Effective Wavelet Algorithm for an Automatic Detection of Atrial Fibrillation

Beatrice ARVINTI[1], Alexandru ISAR[2], Marius COSTACHE[1]
[1]*Fundamental of Physics for Engineers Department,*
[2]*Faculty of Electronics, Telecommunications and Information Technologies,*
Politehnica University of Timisoara, 300006, Timișoara, Romania
marius.costache@upt.ro

***Abstract*—Cardiac anomalies are usually marked through irregular cardiac cycles. Atrial fibrillation is given through a rapid beating of the atria, announcing a possible heart failure or stroke. Electrocardiograms are an efficient way of supervising the electric activity of the heart. We have developed an effective, simple to implement automatic detection algorithm for identifying changes of the cardiac rhythm. The algorithm is based on wavelets and an enhanced time domain thresholding procedure. We take into account a variation of the electrocardiogram's amplitudes, to avoid loss of clinical features. The interval between beats is computed and provided for a reliable diagnosis. The results are validated both with objective evaluation criteria and displayed graphically, assisting the medical diagnosis procedure.**

***Index Terms*—adaptive algorithms, biomedical signal processing, performance evaluation, threshold, wavelet.**

I. INTRODUCTION

An efficient way of supervising the cardiac activity of the heart is given by the noninvasive graphical representation of its electrical activity. At each beat, the heart is pumping blood through the vessels, providing all tissues with nutrients. The action is possible through the electric coordination of depolarisation and repolarisation waves through the cardiac muscles. The electrocardiogram (ECG) is a standard graph of the voltage changes in time, structured in three main waveforms [1]: the P-wave (depolarization of the atria), the high-peaked QRS-complex (repolarisation of the atria and depolarization of the ventricles) and the T-wave (repolarisation of the ventricles).

The ECG waves have an established typical morphology, a range of time duration (interval between their temporal successions) and an accepted amplitude (voltage) range. The highest amplitude is displayed by the QRS-complex, due to the morphologic features of the human heart (up to 5mV): the muscles of the ventricles are thicker than the ones sustaining the atria, as the ventricles have to pump blood at a higher pressure. R-wave progression might show gradual amplitude increase in the chest leads V1 to V5 and an amplitude diminishment in V5 to V6 [2]. Any changes in the sinus rhythm or orderly progression of this pattern may indicate a cardiovascular disease (CVD) [1].

Atrial fibrillation (AF) is a disturbance of the cardiac rhythm, given through a rapid and irregular beating of the atria. It is associated with an increased risk of fainting, stroke, heart failure or dementia [3]. AF is assessed to affect up to 3% of the global population in Europe, being the most common serious heart rhythm disease [4]. One quarter of the patients with AF have no visible symptoms, and are diagnosed only after hospital monitoring due to complications (stroke, dyspnea, thromboembolic events) [5]. ECG screening may reveal the presence of AF. Medical diagnosis of AF is given in case of irregular QRS complexes with almost no visible P-waves (as an example, Fig. 1). Therefore, determination of rate and rhythm of the cardiac cycle is necessary for an efficient clinical interpretation. Usually, the heart rate of an adult is between 60 and 100 beats/minute. The adult pulse in AF can be either normal or faster (between 100 and 150 beats/minute) [1], but the interval between beats is highly irregular. Related risk factors of AF are high blood pressure, coronary artery disease, congenital heart disease, cardiomyopathy, but also smoking, diabetes and obesity [4]. Atrial fibrillation is usually a progressive disease, evolving from acute episodes to persistent episodes. Treatment of AF implies medication targeting at slowing down the heart rate, attempting to restore the normal sinus rhythm. The presence of AF is considered an important health priority and strongly correlated to the occurrence of stroke, its automatic detection being still unsatisfactory [6].

Cardiac changes may occur randomly and at any moment of time, therefore the chance of detecting acute AF episodes increases for a cardiac monitoring outside the clinical environment.

In the present paper, we aimed at proposing a simple to implement algorithm for portable devices, detecting AF episodes, which also could notice the patient the time to take a prescribed medication. Due to the pandemic, CVD add additional health risks for many people – and some of the risky situations should be avoidable. The paper is structured in four sections: Section II describes the wavelet based algorithm for the automatic detection of the AF. The performances obtained upon real ECG data are presented in Section III and in Section IV are drawn the conclusions.

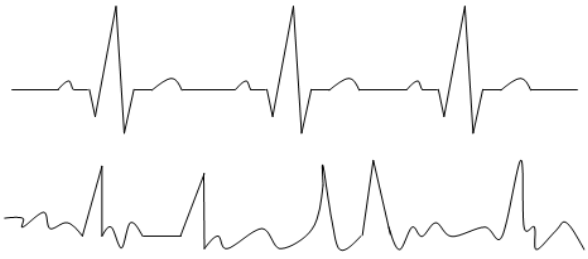


Figure 1. Normal sinus rhythm (top) and atrial fibrillation (bottom)

Digital Object Identifier 10.4316/AECE.2020.03006

II. Feature Detection in the Wavelet Domain

Up to day, ECG monitoring and automatic diagnosing systems are considered rather as preliminary results, the final interpretation being made by the cardiologist. Still, recent advances in wearable technology and the large occurrence of CVD raise the opportunity of developing more devices for automatic interpretation of the patient's health state [7]. Computer misinterpretations should be avoided, thus we tried to keep the algorithm as simple to implement as possible, avoiding too great a number of working parameters.

Wavelets aim at finding an approximate of the original function $f_{ECG}(t)$ using scaled and shifted versions of one mother wavelet $\psi_{i,j}(t)$ and the wavelet coefficients w_{coef} resulted through successive filtering of the original input signal (1). Each wavelet can be generated using a single scaling function (containing all details), as a linear combination of discrete translations of the analyzed function on a smaller scale (containing the needed details). The filter bank decomposition system for wavelets has been implemented for a fast decomposition and reconstruction of the analyzed signal [8, 9].

$$f_{ECG}(t) = \sum_{i=-\infty}^{\infty} \sum_{j=-\infty}^{\infty} w_{coef_{i,j}} \cdot \psi_{i,j}(t), \quad i, j \in \mathrm{Z} \quad (1)$$

where i and j are dilation and translation parameters, respectively.

