Automatic atrial tachyarrhythmia detection from intracardiac electrograms

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Atrial fibrillation; Atrial flutter; Electrophysiology; Automatic detection; Algorithm; Pacemaker.

Background. **Automatic atrial tachyarrhythmia recognition is crucial in order to allow a correct switching-mode function of dual-chamber pacemakers and to avoid inappropriate shocks of ventricular implantable cardioverter-defibrillators. In this paper we considered three algorithms suitable for implantable devices. The first was based on the atrial cycle length; the others analyze different morphologic characteristics of atrial signals.**

Methods. **Intracardiac bipolar electrogram recordings were obtained from the high right atrium during electrophysiological study. Twenty patients were considered, some of them presenting with different types of cardiac rhythm at different intervals of the study. Cardiac rhythms were divided into three groups: sinus rhythm consisting of 2196 s obtained from 12 subjects, atrial fibrillation consisting of 771 s obtained from 7 subjects, and atrial flutter consisting of 1793 s obtained from 7 subjects. The automatic detection was performed on each electrogram segment lasting 1 or 4 s. Atrial segments were separated into two subgroups: the first for the training of the algorithm and the second for testing and validation of results. We considered two types of statistical analysis: comparison between pairs of rhythm (paired classification), and classification among the three different groups (direct classification).**

Results. **The combination of the cycle length algorithm with a morphological method achieved the best performance for both statistical analyses. Paired classification resulted in the following: atrial fibrillation vs sinus rhythm was detected with no error; atrial flutter vs sinus rhythm with a total accuracy of 99.3% (sensitivity 99.4%, specificity 99.2%); atrial fibrillation vs atrial flutter with a total accuracy of 99.1% (sensitivity 98.5%, specificity 99.4%). The total accuracy achieved for the direct classification was 98.6% (average sensitivity 98.5%, specificity 98.8%).**

Conclusions. **Our results support the association of algorithms for future enhancement of atrial tachyarrhythmia detection in dual-chamber devices, thanks to the limited computational effort.**

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Introduction

Intermittent atrial tachyarrhythmias represent a major problem for patients with dual-chamber pacemakers and implantable cardioverter-defibrillators (ICDs).

In dual-chamber pacemakers it is necessary to recognize atrial activity in order to avoid the rapid tracking of the paroxysmal atrial tachyarrhythmias and, consequently, to avoid rapid ventricular rates. Sutton et al.[1] present an elegant review of the most common mode switching algorithms of different manufacturers; they also state that one of the major drawbacks of these devices is poor recognition of atrial tachyarrhythmias. Another objective is to reduce inappropriate therapies of ICDs: this can be obtained by adding an atrial lead (dual-chamber ICDs) which allows an increased specificity of the detection algorithm. It is generally reported in the literature that in the previous generation of ICDs about 20% of shocks delivered were inappropriate and more than a half of them were due to atrial fibrillation (AF)[2]. Trappe et al.[3] showed an inappropriate shock rate of 2% through dual-chamber ICD use.

In this paper we present our experience in recognizing stable sinus rhythm (SR), AF and atrial flutter (AFL) from intracardiac electrograms obtained during electrophysiological studies. The aim of this work was to propose an algorithm running in real time that was compatible both with implantable device requirements and the advantages of a bipolar atrial lead.

Methods

Patient population and data selection. Data were recorded from the lateral wall of the high right atrium of patients undergoing electrophysiological study. Bipolar electrocatheters with 25 mm interspace and a Digital Polygraph model EMS Mennen (Mennen, Rehovot, Tel Aviv, Israel; imported by Manta) were used. Intracardiac electrograms were recorded with a sampling frequency of 1 KHz, a resolution of 8 bits, and digital filtering in the 40-500 or 80-500 Hz frequency band. Gain was adjusted for appropriate peak amplitude.

In the present study 20 patients (15 males and 5 females) were analyzed along with three types of rhythm: SR, AF and AFL. Some of the patients exhibited more than one type of rhythm at different times of the electrophysiological study. In fact, AF tracings were found in 7 patients, SR tracings in 12 patients, and AFL tracings in 7. The cardiologist selected stable electrogram intervals by visual inspection and selection was restricted to bipolar atrial signals. This was in order to simulate as far as possible the condition of the atrial electrocatheter connected to a pacemaker or to an ICD. Finally, all the sets were divided into two separate groups, one for the training of the algorithms and one for their testing (AF, AFL and SR discrimination ability).

