Classification of Atrial Fibrillation Episodes by means of Phase Variations of Time-Frequency Transforms

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Abstract

This study aimed to assess an early classification of paroxysmal and persistent atrial fibrillation (AF) episodes by means of the surface ECG on a heterogeneous cohort of patients (in terms of antiarrhythmic treatment and state of evolution of the arrhythmia), which is similar to the context that clinicians find at tertiary centres in their daily work.

129 consecutive unselected patients suffering from an AF episode conformed the study population (23 paroxysmal and 106 persistent). Modulus and phase features extracted from several time-frequency transforms of the ECG were studied, and it was phase variations which arose as determinant providing the best classification results using a Linear Discriminant Analysis classifier trained with 20 signals. Obtained performances for the latter feature were: Accuracy = 83.5% (total correct classifications), Sensitivity = 78.6% (paroxysmal AF episodes correctly classified), Specificity = 84.2% (persistent subjects properly classified). This results would aid electrophysiologists to choose and prescribe the most suitable treatment to lower recurrence and stop the natural progression of the arrhythmia in general scenarios.

1. Introduction

Atrial fibrillation (AF) is the most common cardiac arrhythmia [1] in clinical practice. It is characterized by rapid, disorganized propagation of electrical signals through the atria. In AF, the atria and ventricles do not longer beat in a coordinate way, creating a fast and irregular heart rhythm.

AF patients can be classified as paroxysmal (who present self-terminating episodes within 7 days), persistent (recurrent episodes which are unlikely to self-terminate and require cardioversion), and permanent (patients where cardioversion is unsuccessful and sinus rhythm can not be restored) [1].

So as to slow the heart rate to normal ranges, AF can be treated with antiarrhythmic drug therapies. Non-pharmacological treatments include surgical and catheter-based therapies to prevent recurrence of AF in certain individuals. Nowadays, it is not possible to differentiate the different subtypes of AF by directly observing the ECG. Thus, there are many references in the state-of-the-art which detect and classify AF episodes by means of the ECG, since the Computers in Cardiology Challenge of 2004 [2] was set out. Other relevant references are [3], [4] and [5], [6], which employ different features and analysis for classification.

Unfortunately, there is still a lack of a classification method able to perform well with heterogeneous cohorts of patients treated with different pharmacological or surgical therapies [7]. Hence, in this paper we present a study to address this problem and find a relevant feature for AF classification. Therefore, our objective is to provide a tool that could help electrophysiologists to choose the most suitable therapy for each subject, depending whether he presents a paroxysmal or a persistent AF episode.

2. Materials

129 consecutive unselected patients (23 paroxysmal and 106 persistent) suffering from an AF episode and whose ECG was acquired in a tertiary center conformed the study population. They included first episodes of AF, and recurrent AF with different pharmacological or electrical cardioversion treatments, which provide a heterogeneous cohort of patients to carry out the study. AF episodes were defined according to the current guidelines [1, 8]. Duration of ECG segments was 5 seconds, which is a common duration for 6×2 printout displays [9].

3. Methods

3.1. Time-frequency transforms

Although the Fourier Transform has been extensively used for ECG signal analysis, it is not able to provide in-

formation on the spectral content along time. This way, time-frequency transforms overcome this drawback, since ECG is a non-stationary signal (i.e. its frequency content varies with time) and it is also known that AF presents time-dependent properties [10]. Below are detailed some of the most popular time-frequency transforms used for biomedical signal analysis studied in this paper.

3.1.1. Wigner-Ville

The Wigner-Ville distribution introduced in [11] is defined as

$$W_f(\tau,\nu) = \int_{-\infty}^{\infty} f(\tau + t/2) f^*(\tau - t/2) e^{-i2\pi\nu t} dt \quad (1)$$

where $*$ represents the complex conjugate [12]. In order to avoid interference between positive and negative regions of the spectrum, the associated analytic signal

$$z(\tau) = f(\tau) + iH[f(\tau)] \quad (2)$$

is used, where $H[f(\tau)]$ is the Hilbert transform of the signal $f(\tau)$. The benefits of using this transform include that it is energy conservative, it gives good time and frequency resolution, and it can be efficiently implemented [13]. Nevertheless, unwanted cross-product terms appear due to the non-linearity.