We need an efficient algorithm for the pretreatment of the ECG, like baseline drift reduction, in order to obtain an accurate method for the detection of AF. Wavelet transforms have been applied to various biomedical signals, such as electrocardiography, electromyography, electroencephalography [10, 11] due to their ability of using different scales to highlight information of interest in non-stationary signals [12, 13]. In [14], AF is detected using a Gaussian mother function to estimate the cycle length (CL) of the atria of the electrocardiogram signal. The time window is large but fixed; the local maximum corresponds to the onset of the CL in that time window. During AF, the interval between beats is of no regular pattern, therefore a fixed time window can fragment an irregular heartbeat. The results in [14] are accurate, but complex, requiring the adjustments of several parameters, to avoid errors due to fragmented depolarization. Fractal analysis and wavelets have been applied in [8] for automatic detection of AF. There are two steps, the discrete wavelet transform (DWT) is used to compute the RR-variability (the interval between two neighboring R-peaks) and identify periods of high frequency rate. The second step is using the Hurst-exponent to classify these high variability periods into normal sinus rhythms or pathological ones (AF). The algorithm is very accurate; still a limitation of the method, as stated by the authors [8], is the necessity of a high number of beats for the computing of the parameters. The detection of short AF episodes is thus limited. We propose in the present paper a simple to implement detection algorithm of the R-waves, allowing the determination of the heart rate. Irregular beating of the atria (AF) will be reflected in irregular intervals between the QRS-complexes. Thus, we will use wavelets and intrinsic characteristics of the ECG signal (local minimal and maximal values of the given signal, for each iteration level k) to extract and localize changes of the cardiac rhythm. The ECG is acquired with electrodes placed on the skin of the patient. Movements and the patient's breathing might change the distance between the heart and the electrodes, resulting in a varying baseline and thus QRS complexes with varying amplitudes. The first step is the removal of baseline wander. A baseline correction algorithm [15] is used for the reduction of baseline variations and to filter out some external interferences, due to changed electric properties of the tissue. The main feature to influence the performance of the algorithm is the mother wavelet (MW), deciding the time-frequency localization properties of the wavelet used for signal analysis [16]. We represented in Fig. 2 and Fig. 3 the waveform and the impulse responses of the filters associated with the Daubechies14 MW. The R-peak detection algorithm uses an adaptive thresholding procedure [17, 18], which has been modified and enhanced to allow the automatic detection of each R-wave. The procedure is adaptive in order to avoid detection of false R-peaks. We will allow only a small variation from the established local threshold. Every 5 seconds a new local maximum will be searched for, and a new threshold level will be established. The diagnosis will thus not be established in real-time, but the time delay will be small, the searching algorithm being computationally efficient. No fixed threshold level is employed, all values lower than a fraction of the local maximum will be rejected and only the peaks retained. The fraction will be established empirically, as no assessment in literature has been found regarding the correct proportion of useful signal. The detection of false R-peaks will be avoided reducing the amplitude, thus at the final check, false R-peaks will have a too small amplitude to be displayed. After each R-peak check, the value and the time occurrence will be stored. The interval between the peaks will provide information about the rhythm of the cardiac cycle, enabling the diagnosis of AF. The time interval between two successive R-peaks (defined as *RR-interval*) will be checked by the physician, which can thus diagnose acute AF-episodes. As a further step, chronically AF episodes, which require the taking in of medication, can be automatically detected putting a threshold level T_{local} to the heart rate variability. The coefficient c is a correction factor, used to compensate the gradual amplitude increase or decrease of a normal ECG (2):

$$R_{peak} = \begin{cases} ECG_{\det(R_{peak})} - c \cdot \mathrm{T}_{local}, & ECG_{\det(R_{peak})} \geq c \cdot \mathrm{T}_{local} \\ 0, & ECG_{\det(R_{peak})} < c \cdot \mathrm{T}_{local} \end{cases} \quad (2)$$

where $ECG_{\det(Rpeak)}$ is the amplitude of the detected R-peak.

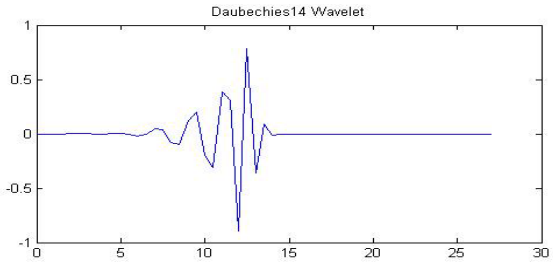


Figure 2. Wavelet function for the db14 mother wavelet

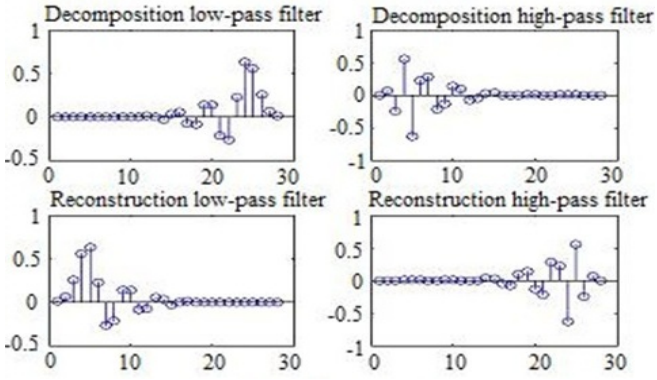


Figure 3. Decomposition and reconstruction filters associated with db14 mother wavelet

Despite all electronic devices available nowadays, a skilled physician is able to detect an acute episode of AF by simply feeling the irregularity of the hand pulse; additional check can be added using the stethoscope - more heart beats are heard than felt. In the same way, an advantage of the proposed method should consist in its simplicity: it should give an alarm and raise the opportunity for further, more detailed investigations - to be carried out in a supervised clinical environment. The heart rate variability (HRV) can be calculated using parameters of time domain measures or frequency domain measures [19-21]. We chose a novel geometric measure, which is more close to real life CVD diagnose model: the *relative RR intervals* (rr_i) [22]. It defines the relative variation of two neighboring R-peaks, with distance, where n is the number of RR-interval terms:

$$rr_i = 2(RR_i - RR_{i-1})/(RR_i + RR_{i-1}) \quad (3)$$

The value is stated to be between -20% and +20% [22], and a higher value indicates a high irregularity of RR-intervals, which is a first symptom of AF. The proposed algorithm is sketched in Fig. 4. Results of the data tests performed will be displayed both graphically and using quantitative estimators, for an objective performance evaluation. The algorithm has been tested on real ECG data, provided by the public database *AF Termination Challenge Database* [23, 24]. We aim thus to offer a reliable basis for performance comparison with other algorithms developed for the automatic detection of AF. The records have been sampled with a sampling rate of 128 samples per second (128 Hz) and are focused on episodes of AF.

III. Experimental Results

The performance of the proposed algorithm has been tested on all three different recordings groups, called *n*-group (non-terminating AF), *s*-group (AF terminating one minute after the recording) and *t*-group (AF terminating one second after the recording) [24]. We aimed at designing the automatic detection algorithm stable enough to face any of the AF development stages.

The AF detection method is based on a modified thresholding algorithm. The intervals between beats will be estimated using a hard-thresholding procedure applied in the time-domain. A simple, but effective procedure for detecting R-peaks has been proposed, computing any maximum of the recordings, using 5 seconds intervals. This maximum value of the processed signal is an intrinsic characteristic of the analyzed ECG, corresponding to the value of the R-peak.