In table I some information about the available atrial data set is presented. The total atrial set is composed of 2196 s of SR, 771 s of AF, and 1793 s of AFL. In particular table I reports:

• information about the set of data collected: type of rhythm, number of recorded seconds and the classification set in which the electrograms obtained from the patient have been included;
• information about the patient: data base identification number, initials of the name, sex, age and the type of cardiac disease.

In table II the global learning and test sets for the three considered groups of rhythms are summarized.

Statistical analysis and classification procedure. The statistical analysis was developed by defining a segment of intracardiac electrogram of 1 or 4 s in length as the single statistical element. Two types of classification

Table II. Summary of the considered atrial sets for the three groups.

	SR Group (2196 s)	AF Group (771 s)	AFL Group (1793 s)
Learning set	1229 s 6 patients	439 s 3 patients	1297 s 3 patients
Test set	967 s 6 patients	332 s 4 patients	496 s 4 patients

Abbreviations as in table I.

Table I. The considered atrial learning and training sets and clinical information about the patients.

File	Name	Rhythm	Set	Recording (s)	Sex	Age (years)	Cardiac disease
96_26	TG	SR	T	107	M	75	Hypertension
97_15	CM	SR	L	5	M	25	None
97_21	RA	SR	L	102	M	73	Sick sinus syndrome
98_01	RG	SR	T	126	M	72	CAD + hypertension
98_1a	RF	SR	L	25	M	75	CAD
98_05	MM	SR	T	141	F	65	CAD
98_18	PM	SR	T	53	M	62	CAD
98_20	FG	SR	L	715	M	68	Hypertension + RF ablation
98_22	TV	SR	L	350	M	73	CAD
98_28	MG	SR	T	136	M	69	None
98_29	BI	SR	L	32	F	60	Dilated cardiomyopathy
98_41	CL	SR	T	404	F	36	None
97_06	PG	AF	L	82	M	67	CAD
97_07	BN	AF	L	46	F	48	Mitral prosthetic valve
98_01	RG	AF	T	64	M	72	CAD + hypertension
98_04	GC	AF	T	119	F	70	None
98_06	MV	AF	T	81	M	66	Hypertrophic cardiomyopathy
98_20	FG	AF	L	326	M	68	Hypertension + RF ablation
99_09	BP	AF	T	68	M	53	Dilated cardiomyopathy
97_01	TR	AFL	L	83	M	78	Sick sinus syndrome
98_20	FG	AFL	L	170	M	68	Hypertension + RF ablation
98_23	NG	AFL	T	100	M	71	CAD
98_28	MG	AFL	L	1044	M	69	None
98_29	BI	AFL	T	184	F	60	Dilated cardiomyopathy
98_31	DA	AFL	T	83	M	61	Aortic prosthetic valve
98_41	CL	AFL	T	129	F	36	None

AF = atrial fibrillation; AFL = atrial flutter; CAD = coronary artery disease; L = learning set; RF ablation = radiofrequency ablation of the atrioventricular node; SR = sinus rhythm; T = test set.

were considered: in the first (called paired classification) paired groups of data were analyzed (SR vs AF; SR vs AFL; AF vs AFL). In the second (called direct classification) each single statistical element was classified to be assigned to one of the three classes. This was the practical situation in which an unknown element (which may pertain to SR, AF or AFL) needed to be classified. Clearly, better performances were expected in the first type of classification. In the paired classification, statistical parameters were total accuracy, sensitivity, and specificity. In the direct classification, statistical parameters were specificity, total accuracy, and average and individual sensitivity for the two arrhythmias (AF and AFL). These parameters were defined following the requirements previously proposed[4].

Figures 1 and 2 report the flow charts of these procedures for both paired classification and direct classification analysis. In the flow charts the learning and test phases for the various algorithms are outlined.