3.1.2. Choi-Williams

Choi and Williams proposed the use of a kernel able to minimise cross-terms of the Wigner-Ville transform rather than smoothing them [14]. This transform is defined as:

$$C_f(\tau,\nu) = 2\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} \frac{\sqrt{\sigma}}{4\sqrt{\pi}|t|} e^{-v^2\sigma/(16t^2)} \times f(\tau + v + \frac{t}{2}) f^*(\tau + v - \frac{t}{2}) e^{-i2\pi\nu t} dv dt \quad (3)$$

where σ is a constant named kernel width that controls the resolution and the cross-product terms diminution.

3.1.3. Short-Time Fourier Transform

The Short-Time Fourier Transform (STFT) of a signal f is defined as

$$F(\tau,\nu) = \int_{-\infty}^{\infty} f(t) w^*(t-\tau) e^{-i2\pi\nu t} dt \quad (4)$$

where w is the window centered at time τ. Thus, this transform divides the signal into segments and multiplies each one by a window. Then, Fourier transform is applied to each segment in order to conform the time-frequency spectrum.

Due to the uncertainty principle, it is not possible to provide good time and frequency resolution simultaneously using a fixed size of window. This is the main drawback of this transform, which will be address in this study by the use of the Stockwell transform (able to provide progressive resolution by an frequency-adaptive size of window).

3.1.4. Stockwell Transform

The Stockwell Transform (ST) was presented in 1996 [15] to provide a tool able to combine the desirable properties of globally referenced phase with progressive resolution. The ST of a signal f is defined as

$$(Sf)(\tau,\nu) = |\nu| \int_{-\infty}^{\infty} g_0(\nu(t-\tau)) e^{-2\pi i\nu t} f(t)\, dt, \quad (5)$$

where g_0 denotes a Gaussian window. It can be seen as a STFT where the window length varies depending on the frequency. However, the main disadvantage of this transform is related to its very high computational cost and memory requirements. Fortunately, an efficient fast and non-redundant implementation based on a dyadic scheme was described in 2010 [16], which is known as as General Fourier-family Transform (GFT). Thus, we have used this implementation in the results presented in this study.

3.2. Feature extraction

Once baseline and powerline noise have been removed from the ECG signals, we proceed to analyze those signals and extract their relevant features. We applied the different time-frequency transforms to each ECG and extracted, for those frequencies below 16Hz, variations of modulus and phase along the time axis.

For this purpose, we previously normalized each time-frequency transform to the range [0-1]. If $\{z_{f1}, z_{f2}, ..., z_{fN}\}$ denote the normalized values of the transformed ECG leads for frequency f along the N samples of the time axis, we consider $\sum_{t=1}^{N-1} r_t$ and $\sum_{t=1}^{N-1} |\theta_t|$ as modulus and phase variations, respectively, for adjacent time samples denoted by the index t, where $r_t e^{i\phi_t} = z_{f\,t+1} - z_{f\,t}$.

Then, we normalized by the mean number of R peaks which each ECG signal contains, to address the interpatient heartbeat rate variability.

3.3. Classification

In this study we propose to use a Linear Discriminant Analysis (LDA) classifier due to its low computational requirements. LDAs are based on maximizing the Fisher's

linear discriminant (i.e. the ratio of the between-class variance to the within-class variance), so as to maximal separability between classes is obtained.

Therefore, dimensionality is reduced by projecting feature vectors to its most discriminative directions. Fisher discriminant finally finds the line that best separates these vectors, guaranteeing maximal separation between classes.

4. Results

As above-said, our dataset consisted of 129 electrocardiograms of AF episodes. Patients corresponded to an heterogeneous group, who has been treated with several antiarrhythmic therapies. There were 23 episodes of paroxysmal AF and 106 episodes of persistent AF.

