AN ALGORITHM FOR THE DETECTION OF ATRIAL FIBRILLATION USING THE PULSE OXIMETRIC SIGNAL

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Abstract: A method for the discrimination of atrial fibrillation and sinus rhythm from the pulse oximetric signal is presented. The method is based on the analysis of the ventricular rhythm irregularity, quantified by the Coefficient of Variation and the Shannon Entropy of the ventricular inter-beat intervals. A classifier based on the Mahalanobis distance is then applied. Sixty patients with an history of recurrent atrial fibrillation were studied. The method yielded a correct classification of 43 out of 43 patients with sinus rhythm, 14 out of 14 patients with atrial fibrillation, and 3 out of 4 patients with other arrhythmias.

1 INTRODUCTION

Atrial fibrillation (AF) is the most common cardiac arrhythmia in western countries. The current prevalence of nontransient AF in the US is 4% in the population of 65 to 70 years of age, and of 10% for people ≥ 80 years of age and is projected to increase considerably by 2050 (Naccarelli et al, 2009). AF is an independent risk factor for death and a major cause of stroke (Go et al, 2001). There are evidences that AF sustains itself through a complex process that is initiated by high atrial rate, cytosolic calcium overload, metabolic depletion and contractile dysfunction. Conversion of AF to sinus rhythm by antiarrhythmic drugs is relatively effective when AF duration is short (Kirchhof et al, 2009), whereas when AF duration exceeds two weeks the efficacy is greatly diminished.

These evidences suggest that early diagnosis is a key element to prevent the progression of AF and reduce atrial fibrillation-related complications. Another significant implication of asymptomatic AF is related to the need for oral anticoagulation. Withdrawal of oral anticoagulation after therapeutic interventions (e.g. electrical or pharmacological cardioversion, radiofrequency ablation) should be considered carefully, based on reliable and objective measures rather than symptoms.

Currently, diagnosis of AF is based on the analysis of the ECG signal. Due to the poor correlation between symptoms and AF (Israel 2004; Rho et al, 2005) the rate of detection of AF episode are strongly affected by the intensity of monitoring. Arya et al, reviewed the various ECG-based follow-up strategies to detect AF recurrencies after radiofrequency ablation and estimated that conventional Holter electrocardiogram (ECG) recordings have a low diagnostic yield for paroxysmal AF, newer technologies like patient-operated or telemetric ECG systems, long-term Holter monitors, or even implanted ECG monitors carry the promise of allowing an early diagnosis of silent AF.

Automatic detection of AF is achieved by analysis of the electrocardiographic signal. The absence of the P-waves is the main criterium for AF detection. Alternative methods have been proposed. These methods are based on the measure of the irregularity of the ventricular rhythm. Various measures of such irregularity are known. These measures quantify the variability of the ventricular inter-beat intervals (RR interval) obtained from the ECG signals, using combinations of various features: standard deviations and probability density

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function (Tateno and Glass, 2001), wavelet transform (Duverney et al, 2002) entropy, Lorenz plots (Esperer et al, 2008), probability density function of an embedded time series (Hong-Wei et al, 2009), turning point ratio, standard deviation and entropy (Dash et al, 2009), Markov modelling in combination with P-wave analysis (Babaeizadeh et al, 2009), Poincarè plots (Park et al 2009).

Some of these parameters does not suit a short-term detection since they requires a relatively large number of beats, others require significant computational effort / memory occupation. In this study, such methods have been excluded.

PP interval, e.g, the ventricular inter-beat interval measured from the pulse oximetric wave, has been proposed as an alternative to RR interval, during normal sinus rhythm (Lu et al, 2008; Foo et al, 2006). The reliability of ventricular rhythm estimation from PP intervals during AF is not known.

2 METHODS AND MATERIAL

2.1 AF Detection Algorithm

The detection of an atrial fibrillation episode is based on the extraction of quantitative indexes from the PP and ΔPP time series.

To distinguish between SR and AF we use the entropy (EN) of the PP interval series and the coefficient of variation (CV) of the ΔPP intervals.

The entropy is estimated as follows:

$$EN_{PP} = -\sum_i p_i \log_2 p_i \quad (1)$$

where p is the estimated probability density function of the PP series.