Basis for the algorithms. AF is a highly unsynchronized process both in time and space. Intracardiac electrograms exhibit baselines which are rarely flat but which wander due to continuous atrial activity. The peaks of the signal are irregular: both amplitude and cycle length can change considerably. On the contrary, SR constantly exhibits a clear baseline, the cycle length shows minimal changes (with respect to its value) and the peak amplitude is almost constant. Finally, AFL signals are morphologically more similar to SR, but they are characterized by a shorter cycle length. The algorithm should evidence such differences in both signal morphology and measured cycle length. In this paper this goal was achieved by considering three types of algorithms:
• algorithm 1: based on the measure of the cycle length[5-7];
• algorithm 2: based on the quantification of electrogram activity at the baseline[8-10];
• algorithm 3: based on the quantification of electrogram activity in the middle amplitude range[11-13].

These algorithms were implemented and a combination of two of them was considered. All the algorithms received an electrogram lasting decision time seconds (1 and 4 s) as input, rectified with respect to the baseline. In the paired classification the electrogram interval can pertain to one of two classes, whilst in direct classification the three rhythms were considered simultaneously.

The procedure for the recognition of intracardiac atrial rhythms considered in this study is summarized below:
• the statistical element (a piece of electrogram lasting decision time seconds, e.g. 4 s) is defined;

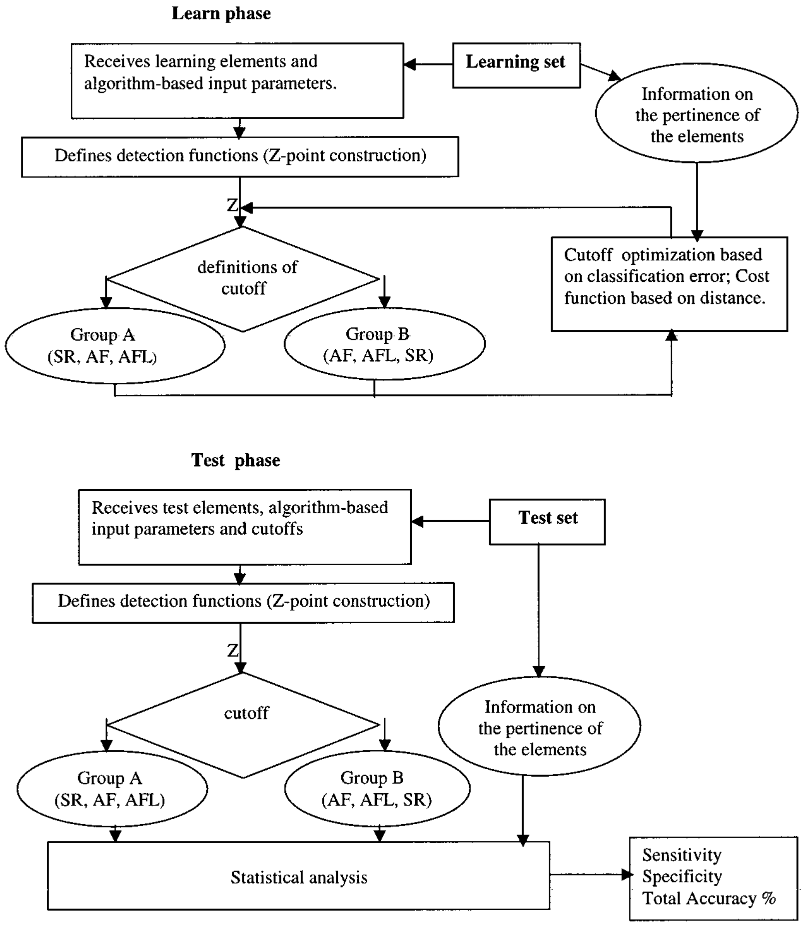

Figure 1. Flow chart for the paired classification type of analysis. AF = atrial fibrillation; AFL = atrial flutter; SR = sinus rhythm.