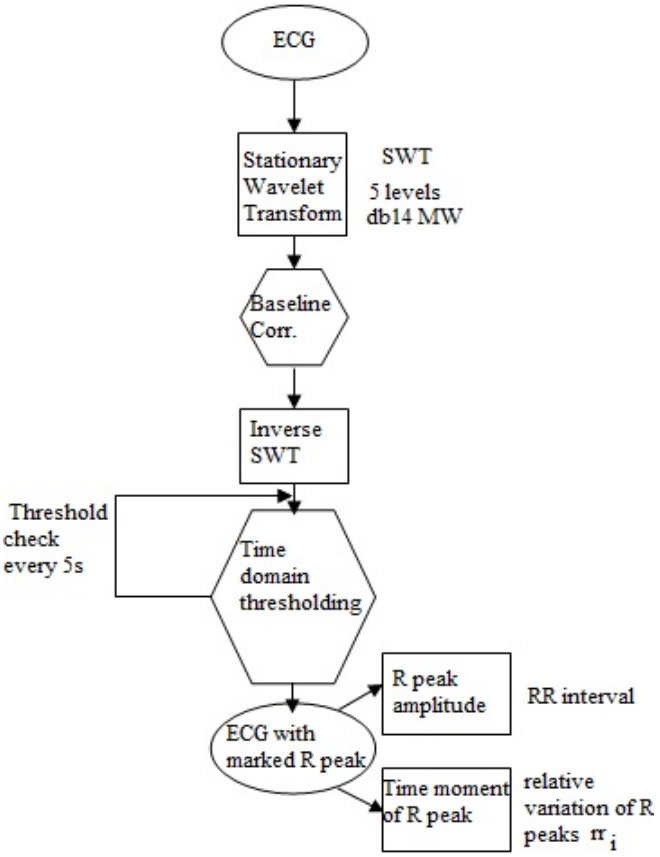


Figure 4. Flowchart of the AF detection algorithm

The searching algorithm is comparing this value with the adaptively established threshold level T_{local}. The system has been implemented in MATLAB. The first examples provided in the present paper are taken from the *n*-Group of recording, where the AF was not noticed to have terminated for the duration of the recording [23, 24]. The original signal, on an approximately 30 seconds recording, has been represented in Fig. 5. We notice also a moderate baseline drift. To prevent errors due to the baseline wandering, we will apply first a baseline correction method [15], using both the approximation A_{wav} and detail D_{wav} wavelet coefficients resulted at the output of the filter bank decomposition system. Baseline variations are reduced, estimating the ECG baseline through filtering of the D_{wav} coefficients [15].

The results are represented in Fig. 6 and Fig. 7. We notice the reduction of the baseline drift. We have applied the Stationary Wavelet Transform (SWT) on 5 levels of decomposition with db14 MW, a MW with a low number of 7 inflexion points, suited for ECGs, as shown by previous studies [25, 26]. The amplitudes of the QRS-peaks are quite similar, the frequency of their occurrence stating the AF.

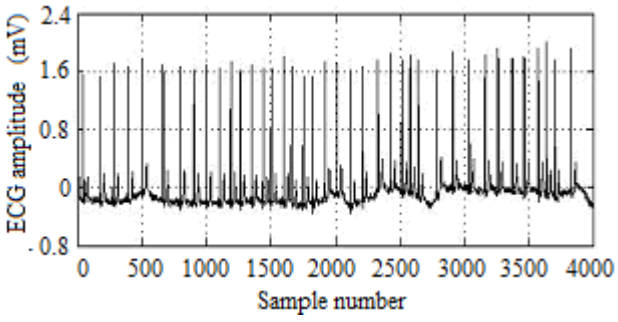


Figure 5. Original ECG data n01m with atrial fibrillation

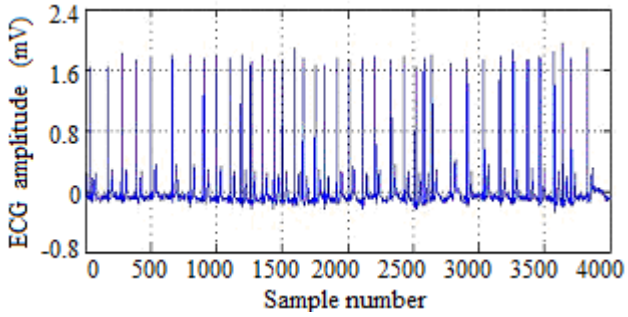


Figure 6. Baseline correction for ECG n01m with atrial fibrillation

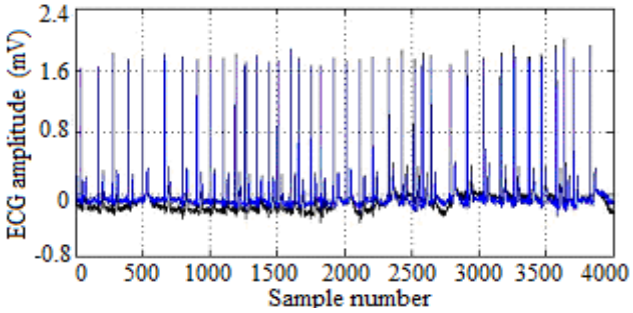


Figure 7. 30 seconds excerpt of ECG_{AF} n01m with superposed original (black colour) and filtered waveforms (blue colour)

Characteristics of AF can be derived from the shape of the P-wave [27]: a sign of AF is also reflected by a weak perception of the P-waves (Fig. 8). After applying the algorithm, values lower than 70% of the detected maximal value (taken as reference values) have been rejected. The values kept will reflect the R-peaks (Fig. 9, Fig. 10 and Fig. 11, the detected peaks are marked in red). If the physician is not present (in case of remote monitoring) the algorithm will detect the peaks and transmit their coordinates for the RR-variability computation, so as to enable the diagnosis of AF. The sample positions corresponding to each detected peak are given in Table I. The interval between beats will be computed dividing the number of samples between beats to the sampling frequency of the recordings (for the MIT-AF database, it corresponds to 128 samples/second). This operation can be executed automatically, once the recording equipment has been chosen by the physician. Analyzing Fig. 10 and Fig. 11, we notice the irregularity of the heart beats' rate, which varies between 0.47–0.77 s (the irregularities are higher than 20 %). The intervals between beats have been represented in Fig. 11. The analyzed data is taken from long-term ECG recordings, therefore AF event-tracking algorithms are an up-to-date challenge and the event should be noticed to the physician as soon as it is taking place, to avoid the development of chronic diseases.