Since the mean of the ΔPP sequence leads to zero, we calculated the CV by dividing the standard deviation of the ΔPP intervals by the mean of the PP sequence

$$CV_{\Delta PP} = \frac{\sigma_{\Delta PP}}{\mu_{PP}} \quad (2)$$

To implement an automatic decision criterion, based on the CV and En, we used the Mahalanobis distance, which takes into account the covariance among the variables in calculating distances.

Mahalanobis distance (D_M) of a multivariate vector x from a group of values with mean μ and covariance matrix S is defined as:

$$D_M(x) = \sqrt{(x-\mu)^T S^{-1} (x-\mu)} \quad (3)$$

In order to have a parameter to discriminate AF vs. SR patient, Mahalanobis distance from AF and SR population was calculated for each patient.
The mean values of CV and EN were calculated for AF and SR patients, and the two covariance matrices were obtained:

$$S_{AF}^{-1} = \begin{bmatrix} 0.0086 & 0.0076 \\ 0.0076 & 0.0198 \end{bmatrix} \quad (4)$$

$$S_{SR}^{-1} = \begin{bmatrix} 0.0022 & 0.0054 \\ 0.0054 & 0.2129 \end{bmatrix} \quad (5)$$

For the i[th] patient the Mahalanobis distances from the two groups are obtained as

$$D_{SR}^2(i) = [CV_i - \mu CV_{SR} \quad EN_i - \mu EN_{SR}]\, S_{SR}^{-1} \begin{bmatrix} CV_i - \mu CV_{SR} \\ EN_i - \mu EN_{SR} \end{bmatrix} \quad (6)$$

$$D_{AF}^2(i) = [CV_i - \mu CV_{AF} \quad EN_i - \mu EN_{AF}]\, S_{AF}^{-1} \begin{bmatrix} CV_i - \mu CV_{AF} \\ EN_i - \mu EN_{AF} \end{bmatrix} \quad (7)$$

We classified the patient as belonging to the group for which the Mahalanobis distance is minimal and it is below a given threshold. In the case the distances from both groups are greater than the respective thresholds, the rhythm is classified as "other arrhythmia". In this study the squared thresholds were set at 10, on empirical basis.

2.2 Clinical Validation Protocol

The study was conducted at the Atrial Fibrillation Unit of S. Filippo Neri Hospital, in Rome. We studied 60 patients undergoing standard 12-lead ECG exam for a history/suspect of AF. Heart rhythm at the time of the examination was classified by an expert cardiologist as AF, SR or other arrhythmia.

Then, a 5-minute pulse oximetric signal was acquired from the index of the non-dominant hand using a MIROXY device (Medical International Research, Italy). The device firmware was modified to allow the real-time transmission of the pulse signal to a PC, using the RS-232 connection.

A single ECG lead was also recorded and digitized using a National Instrument NI-USB6218 DAQ card, for a further confirmation of the actual patient rhythm. Patients with pacemaker and/or defibrillator were excluded from the study.

3 RESULTS

Table 1 shows the characteristics of the patients and the heart rhythm at the moment of the test, as classified by the cardiologist from the ECG trace.

Table 1: Characteristics of patients' population.

Rhythm	N	Age (mean+/- sd, range)	Sex (M/F)
SR	43	65.27 +/- 11.96, 21-87	26/17
AF	13	78.14 +/- 8.29, 67-89	7/6
Other	4	67.75 +/- 10.51, 61-73	4/0

The results of the automated classification from the ventricular rate irregularity obtained by the pulse oximetric waveforms are reported in the Tables 2,3,4 for AF, SR and OTHER patients, respectively. The Tables also report the CV and EN values for each patient, as well as the distance obtained using the Mahalanobis metrics. The mean values of CV and EN of each group are also reported.

Table 2: Classification results of AF group.

Rhythm /Pt	$CV_{\Delta PP}$	EN	D^2 SR	D^2 AF	Classification
AF1	0.368	3.697	50.01	1.39	AF
AF2	0.296	3.492	29.48	0.15	AF
AF3	0.254	3.384	20.34	1.62	AF
AF4	0.321	3.496	35.93	0.79	AF
AF5	0.312	3.491	33.53	0.43	AF
AF6	0.365	3.668	49.12	1.20	AF
AF7	0.331	3.543	38.84	0.50	AF
AF8	0.379	3.626	53.92	3.08	AF
AF9	0.350	3.769	44.68	3.71	AF
AF10	0.283	3.566	26.75	2.08	AF
AF11	0.218	3.235	13.78	5.06	AF
AF12	0.282	3.603	26.77	3.66	AF
AF13	0.315	3.503	34.41	0.37	AF
mean	0.313	3.544	35.198	1.851	

Figure 4 gives a pictorial representation of the population EN and CV (circles), as well as of the classification results (crosses).