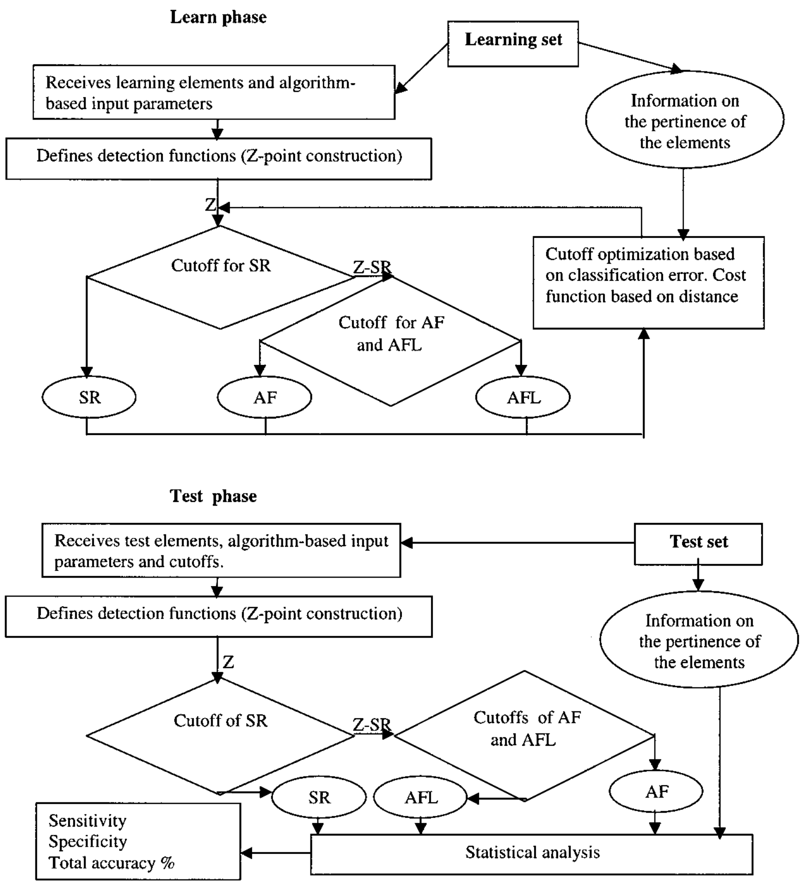

Figure 2. Flow chart for the direct classification type of analysis. Abbreviations as in figure 1.

• the elements are divided for the learning and test set;
• different detection functions are defined for the specified decision time-second interval and computed. The considered detection functions are: A) averaged cycle length (algorithm 1); B) time above the baseline threshold (B_T) (algorithm 2); C) number of crossings of the B_T (algorithm 2); D) time during middle amplitude range (algorithm 3); E) difference of the number of crossings of the two thresholds of middle amplitude range (algorithm 3). Note that the detection function A identifies fast and slow rhythms, whilst B, C, D, and E discriminate AF from AFL and SR. Consequently, combinations of ABC or ADE are considered;
• each fragment of signal lasting decision time seconds is associated with one or more numbers that define(s) a vector called Z-vector in figure 1 and 2. This is necessary in order to classify and to compare each segment. For example, in the case of the combination of algorithm 1 and 2, Z-vector is defined by the three numbers A, B, and C (above mentioned) which are the coordinates of a single Z-point in the three-dimensional classification space. The dimension of the classification space is given by the number of considered detection functions (three in the present case) (Fig. 3);
• the same is done for all the elements of each rhythm group; consequently, three clouds in the three-dimensional classification space are obtained;

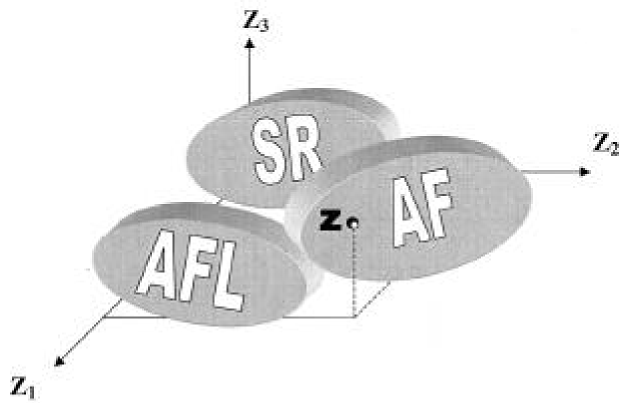

Figure 3. Example of an ideal three-dimensional classification space. Abbreviations as in figure 1.

• the three-dimensional classification space associated with the learning set is selected and a plane is optimized in order to enable discrimination between two groups. First of all we identify the SR group with respect to AF + AFL; then we search for a second discriminating plane to classify AF from AFL;
• the equation of every discriminating plane is obtained by optimizing the plane coefficients through minimization of a cost function defined on the basis of the distance of each point from the discriminating plane. The

optimization method is presented by Hooke and Jeeves[14] and is particularly suitable for local minimal searches;
• elements of the test set are classified as pertaining to the different classes as defined by the discriminating plane, the equation of which is optimized during the previous stage.

