Abstract

In this work, the aim is to discriminate terminating from non terminating atrial fibrillation (AF) episodes. A database including a learning set with 20 recordings and a test set with 30 recordings was provided. We hypothesized that the most relevant information about the mechanisms that trigger the AF is contained in the atrial fibrillatory wave (FW), which was estimated using a QRST cancellation technique. Spectral and time-frequency analysis of the estimated FW was then performed. Patients corresponding to the non-terminating group showed a higher frequency than patients from the terminating group, being 6.73±0.63Hz and 5.13±0.34Hz, respectively. A simple threshold on the main frequency classified correctly 27 out of 30 patients in the test set.

In addition, two different patterns were observed for the terminating group. In some patients, it was observed a unique and stable frequency, whereas in other cases it was not possible to track a main frequency, showing an irregular and chaotic pattern.

1. Introduction

Atrial fibrillation (AF) is the most frequent cardiac arrhythmia, with a prevalence of 10% in population over 70 [1], affecting more than two million people in the US alone [2]. The exact mechanisms that cause PAF are still an open issue, but evidence suggests that PAF is a precursor to the development of persistent AF [3][4]. Any improved information that could be extracted from the ECG about the mechanisms of PAF and sustained AF may provide important advances in the treatment of AF. With this aim, the organization of Computers in Cardiology in cooperation with PhysioNet has recently thrown down a challenge consisting in the prediction of the spontaneous termination of AF from the analysis of terminating and non-terminating AF ECG recordings [5].

In this work it is expounded in detail how this challenging problem has been tackled. Next section describes the materials provided by PhysioNet, which consist of freely distributed ECG databases, thus the results obtained with different algorithms can be further discussed and compared to the results presented in this paper. Section 3 presents the method employed for the analysis and classification of non-terminating and terminating AF. The results are shown in section 4, which are finally discussed immediately after.

2. Materials

PhysioNet provided free access to 50 one minute ECG recordings extracted from 24-hour holter recordings from 50 different patients, which are available through PhysioBank [6]. This database includes non-terminating AF (group N), which were observed to continue for at least one hour following the end of the excerpt, and AF terminating immediately after the end of the extracted segment (group T). Ten labeled recordings of each group were supplied as a learning set. The remaining 30 recordings were provided as the test set. The challenge was to identify to which group belongs each of the ECGs in the test set, which is not a priori known by the participants.

3. Methods

The methods employed in this study can be divided into four main stages: estimation of the atrial fibrillatory wave (FW), parameter extraction, discrimination of N and T groups from the learning set and classification of the test set.

Regarding FW estimation, several techniques have been already proposed. The most successful approaches in AA estimation are those that exploit the spatial information in multilead ECGs [7][8][9]. However, in this case the ECGs were obtained from 2-lead holter recordings, thus the spatial information to be exploited is practically negligible, and an adaptive QRST cancellation
technique based on PCA concepts was employed [10].

After having cancelled the QRST, the FW wave was analysed in order to extract useful information that permits the characterization of groups N and T. It has already been demonstrated that the spectral analysis of the AA signal can provide important information regarding the atrial refractoriness and the organization degree of the atrial depolarization [11]. In addition, time-frequency analysis reveals any short-term information that could be masked by the spectral analysis, as well as its evolution with time [12]. In this study it has been exploited both spectral and time-frequency properties.

After computing the FW spectrum using the Welch’s method with 8192 FFT points, 4096 points length Hamming window and 50% overlapping, the following spectral parameters were computed: main peak frequency ($f_1$), secondary peak frequency ($f_2$), bandwidth (BW) and spectral concentration.

The time-frequency analysis wave was carried out using the Choi-Williams transform. The short-term analysis permitted the monitoring of the following parameters on a second-to-second basis:

- Instantaneous main frequency ($f_{i1}$): after tracking the main frequency, its mean value $m_{f_{i1}}$ and standard deviation $\sigma_{f_{i1}}$ was obtained.
- Instantaneous secondary frequency ($f_{i2}$): after tracking the main frequency, its mean value $m_{f_{i2}}$ and standard deviation $\sigma_{f_{i2}}$ was obtained.
- Number of secondary peaks ($n_{sp}$): is the number of secondary peaks that have a level which is comparable to the level of the main peak. After tracking the number of secondary peaks, its mean value ($m_{n_{sp}}$) and standard deviation ($\sigma_{n_{sp}}$) was also obtained.

In addition to these spectral and time-frequency features, the set of parameters was completed with the R-R interval series.

The significance of the parameters was computed using a non-parametric test, specifically the Mann-Whitney test. The discrimination of N and T groups was carried out by means of a bivariate logistic regression over the learning set in order to derive a classification rule to be applied in the test set. In addition, the test set was also classified after performing a cluster analysis. The results provided by both methods will be compared and discussed in next sections.

