morphologies changed a lot from beat to beat, leading to a modest performance of the QRS-subtractor. Therefore we introduced the blanking of the QRS complexes to our algorithm.

Finally, our learning-set contained 14 signals of type N (10 files from the learning-set plus four signals from test-set-a of whom we know, that they are type N because of our five different entries to the challenge). On the other hand we have 43 signals of type “not terminating” (10xS plus 10xT from the learning-set, 20x S or T from test-set-b plus 3 established signals from the test-set-a). Therefore, there was a lack of signals of type N which complicated the classification process.

The results of our initial entry to the Computers in Cardiology Challenge were produced using the major AF frequency only. We reached a score of 90% (27/30) that way. For our later entries we optimized the QRST cancellation process as well as the spectral analysis parameters. Further on we included the mean RR interval as another parameter in the classification process.

Since the results improved only modest (only a single additional signal could correctly be classified) and according to our experience after having analyzed all 80 files of the database, the RR-interval is not a strong predictor in discriminating terminating and not-terminating AF. As can be seen in Fig. 3, both types of ECGs (“terminating” and “not-terminating”) are distributed over the whole RR-interval axis. The slightly smaller distribution of the N files might only be caused by their lower number. The separation of the two cases in equation 1 (RR-interval < 0.85s and RR-interval > 0.85s) was actually done to capture one single signal only. This may turn out to be of no value at all when applying the algorithm with new training data.

The major AF frequency on the other hand was able to classify 90% (27/30) of all ECGs of test-set-a and 96.25% (77/80) of the whole AF Termination Challenge Database. Unlike described in [5] it seems to decrease during the final phase before spontaneous termination occurs, just like it behaved before drug-induced termination and during successful catheter ablation in previous studies [3,4].

We also tried to use our algorithm for separating files of type S (terminating 60 seconds after the end of the signal) from type T (terminating within one second after the end of the signal). We could not find any parameter with statistical relevance for this classification process.

The application of our algorithm to the AF Termination Challenge Database resulted in a classification accuracy of more than 90%, thus indicating, that the major AF frequency has some potential in predicting spontaneous termination of AF. Future studies on extended datasets are necessary to determine, whether this concept can be successfully applied in a clinical setting, e.g. for choosing the optimal therapy for AF patients.

References

[1] American Heart Association. Heart Disease and Stroke Statistics — 2004 Update. Dallas (Texas): American Heart Association; 2003.

[2] Savelieva I, Camm AJ. Silent atrial fibrilation - another Pandora's box. PACE 2000;23:145-8.

[3] Haissaguerre M, Sanders P, Hocini M, Hsu LF, Shah DC, Scavee C, et al. Changes in atrial fibrillation cycle length and inducibility during catheter ablation and their relation to outcome. Circulation 2004 Jun 22;109(24):3007-13. Epub 2004 Jun 07.

[4] Lombardi F, Tarricone D, Tundo F, Colombo F, Belletti S, Fiorentini C. Autonomic nervous system and paroxysmal atrial fibrillation: a study based on the analysis of RR interval changes before, during and after paroxysmal atrial fibrillation. Eur Heart J 2004 Jul;25(14):1242-8.

[5] Fujiki A, Sakabe M, Nishida K, Mizumaki K, Inoue H. Role of fibrillation cycle length in spontaneous and drug-induced termination of human atrial fibrillation. Circ J 2003;67(5):391-5.

[6] Goldberger AL, Amaral LAN, Glass L, Hausdorff JM, Ivanov PCh, Mark RG, et al. PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals. Circulation 2000;101(23):E215-20.

[7] Schreier G, Kastner P, Marko W. An automatic ECG processing algorithm to identify patients prone to paroxysmal atrial fibrillation. Comput Cardiol 2001;28:133-5.

[8] Schreier G, Hayn D, Lobodzinski S. Development of a new QT algorithm with heterogenous ECG databases. J Electrocardiol 2003;36:145-50.

Address for correspondence

Dieter Hayn
ARC Seibersdorf research GmbH – Graz Office
Reininghausstr. 13/1, 8020 Graz, Austria
dieter.hayn@arcs.ac.at