Algorithm 1 (cycle length analysis). This is the reference algorithm normally used by the pacemaker to recognize a transition between types of rhythms[5-7,15]. The analysis is based on the peak recognition, thus the detection function is the cycle length. In figure 4, the peaks of single electrograms obtained from the three rhythms are shown for the typical decision time interval of 4 s. Note how the peaks are much closer in AF and AFL than in SR. Since the present analysis is based on the single statistical element (e.g. 4-s electrogram), an average cycle length was defined.

Algorithm 2 (baseline crossing analysis). Having fixed a 4-s interval as the decision time and a B_T below which the electrogram is considered to be at the baseline, this algorithm counts the time fractions spent by the signal at the baseline and the number of crossings of the baseline. B_T was assumed as 6% of the full amplitude range. Detection functions are the time fraction above the B_T and the number of crossings of the B_T. Figure 5 shows the outcome of algorithm 2 defined as the time spent above the B_T (the Over B_T in figure 5). Note how the function Over B_T is much greater during AF than during SR or AFL.

Algorithm 3 (middle amplitude range analysis). In the study of Bloem et al.[11] the middle amplitude range of intracardiac signals was seen to be qualitatively strongly different in AF than in SR. However, these findings were not at that stage utilized in practical application. Rossi et al.[12,13] proposed a simple method able to quantify the activity of the electrogram in the middle amplitude range. The detection functions in this case are a) the time spent by the electrogram in the middle amplitude range, and b) the difference in the number of times that the electrogram crosses the two middle amplitude range-defining thresholds.

The results of this choice are shown in figure 6 which reports the rectified electrogram and the time spent by the electrogram in the middle amplitude range (represented by the function Signal in MAR) for three randomly chosen 4-s electrogram intervals, obtained from the different rhythm groups. Significantly, the difference in the amplitude distribution of the electrogram for the three different rhythms is much greater in AF than during SR or AFL.

Results

Results are presented for the two combinations of algorithm 1 and 2 (cycle length + baseline crossing) and 1 and 3 (cycle length + middle amplitude range). The decision time interval was of 4 s; a trial was carried out with

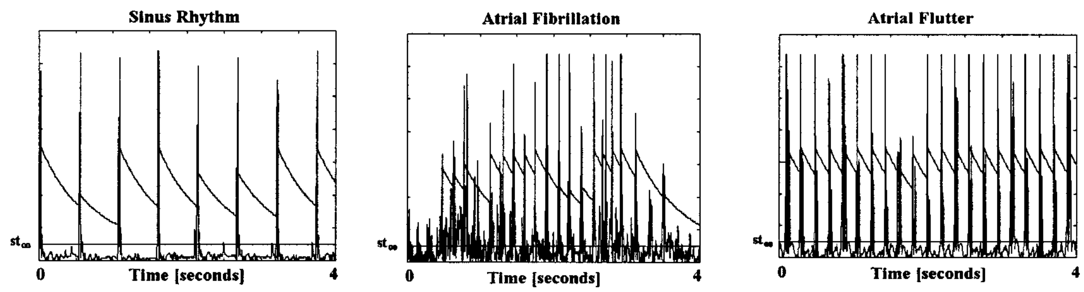

Figure 4. Typical beat-to-beat recognition analysis for the different types of rhythms (automatic sensing threshold adjustment); st$_y$ is the programmed sensitivity set to 4% of the full amplitude range.

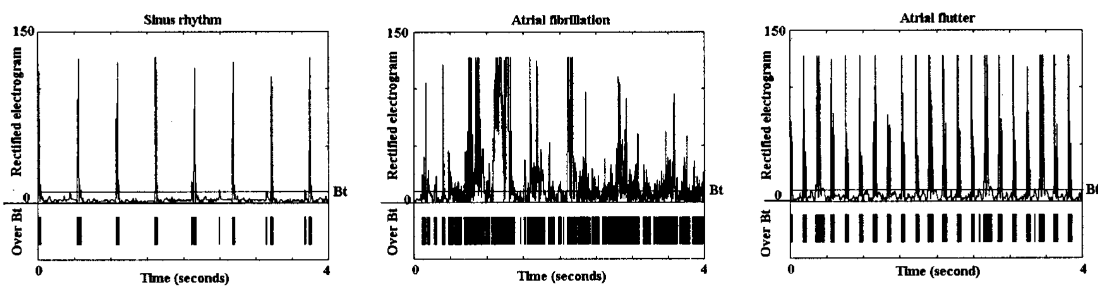

Figure 5. The outcome of algorithm 2 defined as the time spent above the baseline threshold (in the figure the detection function Over B_T).