Table 3: Classification results of SR group.

Rhythm /Pt	$CV_{\Delta PP}$	EN	D^2 SR	D^2 AF	Classification
SR1	0.030	2.019	0.78	154.39	SR
SR2	0.041	2.528	2.35	54.08	SR
SR3	0.055	1.958	0.04	185.75	SR
SR4	0.062	1.349	2.01	457.45	SR
SR5	0.038	2.320	1.38	85.67	SR
SR6	0.019	1.926	1.19	176.53	SR
SR7	0.052	1.953	0.07	185.54	SR
SR8	0.019	1.835	1.07	206.13	SR
SR9	0.060	2.376	0.80	80.05	SR
SR10	0.021	1.612	1.05	292.12	SR
SR11	0.095	1.159	5.52	610.45	SR
SR12	0.093	1.935	0.72	218.11	SR
SR13	0.061	2.085	0.06	149.66	SR
SR14	0.165	2.346	5.84	129.77	SR
SR15	0.085	1.146	4.83	604.87	SR
SR16	0.082	1.866	0.46	236.45	SR
SR17	0.024	1.683	0.86	265.31	SR
SR18	0.068	2.334	0.51	90.34	SR
SR19	0.016	1.091	3.25	550.87	SR
SR20	0.057	2.131	0.16	135.21	SR
SR21	0.044	1.783	0.24	240.97	SR
SR22	0.071	2.035	0.03	169.90	SR
SR23	0.170	2.994	7.04	16.00	SR
SR24	0.023	1.730	0.87	246.39	SR
SR25	0.059	0.875	5.93	749.36	SR
SR26	0.026	1.904	0.78	187.41	SR
SR27	0.060	2.927	4.46	28.99	SR
SR28	0.082	2.184	0.23	131.65	SR
SR29	0.019	1.857	1.08	198.79	SR
SR30	0.109	2.858	3.03	24.64	SR
SR31	0.122	2.378	1.92	100.00	SR
SR32	0.020	1.442	1.50	366.75	SR
SR33	0.011	1.647	1.47	270.47	SR
SR34	0.061	2.071	0.04	153.98	SR
SR35	0.019	1.463	1.47	356.08	SR
SR36	0.084	2.232	0.32	120.02	SR
SR37	0.165	2.294	5.87	144.92	SR
SR38	0.157	2.738	5.04	41.58	SR
SR39	0.092	1.891	0.77	233.82	SR
SR40	0.056	2.952	4.96	30.34	SR
SR41	0.065	1.926	0.03	202.50	SR
SR42	0.028	2.361	2.21	76.53	SR
SR43	0.019	1.409	1.62	382.73	SR
mean	0.063	1.991	1.951	217.269	

Table 4: Classification results of OTHER group.

Rhythm /Pt	$CV_{\Delta PP}$	EN	D^2 SR	D^2 AF	Classification
OTHER1	0.167	1.523	11.13	486.25	OTHER
OTHER2	0.309	3.207	32.72	18.45	OTHER
OTHER3	0.232	0.942	34.30	998.65	OTHER
OTHER4	0.148	2.695	**4.18**	45.92	SR

The proposed method yielded a correct classification of all the patients with AF (13/13), as well as of all the patients in SR (43/43). One patient of the OTHER group, who had a low frequency atrial flutter, was misclassified as normal sinus rhythm, because he had a Mahalanobis distance from the SR group below the threshold (see table 4).