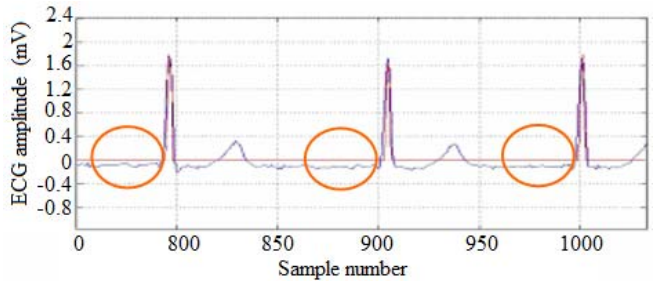


Figure 8. Zoom on three heartbeats of ECG n01m. We notice the weak perception of P-waves. The R wave is represented in red

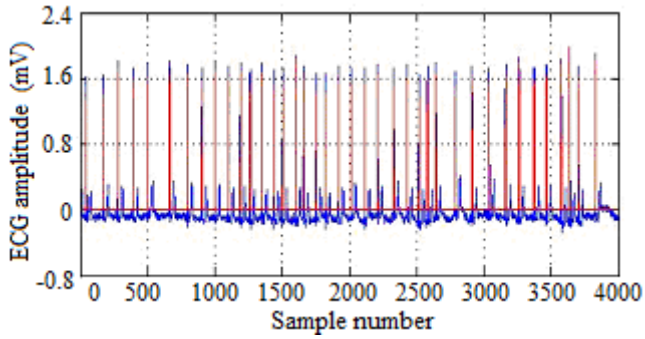


Figure 9. Automatic detection of RR-intervals (before thresholding-blue, after thresholding-red)

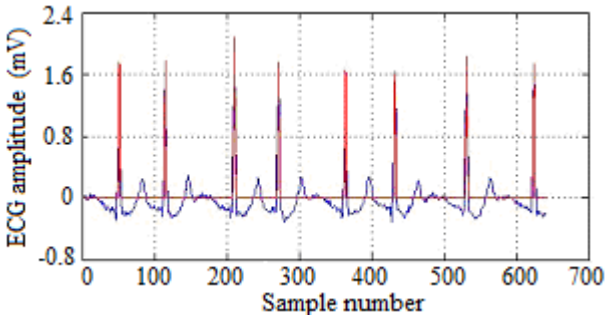


Figure 10. Zoom upon detected RR-intervals on a 5 seconds excerpt (n01m) (before thresholding-blue, after thresholding-red)

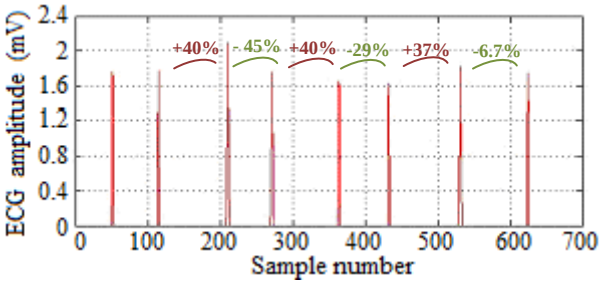


Figure 11. RR-intervals of ECG_{AF} n01m

TABLE I. VALUES OF THE RR-INTERVALS FOR ECG N01M

First R-peak sample position	Next R-peak sample position	RR-interval [s]	RR-interval [ms]
51	115	0.5	500
115	211	0.75	750
211	272	0.47	476
272	364	0.71	718
364	433	0.53	539
433	532	0.77	773
532	625	0.72	726

Other examples of 5 seconds excerpts for the next 4 recordings (n02m, n03m, n04, n05m) have been represented Fig. 12 and Fig. 13.

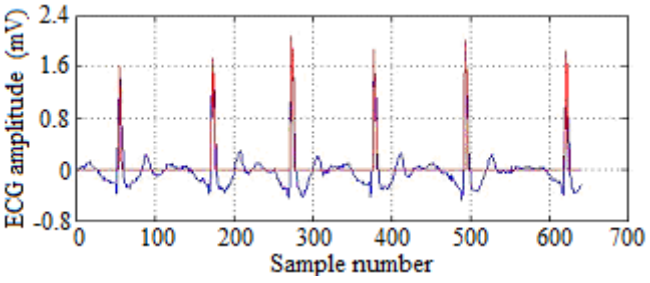


Figure 12a. Automatic detection of RR-intervals (before thresholding-blue, after thresholding-red) for ECG n02m

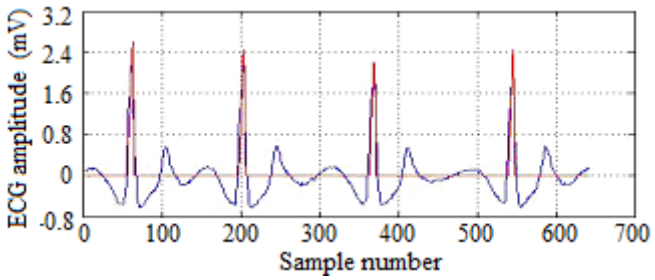
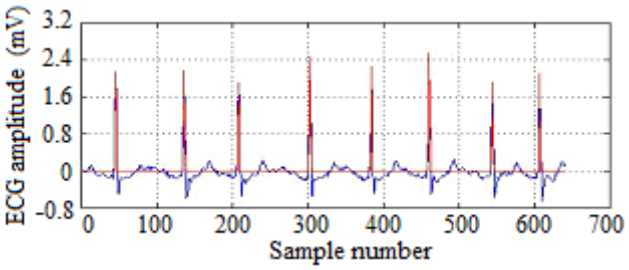


Figure 12b. Automatic detection of RR-intervals (before thresholding-blue, after thresholding-red) for ECG n03m

The clinically relevant values, corresponding to each recording are displayed in Table II. The MIT-AF database provides also ECG signals for enabling the study of the electric variations occurring at the end of AF (ECG signals of the *s*-group). The questions arise whether there can be noticed the re-establishment of the cardiac rhythm towards the end of the acute AF-episode. Choosing to implement an adaptive algorithm, we avoid fixed time intervals and aim to track ECG rhythm changes with high accuracy. An example with a high baseline wander is provided in Fig. 14. The results obtained by applying the proposed algorithm are shown in Fig.15 – Fig. 19, in Table III and Table IV. We notice the correction of the baseline drift and an accurate detection of the succeeding R-peaks, although they show varying amplitudes.