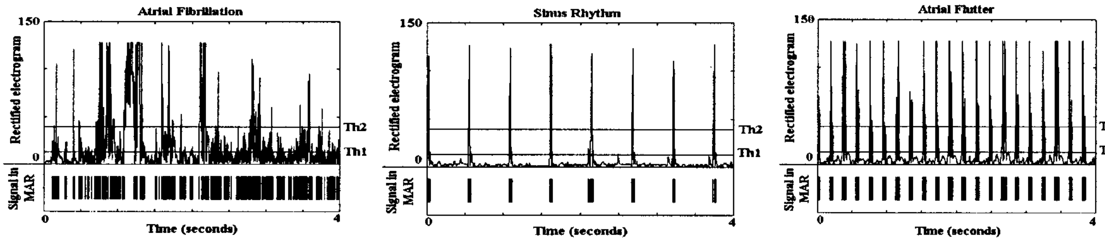

Figure 6. The outcome of algorithm 3 defined as the time spent in the middle amplitude range (MAR) of the electrogram (in the figure the detection function Signal in MAR). Th1 and Th2 are the two thresholds which define the MAR. They are defined to the 10% and 30% of the full amplitude range, respectively.

decision time of 1 s.

Paired classification. Results are presented in table III.

The ability to discriminate between AF and SR groups was excellent for both combinations: total accuracy of 100% in both cases was obtained on the data base.

Excellent performances were also obtained in the classification between the SR and AFL groups for both combinations: a total accuracy of 99.7% (99.2% sensitivity and 100% specificity) was obtained. Poorer performances were obtained from the classification between the AF and AFL groups: 82% total accuracy (95.8% sensitivity and 73.6% specificity) was obtained combining 1 and 2, whilst a total accuracy of 100% (100% sensitivity and 100% specificity) was achieved combining algorithms 1 and 3. This suggests that equivalent performances can be obtained by combining cycle length and baseline crossing or middle amplitude range analysis if the SR requires to be separated from AF or AFL. However, the combination 1 + 3 is considerably more effective in discriminating AF and AFL.

Direct classification. As mentioned previously, during direct classification the ability of the various algorithms was tested to assign an unknown decision time-second electrogram interval to one of the three possible groups (SR or AF or AFL). In table IV results are presented for the two combinations of algorithms 1 and 2 and algorithms 1 and 3 for 1-s and 4-s decision time intervals.

Best performances continued to be obtained by combining cycle length and middle amplitude range analysis which led to a total accuracy of 98.6% with a specificity of 98.8% and an average sensitivity of 98.5%.

Table III. Performances obtained for the paired classification for both combinations of the cycle-length method with the baseline crossing and the middle amplitude range analyses. The detection time interval is always set to 4 s.

Algorithms	Groups	Total accuracy (%)	Specificity (%)	Sensitivity (%)
1 + 3	SR vs AF	100	100	100
1 + 3	SR vs AFL	99.7	100	99.2
1 + 3	AFL vs AF	100	100	100
1 + 2	SR vs AF	100	100	100
1 + 2	SR vs AFL	99.7	100	99.2
1 + 2	AFL vs AF	82	73.6	95.8

Abbreviations as in table I.

Discussion

We have presented a relatively original idea based on the association of three algorithms aimed at the future enhancement of atrial tachyarrhythmia detection on dual-chamber devices. Our purpose was focused on the methodology, and it did not take into account the clinical validation of the obtained results. For this reason we have considered a relatively small number of subjects, but we have analyzed a significant amount of data (in terms of recorded seconds) for every group. Furthermore, only stable atrial rhythms were carefully selected by the cardiologist and all recordings with artifacts and pre-

Table IV. Performances obtained for the direct classification for both combinations of the cycle-length method with the baseline crossing and the middle amplitude range analyses.