As there were much more paroxysmal than persistent patients, the leaving-one-out technique was not appropriate. Therefore, the dataset was divided into two groups, one for training the classifier, and the other one for testing. We first trained the LDA classifier using 20 signals, and then test was performed with the rest of the 109 patients (14 paroxysmal and 95 persistent).

The LDA classifier was trained to maximize the global accuracy (i.e. proportion of correctly classified patients):

$$ACC = \frac{TP}{TP + FP} \tag{6}$$

where TP (true positives) is the number of paroxysmal and persistent patients correctly classified, whereas FP is the number of paroxysmal and persistent patients erroneously classified.

We also provide sensitivity and specificity performances (proportion of paroxysmal and persistent patients correctly classified, respectively), which are defined as:

$$Sensitivity = \frac{TP_{pa}}{TP_{pa} + FP_{pe}} \tag{7}$$

$$Specificity = \frac{TP_{pe}}{TP_{pe} + FP_{pa}} \tag{8}$$

where TP_{pa} and TP_{pe} are the paroxysmal and persistent segments correctly classified, whereas FP_{pa} are the paroxysmal segments which are classified as persistent, and FP_{pe} are the persistent segments which are erroneously classified as paroxysmal.

Table 1 shows performances and classification results for the test dataset (i.e. results obtained by excluding the training signals, only taking into account the test signals) for the different time-frequency transforms.

It can be observed that best performances are obtained when using the phase variations obtained along the time axis for frequencies below 16Hz, whereas results are much worse when just the modulus variations are used as features. Thus, the worst performances are obtained for Wigner-Ville and Choi-Williams time-frequency transforms, since they are always real-valued and not phase-referenced.

Table 1. Classification results for the test data set with features obtained using different time-frequency transforms. *Mod.* refers to modulus, *var.* to variations, *Both* refers to modulus and phase variations. STFT has been obtained by using a Gaussian window of size 256 samples.

	Features	Acc.	Sensitiv.	Specific.
Wigner-Ville	Mod. var.	0.532	0.786	0.494
Choi-Williams	Mod. var.	0.596	0.571	0.600
STFT				
	Mod. var.	0.633	0.571	0.642
	Phase var.	0.716	0.929	0.684
	Both var.	0.716	0.929	0.684
GFT				
	Mod. var.	0.624	0.571	0.632
	Phase var.	**0.835**	**0.786**	**0.842**
	Both var.	0.807	0.643	0.832

Best classification percentages (around 83% in accuracy, with similar sensitivity and specificity measures) are obtained when using as features the phase variations, for the efficient and non-redundant implementation of the Stockwell Transform (this is the GFT, figures emphasized in Table 1). This may be due to the high significance of the phase [17], which makes that performances drop significantly when only modulus variations are used as features.

Therefore, AF episodes can be mostly correctly classified just using the variations of phase for the different frequencies that correspond to the relevant part of the spectrum in AF (below 16Hz). We obtain good classification results despite the drawbacks of the heterogeneous dataset of patients and the unbalanced number of episodes of each clinical AF subtype.

5. Conclusions

In this paper we have presented a study that points to phase information of time-frequency transforms as relevant feature to classify paroxysmal and persistent atrial fibrillation episodes. A comparison between the most relevant time-frequency transforms for biomedical signal processing is presented to evince this fact, and results are presented on a cohort of patients with different treatments, different state of progression of the arrhythmia, and several of them with other comorbidities.

Future work will focus on improving results and enlarge the duration and number of signals available in the dataset, even increasing, if possible, the heterogeneity of the subjects.

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References

[1] Fuster V, Rydén L, Cannom D, Crijns H, Curtis A, Ellenbogen K, Halperin J, Heuzey JL, Kay G, Lowe J, Olsson S, Prystowsky E, Tamargo J, Wann S, Smith S, Jacobs A, Adams C, Anderson J, Antman E, Halperin J, Hunt S, Nishimura R, Ornato J, Page R, Riegel B, Priori S, Blanc J, Budaj A, Camm A, Dean V, Deckers J, Despres C, Dickstein K, Lekakis J, McGregor K, Metra M, Morais J, Osterspey A, Tamargo J, Zamorano J. Acc/aha/esc 2006 guidelines for the management of patients with atrial fibrillation: a report of the american college of cardiology/american heart association task force on practice guidelines and the european society of cardiology committee for practice guidelines (writing committee to revise the 2001 guidelines for the management of patients with atrial fibrillation): developed in collaboration with the european heart rhythm association and the heart rhythm society. Circulation August 2006;114(7):e257–e354.