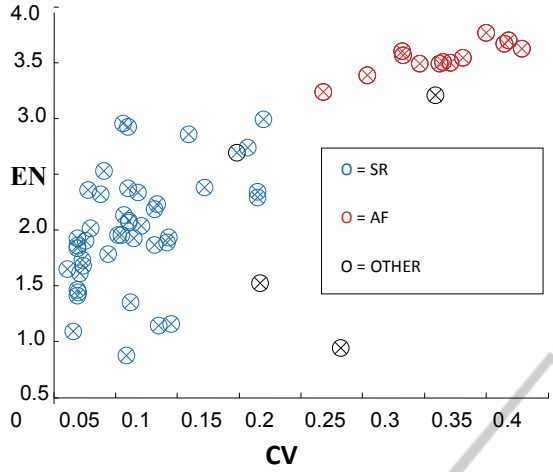

Figure 1: Result of the rhythm classification.

4 CONCLUSIONS

In this work, a AF detection algorithm based on the pulse oximeter signal is proposed. The algorithm is based on the measure of the irregularity of the ventricular rate during AF. The experimental validation demonstrated both high sensitivity and high specificity in AF and SR discrimination, so the algorithm can precisely detect AF episodes from a pulse oximeter device.

The high sensitivity of the algorithm, the relatively short data required (5 minutes), and its implementation on a microcontroller suggest that it is possible to design an home-care device for the accurate detection of AF episodes, based on commercial pulse oximeters.

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REFERENCES

Naccarelli, GV., Varker, H., Lin, J., Schulman, KL., 2009. Increasing prevalence of atrial fibrillation and flutter in the United States. Am J Cardiol. Dec 1;104(11):1534-9.

Go, A. S., Hylek, E. M., Phillips, K. A., et al., 2001. Prevalence of diagnosed atrial fibrillation in adults: national implications for rhythm management and stroke prevention: the AnTicoagulation and Risk Factors in Atrial Fibrillation (ATRIA) Study. JAMA. May 9;285(18):2370-5.

Kirchhof, P., 2009. Can we improve outcomes in A. F. patients by early therapy? *BMC Med*. Nov 26;7:72.

Israel, C. W., 2004. Is there a role for pacing in the prevention of atrial tachyarrhythmias? *Europace*. 6(5):380-3.

Rho, R. W., Page, R. L., 2005. Asymptomatic atrial fibrillation. *Prog Cardiovasc Dis*.48(2):79-87.

Arya, A., Piorkowski, C., Sommer, P., Kottkamp, H., Hindricks, G., 2007. Clinical implications of various follow up strategies after catheter ablation of atrial fibrillation. *Pacing Clin Electrophysiol.* Apr;30(4):458-62.

Tateno, K., Glass, L., 2001. Automatic detection of atrial fibrillation using the coefficient of variation and density histograms of RR and delta RR intervals. *Med Biol Eng Comput*. Nov;39(6):664-71.

Duverney, D., Gaspoz, J. M., Pichot, V., et al., 2002. High accuracy of automatic detection of atrial fibrillation using wavelet transform of heart rate intervals. *Pacing Clin Electrophysiol.* 25(4 Pt 1):457-62.

Esperer, H. D., Esperer, C., Cohen, R. J., 2008. Cardiac Arrhythmias Imprint Specific Signatures on Lorenz Plots. *Annals of Noninvasive Electrocardiology* 13(1):44–60.

Hong-Wei, L., Ying, S., Min, L., Pi-Ding, L., Zheng, Z., 2009. A probability density function method for detecting atrial fibrillation using R-R intervals. *Med Eng Phys*. 31(1):116-23.

Dash, S., Chon, K. H., Lu, S., Raeder, E. A., 2009. Automatic real time detection of atrial fibrillation. *Ann Biomed Eng. Sep;37(9):1701-9.*

Babaeizadeh, S., Gregg, R. E., Helfenbein, E. D., Lindauer, J. M., Zhou, S. H., 2009. Improvements in atrial fibrillation detection for real-time monitoring. *J Electrocardiol*. 42(6):522-6.

Park, J., Lee, S., Jeon, M., 2009. Atrial fibrillation detection by heart rate variability in Poincare plot. *BioMedical Engineering OnLine* 8:38.

Lu, S., Zhao, H., Ju, K., et al., 2008. Can photoplethysmography variability serve as an alternative approach to obtain heart rate variability information? *J Clin Monit Comput. 22(1):23-9.*

Foo, J. Y., Wilson, S. J., 2006. Detection method to minimize variability in photoplethysmographic signals for timing-related measurement. J Med Eng Technol. 30(2):93-6.