TABLE II. VALUES OF THE R-R INTERVALS FOR 5 SECONDS EXCERPT FOR ECG OF THE *N*-CLASS

ECG	Maximal R-peak wavelet value [mV]	Detected RR-intervals [s]				
n02m	**1.75**	0.91	**0.78**	0.81	0.9	1.0
n03m	**2.17**	**1.10**		**1.28**		**1.38**
n04m	**2.12**	0.71	**0.56**	0.73		0.64
		0.59	0.65			**0.49**
n05m	**1.96**	**0.50**	**0.53**	0.78		0.74
		0.82	**0.49**			0.60



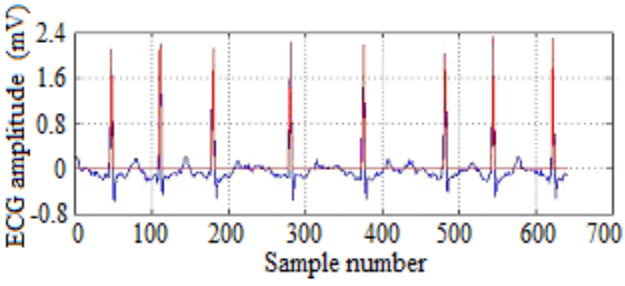


Figure 13. Automatic detection of RR-intervals (before thresholding-blue, after thresholding-red) for ECG n04m (top) and for ECG n05m (bottom)

Each ECG-group provided by the MIT-database has been studied, to draw accurate conclusions about the algorithm's performances. The irregularity of the RR-interval succession can be noticed in Fig. 17.

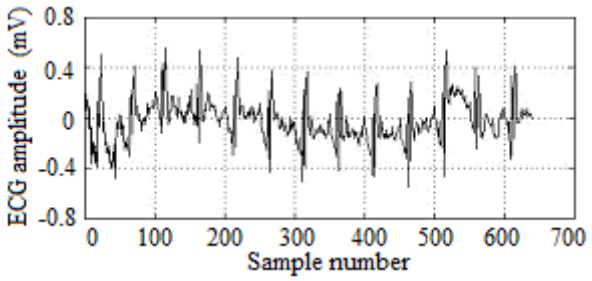


Figure 14. ECG_{AF} s01m. 5 seconds excerpt - original signal

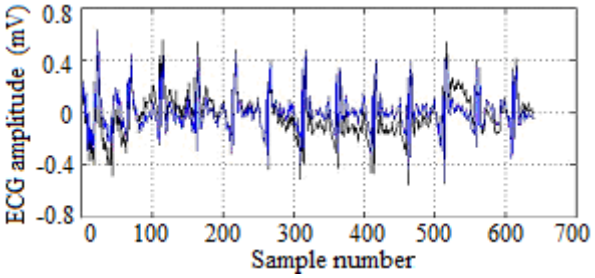


Figure 15. ECG_{AF} s01m. 5 seconds excerpt with superposed original (black colour) and filtered waveforms (blue colour)

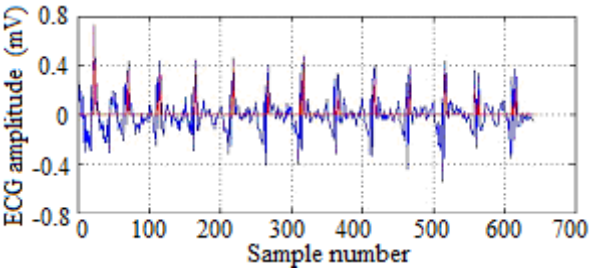


Figure 16. Automatic detection of RR-intervals of ECG_{AF} s01m (before thresholding-blue, after thresholding-red)

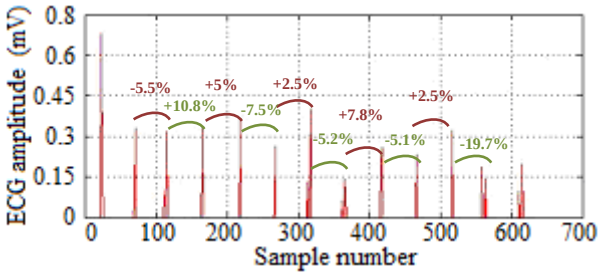


Figure 17. RR-intervals of ECG_{AF} s01m

TABLE III. VALUES OF THE R-R INTERVALS FOR ECG S01M

First R-peak sample position	Next R-peak sample position	RR-interval [s]	RR-interval [ms]
23	71	0.37	375
71	116	0.35	351
116	166	0.39	390
166	219	0.41	414
219	268	0.38	382
268	318	0.39	390
318	366	0.37	375
366	418	0.40	406
418	467	0.38	382
467	517	0.39	390
517	558	0.32	320

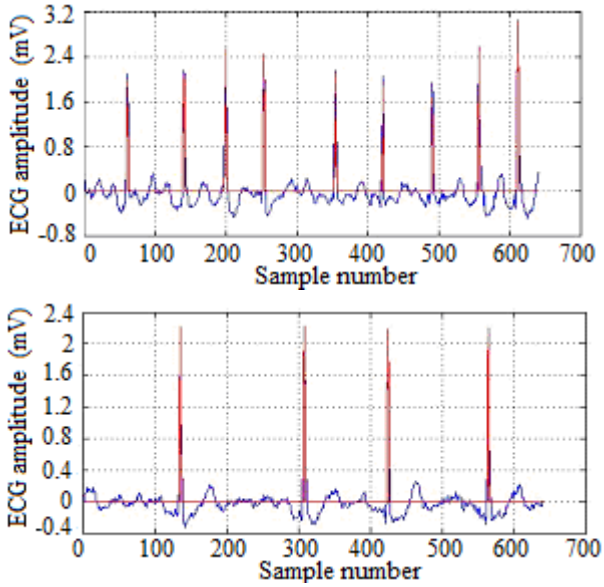


Figure 18. Automatic detection of RR-intervals (before thresholding-blue, after thresholding-red) for ECG s02m (top) and for ECG s03m (bottom)

TABLE IV. VALUES OF THE R-R INTERVALS FOR 5 SECONDS EXCERPT FOR ECG OF THE *S*-CLASS

ECG	Maxim R-peak value [mV]	Detected RR-intervals [s]					
s02m	**2.57**	**0.61**	0.46	0.42	**0.78**		
		0.52	0.53	0.51	0.42		
s03m	**1.87**	**1.35**		0.9		1.09	
s04m	**3.47**	0.4	0.4	0.3	0.3	0.4	0.3
		0.35	0.36	**0.68**	0.3	0.4	
s05m	**3.10**	1.05	0.85	**0.52**	1.2	0.7	