[2] Moody G. Spontaneous termination of atrial fibrillation: A challenge from physionet and computers in cardiology. Computers in Cardiology 2004;31:101–104.

[3] Alcaraz R, Sandberg F, Sörnmo L, Rieta J. Classification of paroxysmal and persistent atrial fibrillation in ambulatory ecg recordings. IEEE Trans Biomed Eng May 2011; 58(5):1441–1449.

[4] Sandberg F, Stridh M, Sörnmo L. Frequency tracking of atrial fibrillation using hidden markov models. IEEE Trans Biomed Eng February 2008;55(2):502–511.

[5] Nilsson F, Stridh M, Bollmann A, Sörnmo L. Predicting spontaneous termination of atrial fibrillation using the surface ecg. Med Eng Phys October 2006;28(8):802–808.

[6] Ortigosa N, Cano O, Ayala G, Galbis A, Fernández C. Atrial fibrillation subtypes classification using the General Fourier-family Transform. Med Eng Phys April 2014; 36(4):554–560.

[7] Sahoo S, Lu W, Teddy S, Kim D, Feng M. Detection of atrial fibrillation from non-episodic ecg data: a review of methods. Conf. Proc. IEEE Eng. Med. Biol. Soc., September 2011; 4992–4995.

[8] Wann L, Curtis A, January C, Ellenbogen K, Lowe J, Estes N, Ezekowitz M, Slotwiner D, Jackman W, Stevenson W, C.M Tracy; 2011 Writing Group Members VF, Rydén L, Cannom D, Heuzey JL, Crijns H, Lowe J, Curtis A, Olsson S, Ellenbogen K, Prystowsky E, Halperin J, Tamargo J, Kay G, L. Wann; 2006 Writing Committee Members AJ, Anderson J, Albert N, Hochman J, Buller C, Kushner F, Creager M, Ohman E, Ettinger S, Stevenson W, Guyton R, Tarkington L, Halperin J, Yancy C. 2011 accf/aha/hrs focused update on the management of patients with atrial fibrillation (updating the 2006 guideline): a report of the american college of cardiology foundation/american heart association task force on practice guidelines. Circulation 2011; 123(1):104–123.

[9] Ortigosa N, Giménez V. Raw data extraction from electrocardiograms with portable document format. Comput Meth Programs Biomed January 2014;113(1):284–289.

[10] Rieta J, Alcaraz R. Atrial Fibrillation - Mechanisms and Treatment (Chapter 7: Applications of Signal Analysis to Atrial Fibrillation). Intech, 2013.

[11] Ville J. Theorie et applications de la notion de signal analytique. Cables et Transmissions 1948;2A:61–74.

[12] Cohen L. Time-Frequency analysis. Boston, MA: Prentice Hall, 1995.

[13] Boashash B, Black PJ. An efficient real-time implementation of the wigner-ville distribution. IEEE Transactions on Acoustics Speech and Signal Processing 1987; 35(11):1611–1618.

[14] Choi H, Williams W. Improved time-frequency representation of multicomponent signals using exponential kernels. IEEE Transactions on Acoustics Speech and Signal Processing june 1989;37(6):862–871.

[15] Stockwell R, Mansinha L, R.P.Lowe. Localization of the complex spectrum: The S transform. IEEE Trans Signal Process April 1996;44(4):998–1001.

[16] Brown R, Lauzon M, Frayne R. A general description of linear time-frequency transforms and formulation of a fast, invertible transform that samples the continuous S-transform spectrum nonredundantly. IEEE Trans Signal Process January 2010;58(1):281–290.

[17] Guo Q, Molahajloo S, Wong MW. Phases of modified stockwell transforms and instantaneous frequencies. J Math Phys May 2010;51(5):052101.

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