4. Results

The parameters defined in section 3 were computed for all recordings in the learning set. Table 1 presents the mean and standard deviation values of the spectral and time-frequency parameters, respectively, for both T and N groups, as well as the p-values.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Group T</th>
<th>Group N</th>
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</thead>
<tbody>
<tr>
<td>$f_1$</td>
<td>4.96 Hz</td>
<td>6.57 Hz</td>
</tr>
<tr>
<td></td>
<td>0.51 Hz</td>
<td>0.68 Hz</td>
</tr>
<tr>
<td>$f_2$</td>
<td>7.04 Hz</td>
<td>5.36 Hz</td>
</tr>
<tr>
<td></td>
<td>2.64 Hz</td>
<td>0.842</td>
</tr>
<tr>
<td>BW</td>
<td>2.84 Hz</td>
<td>1.07 Hz</td>
</tr>
<tr>
<td></td>
<td>0.82 Hz</td>
<td>0.661</td>
</tr>
<tr>
<td>SC</td>
<td>0.511</td>
<td>0.154</td>
</tr>
<tr>
<td></td>
<td>0.093</td>
<td>0.02*</td>
</tr>
<tr>
<td>$m_{f_{i1}}$</td>
<td>5.13 Hz</td>
<td>0.63 Hz</td>
</tr>
<tr>
<td></td>
<td>0.34 Hz</td>
<td>&lt;0.0001*</td>
</tr>
<tr>
<td>$\sigma_{f_{i1}}$</td>
<td>0.558 Hz</td>
<td>0.207 Hz</td>
</tr>
<tr>
<td></td>
<td>0.271 Hz</td>
<td>0.831</td>
</tr>
<tr>
<td>$m_{f_{i2}}$</td>
<td>5.11 Hz</td>
<td>0.57 Hz</td>
</tr>
<tr>
<td></td>
<td>0.26 Hz</td>
<td>&lt;0.0001*</td>
</tr>
</tbody>
</table>

* significant value

As it can be observed, the most significant parameter is the mean of the instantaneous frequency $f_{i1}$, which is lower in the case of group T (5.13±0.34) than in group N (6.73±0.63). It was also observed that $f_1$ and the mean of $f_{i1}$ offered redundant information, with a correlation index of 0.949, thus employing one of these two parameters should be sufficient. In addition, the mean of $f_{i2}$ was also highly correlated with the mean of $f_{i1}$, with a correlation index of 0.985. The remaining parameters did not present significant correlation values, thus could also be included in the statistical analysis.

After performing a bivariate logistic regression it was concluded that a classification rule based on a single parameter ($f_{i1}$) would be the most appropriate option. A simple threshold of 5.7Hz on the main frequency was able to discriminate among N and T groups in the learning set. This rule was applied in the test set, obtaining 27 correct classifications out of 30 patients (90%).

AF terminating signals could be further classified into two differentiated subgroups. It was also observed that both groups corresponded to different fashions when performing the time-frequency analysis. In some patients, the time-frequency domain of the FW showed a main frequency which was very stable during the whole interval. In other patients it was not possible to identify a main frequency, but the FW was irregular and chaotic. In the first case, the AA spectrum showed a clear frequency peak with a bandwidth of 2.27±0.15Hz, whereas in the second case it was not observed a main frequency peak, but an important spectral content with an increased bandwidth of 3.69±0.64Hz. The exact interpretation of these differences is still uncertain, but possible causes related to the internal organization of the atria are discussed in next section.

Figure 1 shows the FW, its spectrum and time-frequency analysis from patients belonging to each one of the clusters. Figure 1.a is an example corresponding group N (patient 02), and figures 1.b and 1.c are examples related to group T, with organized (patient 10) and disorganized (patient 05) frequency patterns, respectively.
5. Discussion and conclusions

The first important conclusion derived from this study is that it is possible to determine if AF will terminate with high accuracy. The prediction of AF termination is based on the analysis of the AA signal, what confirms the initial hypothesis that any useful information about the mechanisms that cause AF should be extracted from atrial fibrillatory wave. The results presented point out that the most important difference of terminating and non-terminating AF is the main frequency of the AA signal, being the frequency of group T lower than in group N. This is an important observation, since the atrial refractory cycle is closely related to the inverse of the main frequency, being of 223±14ms for group T and 154±16ms for group N. These results are coherent with existing AF theories, such as the bioelectric remodeling, since the refractory cycle tends to decrease with the perpetuation of the arrhythmia [13].

Regarding the ECG corresponding to the terminating group, the fact that two different behaviors have been observed should be highlighted, thus suggesting two different physiological mechanisms that may trigger the extinction of the arrhythmia. In cases where a stable and unique frequency peak was sustained, they correspond to a termination pattern where the electrical wavefronts are synchronously activated. In the other cases, where it was not possible to track a main frequency peak in the time-frequency domain, several non-organized wavefronts are activated independently. Finally, this study reflects that it is possible to extract information of important clinical use by means of noninvasive techniques, such as the ECG.

Figure 1: The figure shows the spectrum in function of time, the mean spectrum and the atrial activity signal, a corresponds to the N signal, b and c correspond to the two types of T found.
analysis, which may lead towards the development of improved therapeutic interventions for the treatment of extinction of the arrhythmia. In cases where a stable and unique frequency peak was sustained, they correspond to a termination pattern where the electrical wavefronts are synchronously activated. In the other cases, where it was not possible to track a main frequency peak in the time-frequency domain, several non-organized wavefronts are activated independently. Finally, this study reflects that it is possible to extract information of important clinical use by means of noninvasive techniques, such as the ECG analysis, which may lead towards the development of improved therapeutic interventions for the treatment of AF.

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References


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