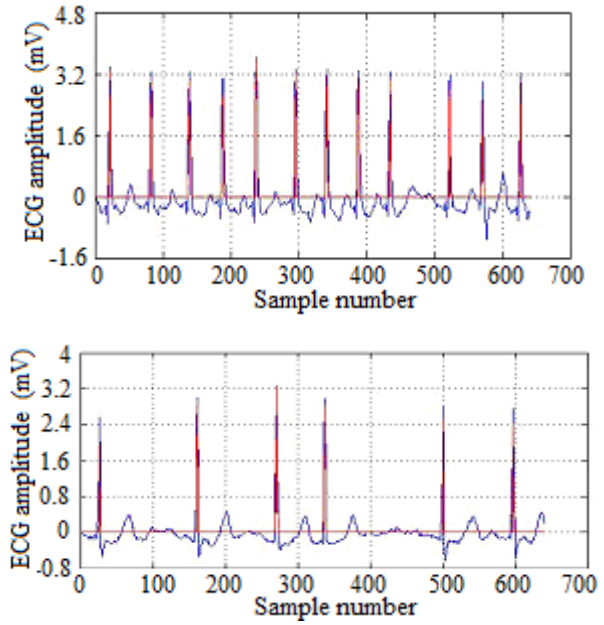


Figure 19. Automatic detection of RR-intervals (before thresholding-blue, after thresholding-red) for ECG s04m (top) and for ECG s05m (bottom)

The method has been applied on the next s-group signals and the results are shown in Fig. 20, Table V and Table VI. The drift of the baseline is usually attributed to mechanical effects, such as movements of the patient or artifacts due to surrounding electronic devices) and makes the CVD diagnosis difficult. After baseline drift correction, the R-peaks are detected using the described algorithm. As signals may vary in intensity and number of heartbeats on a time interval of 5 s, an adaptive threshold is advisable for a highly accurate analysis and detection of AF.

As an example, for the s-class ECG signals there are 13 heartbeats in s01m, while n01m displays only 8 heartbeats. The excerpt s01m is taken from the ECG group where the AF is marked as approaching towards the end-term. Indeed, the randomly selected interval is almost regular, the RR-interval varies between 0.32 – 0.41 seconds (the variation is not too great). Still the number of heartbeats is too high, a graphic rhythmogram could provide useful information [28]. The aim of the paper is to propose a useful algorithm, which should be easy to implement, as AF is an important cardiac disease. We can highlight the RR-intervals deviating from the mean RR-interval (values too high or too low) during the investigated ECG recording. Any deviations from the normal sinus rhythm will attract the attention that further investigations are necessary.

Investigating the class of terminal AF (ECG signals of the *t*-group), we notice the detection of the succeeding R-peaks. Several examples are provided in Fig. 20, Fig. 21 and Fig. 22. Analyzing Fig. 20, we notice that the proposed algorithm identified the problematic areas between the 50 and 150 samples (between 0.4 s and 1.2 s) of registration, where the R-peak, preceding the peak of the sample 100, and the R-peak, succeeding the peak of sample 100, show both low values. The shape of the highlighted area is preserved and will allow the physician to make further investigations before final diagnosis (detailed ECG values are stated in Table V).

The choice of an adaptive threshold value enables the detection of the low peaked R-waves (Fig. 22), as contained by the ECG t01m recording. We aimed thus to avoid the loss of data, significant for medical diagnosis.

The results obtained for other members of the t-group are summarized in Fig. 23, Fig. 24 and Table VI.

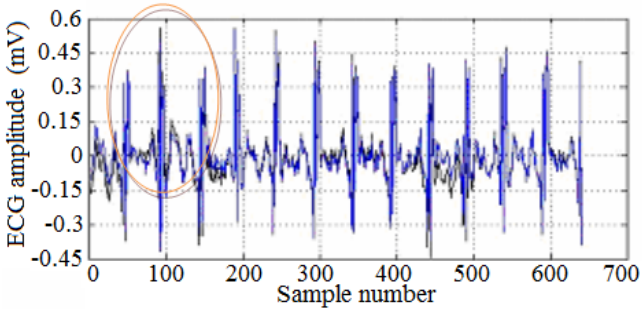


Figure 20. ECG_{AF} t01m. 5 seconds excerpt with superposed original (black colour) and filtered waveforms (blue colour)

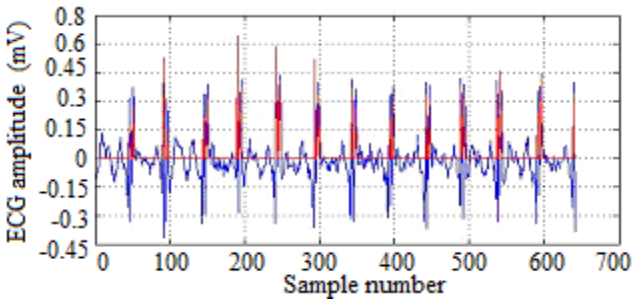


Figure 21. Automatic detection of RR-intervals (before thresholding-blue, after thresholding-red) of ECG_{AF} t01m

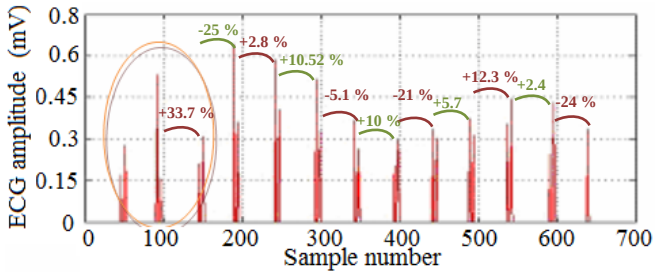


Figure 22. RR-intervals of ECG_{AF} t01m

TABLE V. VALUES OF THE R-R INTERVALS FOR ECG T01M

First R-peak sample position	Next R-peak sample position	RR-interval [s]	RR-interval [ms]
51	92	0.32	320
92	150	0.45	453
150	195	0.35	351
195	242	0.36	367
242	294	0.40	406
294	343	0.38	382
343	398	0.42	429
398	442	0.34	343
442	489	0.36	367
489	542	0.41	414
542	596	0.42	421
596	639	0.33	335

TABLE VI. VALUES OF THE R-R INTERVALS FOR 5 SECONDS EXCERPT FOR ECG OF THE *T*-CLASS

ECG	Maximal R-peak wavelet value [mV]	Detected RR-intervals [s]				
t02m	**2.35**	**0.44**	0.69	0.67	**0.40**	
		0.42		**0.49**	0.68	
t03m	**2.02**	**0.88**	**1.00**	**1.07**	**0.89**	**0.98**
t04m	**3.47**	0.45	**0.76**	0.44	0.36	0.39
		0.44	0.46	0.36	**0.68**	0.35
t05m	**3.10**	**1.16**		**0.57**	0.76	
		0.92		0.87	**0.52**	

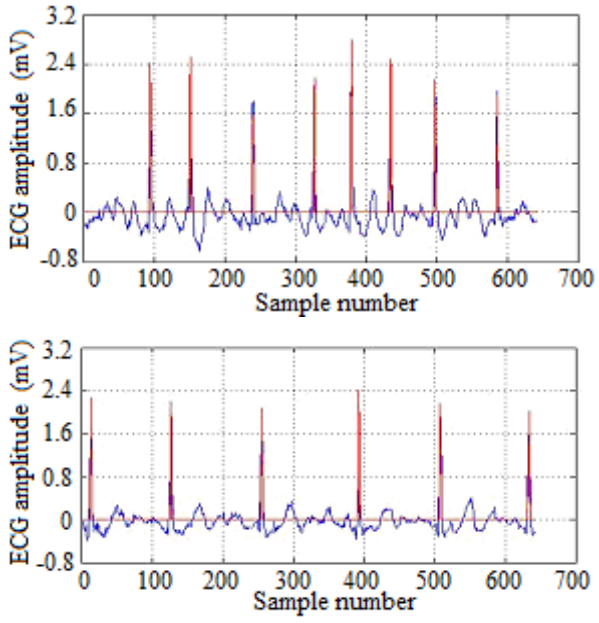


Figure 23. Automatic detection of RR-intervals for ECG t02m (top) and for ECG t03m (bottom)

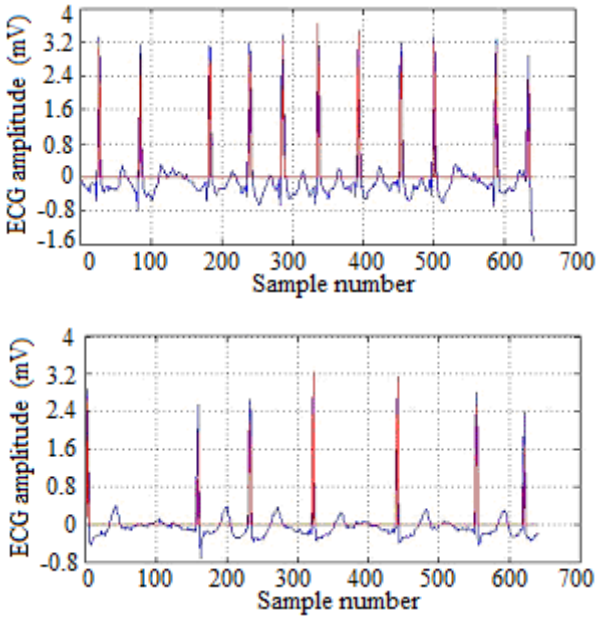


Figure 24. Automatic detection of RR-intervals for ECG t04m (top) and for ECG t05m (bottom)

IV. CONCLUSION

Significant health risks are associated with atrial fibrillation (AF), therefore early identification and diagnosis is desired to help the patients benefit from medical treatment. Intermittent ECG monitoring, at regular time intervals, or when having acute cardiac symptoms (during a four-week period) is more effective than a single, routine 24-hour Holter-ECG recording [29]. P-wave duration and amplitude is not considered up-to-day as the sole predictor of AF, therefore we have focused in this study upon the detection of the RR-variability rate.

The proposed procedure has been aimed for remote monitoring outside the clinical environment. To prevent misinterpretations due to the movements of the patient, a wavelet based procedure will be previously applied in order to reduce large valued baseline wanderings. Targeting at covering a large number of cases, the algorithm has been designed as general as possible, but taking intrinsic characteristics of the analyzed ECG into consideration. Any local maximum of the recording will be computed, reflecting the R-amplitude, due to its high positive level and to the nature of electric recordings. A fast searching algorithm, combining wavelet analysis procedures applied in the time domain, was designed for the identification of the succeeding R-peaks. The proposed thresholding algorithm will retain only the wavelet values higher than 70% of the local maximum detected. We take thus into account a variation of the QRS-amplitudes, to avoid loss of clinical features. The interval between beats is computed and provided for AF diagnosis. The performance has been analyzed through graphical display of the results (Fig. 11, Fig. 17, Fig. 22), as the diagnosis is given through visual inspection by a cardiologist in any clinical environment. Examples are provided for different development stages of AF, in each case the algorithm displaying a good performance. As objective parameter for the identification of AF, the relative RR-intervals between two successive beats has been computed: high variability indicates irregular

beats. Once the parameters chosen (sampling rate of the acquisition equipment), the algorithm can be implemented for an automatic detection and computation of the RR-intervals, enabling the diagnosis of atrial fibrillation. The advantage of the proposed method consists in its simplicity: it is intended to raise an alarm signal and enable the opportunity for further, more detailed investigations - to be carried out in a supervised clinical environment. Future research directions will aim not only at the efficient detection of an acute AF episode, but also at an early prediction of AF development.

REFERENCES

[1] Kannathal N, Rajendra Acharya U, Joseph P, Lim Choo Min, Suri J.S, "Analysis of Electrocardiograms", Springer, Berlin Heidelberg, 2010. https://doi.org/10.1007/978-3-540-36675-1_2

[2] A. Dupre, S. Vincent, P. A. Iaizzo, "Basic ECG Theory, Recordings and Interpretation", In: Iaizzo P.A. (eds) Handbook of Cardiac Anatomy, Physiology, and Devices, Humana Press, pp. 191-201, 2005, https://doi.org/10.1007/978-1-59259-835-9_15

[3] J.N. Watson, P.S. Addison, N. Grubb, G.R. Clegg , C.E. Robertson, K.A.A. Fox, "Wavelet-Based Filtering for The Clinical Evaluation Of Atrial Fibrillation", 23rd Annual International Conference Of The IEEE Engineering in Medicine and Biology Society, Istanbul, Turkey, 2001, doi: 10.1109/IEMBS.2001.1018919

[4] Konstantinos C. Siontis, Jeffrey B. Geske, Bernard J. Gersh, "Atrial Fibrillation Pathophysiology and Prognosis. Insights From Cardiovascular Imaging", Circ Cardiovasc Imaging, vol.8, No.6, 2015, doi: 10.1161/CIRCIMAGING.115.003020

[5] Raul Alcaraz, Jose Joaquín Rieta, "Central Tendency Measure and Wavelet Transform Combined in the Non-Invasive Analysis of Atrial Fibrillation Recordings", Biomedical Engineering Online, 11:46, 2012, doi:10.1186/1475-925X-11-46

[6] Munger TM, Wu LQ, Shen WK, "Atrial fibrillation", Journal of Biomedical Research, vol. 28 (1), pp.1-17, Jan. 2014, doi: 10.7555/JBR.28.20130191

[7] Alma Secerbegovic, Asmir Gogic, Nermin Suljanovic, Matej Zajc, Aljo Mujcic, "Computational Balancing Between Wearable Sensor And Smartphone Towards Energy-Efficient Remote Healthcare Monitoring", Advances in Electrical and Computer Engineering, vol. 18, number 4, pp. 3-10, 2018, doi: 10.4316/AECE.2018.04001

[8] Duverney D, Gaspoz J-M, Pichot V, Roche F, Brion R, Antoniadis A, Barthélémy J-C, "High Accuracy Of Automatic Detection Of Atrial Fibrillation Using Wavelet Transform Of Heart Rate Intervals", Journal of Pacing and Clinical Electrophysiology, Vol 25 (4), Part 1, April 2002, doi: 10.1046/j.1460-9592.2002.00457.x

[9] Dwight F. Mix, Kraig J. Olejniczak, "Elements of Wavelets for Engineers and Scientists", John Wiley & Sons, Inc., Hoboken, New Jersey, 2003, doi/pdf/10.1002/0471668885

[10] Alan S. Said Ahmad, Majd S. Matti, Omar A.M. ALhabib, Sabri Shaikhow, "Denoising of Arrhythmia ECG Signals", International Journal of Medical Research & Health Sciences, vol. 7(3), pp. 83-93, 2018, ISSN No: 2319-5886, WOS:000429485200011

[11] D. Arotăriței, H. Costin, A. Păsărică, C. Rotariu, "A Proposal For Cardiac Arrhythmia Classification Using Complexity Measures", Advances in Electrical and Computer Engineering, vol 17, nr 3, pp. 29-34, 2017, doi: 10.4316/AECE.2017.03004

[12] Miguel Martínez-Iniesta, Juan Ródenas, José J. Rieta, Raúl Alcaraz, "Application of Joint Notch Filtering and Wavelet Transform for Enhanced Powerline Interference Removal in Atrial Fibrillation Electrograms", Computing in Cardiology 2018; vol 45, ISSN: 2325-887X, doi: 10.22489/CinC.2018.201

[13] E. Castillo, D. P. Morales, A. García, F. Martínez-Martí, L. Parrilla, and A. J. Palma, "Noise Suppression in ECG Signals through Efficient One-Step Wavelet Processing Techniques", Journal Of Applied Mathematics, Volume 2013, Article Id 763903, 2013, doi: : 10.1155/2013/763903

[14] R. Dubois, P. Roussel, M. Hocini, F. Sacher, M. Haissaguerre, G. Dreyfus, "A Wavelet Transform for Atrial Fibrillation Cycle Length Measurements", Computers in Cardiology Conference, vol.36, ISSN 0276−6574, pp. 501-504, 2009, WOS:000279344300126

[15] B. Arvinti, M. Costache, D. Toader, A. Isar, "Electrocardiogram Baseline Wander Removal Using Stationary Wavelet Approximations", 12th International Conference Optimization of Electrical and Electronic Equipment OPTIM 2010, Brasov, Romania, 2010, pp. 890-895, doi: 10.1109/OPTIM.2010.5510421

[16] A. Graps (1995), "An Introduction to Wavelets", IEEE Computational Science and Engineering, 2: 50-61, published 12 March 2013, doi: 10.1109/99.388960

[17] D. L. Donoho, "De-Noising by Soft-Thresholding" IEEE Transactions On Information Theory, Vol. 41, No. 3, 1995, pp. 613-627, doi: 10.1109/18.382009

[18] Somesh Morya, Sudhir Agrawal, Shivangini Morya, "Denoising of ECG Signal using Soft Thresholding and Empirical Mode Decomposition", International Journal on Recent and Innovation Trends in Computing and Communication, Volume: 5 Issue: 4, 2017, pp. 131 – 137, ISSN: 2321-8169, doi:10.17762/ijritcc.v5i4.376.

[19] Ahsan A. Khan, Gregory Y. H. Lip, Alena Shantsila, "Heart rate variability in atrial fibrillation: The balance between sympathetic and parasympathetic nervous system", *Eur J Clin Invest.* 2019;49:e13174, doi: 10.1111/eci.13174.

[20] C. Rotariu, H. Costin, "Wireless Monitoring System for Patients Having Cardiac Pacemakers with Atrial Fibrillation Detectors", Environmental Engineering and Management Journal (EEMJ), Vol. 12, No. 6, 2013, pp. 1215-1221, print ISSN: 1582-9596, eISSN: 1843-3707, doi: 10.30638/eemj.2013.150.

[21] H. Costin, C. Rotariu, A. Pasarica, "Atrial Fibrillation Onset Prediction using Variability of ECG Signals", Proc. of the 8th Int. Symp. on Advanced Topics in Electrical Engineering (ATEE), Univ. POLITEHNICA of Bucharest, May 23-25, 2013, section EMB3, ISBN: 978-1-4673-5978-8, doi: 10.1109/ATEE.2013.6563419.

[22] Marcus Vollmer, "Robust, Simple And Reliable Measure Of Heart Rate Variability Using Relative RR Intervals", Computing in Cardiology Conference, France, 2015, doi: 10.1109/CIC.2015.7410984.

[23] Moody GB, "Spontaneous Termination of Atrial Fibrillation: A Challenge from PhysioNet and Computers in Cardiology 2004", Computers in Cardiology, vol. 31, pp. 101−104, 2004, doi: 10.1109/CIC.2004.1442881

[24] Moody GB, Mark RG, Goldberger AL, "PhysioNet: A research resource for studies of complex physiologic and biomedical signals", Computers in Cardiology 2000, pp. 179–182, 2000, doi: 10.1109/CIC.2000.898485

[25] B. Arvinti, A. Isar, D. Toader, M. Costache, "Optimization of an Electrocardiogram Compression Technique Based on Wavelets", 13th Optimization of Electrical and Electronic Equipment OPTIM 2012, Romania, pp. 1140-1145, 2012, doi: : 10.1109/OPTIM.2012.6231885

[26] B. Arvinti, M. Costache, "The Performance of the Daubechies Mother Wavelets on ECG Compression", 11th IEEE International Symposium on Electronics and Telecommunications (ISETC), Proceedings of the ISETC 2014, Timisoara, Romania, ISBN 978-1-4799-7265-4, 2014, doi: 10.1109/ISETC.2014.7010808

[27] Salim Graja, Jean Marc Boucher, "SVM Classification of patients prone to atrial fibrillation", IEEE International Workshop On Intelligent Signal Processing (Wisp), Faro, Portugal, 2005, pp. 370-374, doi: 10.1109/WISP.2005.1531687

[28] Trong Tuyen Nguyen, Trong Huu Tran, Mau Thach Nguyen, Z.M. Yuldashev, "Heart Rhythm Intelligent Monitoring Algorithm for the Atrial Fibrillation Episodes Detection in the Telemedicine System", 13th International Symposium "Intelligent Systems" (INTELS'18), Procedia Computer Science 150 (2019), pp. 352–360, doi: 10.1016/j.procs.2019.02.063

[29] Tijn Hendrikx, Mårten Rosenqvist, Per Wester, Herbert Sandström and Rolf Hörnsten, "Intermittent short ECG recording is more effective than 24-hour Holter ECG in detection of arrhythmias", BMC Cardiovascular Disorders 2014, 14:41, April 2014, doi: 10.1186/1471-2261-14-41