Algorithms	Decision time (s)	Total accuracy (%)	Specificity (%)	Average sensitivity (%)	Sensitivity AF (%)	Sensitivity AFL (%)
1 + 3	4	98.6	98.8	98.5	98.2	98.4
1 + 3	1	96.5	95.3	97.1	95.3	98.8
1 + 2	4	89.9	100	80.2	87.5	72.9
1 + 2	1	88.1	94.9	83	91.9	74.2

Abbreviations as in table I.

mature beats were excluded.

The principal comments concern the methodology of the proposed algorithms and they are related to the decision time interval, the detection functions and the cut-off definitions:

• we obtained our results for a 4-s segment considered to be a reasonable interval for both pacemakers and ICDs. Only slight improvements were to be expected from a small increase of the decision time interval. Satisfactory performances were obtained with a 1-s interval;

• for each decision time interval (e.g. 4 s of electrogram) we did not consider the variability of the detection functions. For example, for the algorithm A (interbeat interval detection function) we considered the average cycle length within the 4-s windows, which we can call a static detection function. It would have been possible to consider the variability of the interbeat length within the 4-s interval; in this case we would have defined it a dynamic detection function. Similarly other types of algorithms can quantify dynamic properties of the electrogram within the chosen decision time interval. This investigation will be part of our future work;

• in the case these algorithms were applied to implantable device, it is worth noting that the number of operations required by the device is only the comparison with predefined thresholds. The optimization of such thresholds (which is the computationally costly phase) can be adjusted by a new learning phase, tailored to the individual subject during the follow-up. Thus, the optimization is off-line and does not require to be done by the device. Its outcomes are the new cut-offs that are considered for the classification of the new events. During real time the device only needs a) to compute the selected detection function; and b) to classify each multidimensional element (Z-point) with respect to the defined thresholds.

Different approaches for automatic recognition of the SR from other types of rhythm, including AF or ventricular fibrillation, have been described in the literature. Some of the principal results are summarized in table V[6-9,16,17].

Table V presents the apparently poor results found by Shkurovich et al.[16]. In that paper the authors considered the previous generation of ICDs that did not monitor the atrial activity directly which, therefore, had to be approximated. The other studies reported in table V take advantage of the atrial lead which allows much easier atrial rhythm recognition.

A final comment relates to ambiguous interpretations which may arise in the case of tachyarrhythmias with stable 1:1 atrioventricular ratio (ventricular tachycardia with retrograde VA conduction or supraventricular tachycardia with fast atrioventricular conduction). This is still an unresolved problem, which we have not considered in the present work, and that has been addressed by the SMART algorithm which proposes a discrimination delivering premature atrial or ventricular extrastimuli[18].

In conclusion, this paper discusses three algorithms and their combination for the analysis of intracardiac atrial electrograms aimed at discriminating AF, AFL and SR. The first algorithm was based on the cycle length, the second was obtained by monitoring the electrogram baseline activity and the third by quantifying the time spent by the electrogram in the middle amplitude range. Furthermore, combinations of the first with the second algorithm and of the first with the third were con-

Table V. Comparison with the literature.

Reference	Sensitivity (%)	Specificity (%)	Detection functions	Decision time interval	Electrogram acquisition
AF[6]	97		Cycle length	12 atrial peaks triggered	Bipolar leads in the right atrium and right ventricular apex and one lead for tachyarrhythmia simulation
AF[7]	90	96	Scanning sensing threshold, cycle lenght	10 s	Unipolar lead during electrophysiological studies
AF[8]	94	96	Electrogram morphology algorithm	4 s	Bipolar lead in the right atrium
AF[9]	98.4	100	Quiet interval analysis, baseline crossing	8 s	Multipolar leads in the right atrium and coronary sinus, bipolar lead in the right ventricle
AF[16]	78	93	Reminder electrogram, histogram, power spectrum	4 s	One lead with distal defibrillation coil in the right ventricle and proximal coil in the superior vena cava
VF[17]	100	100	Cross correlation, standard deviation, interquartile range	150 ms triggered	Distal and proximal unipolar lead, reference in the femoral vein; VF recognition, not AF

AF = atrial fibrillation; VF = ventricular fibrillation.

sidered.

Results have been expressed in terms of total accuracy, specificity and sensitivity. The best performances obtained in the paired classification were: SR vs AF classified with no error; SR vs AFL classified with a total accuracy of 99.7%; AFL vs AF classified with no error. The direct classification (on receiving an element, the procedure decides to which group it pertains) achieved a total accuracy of 98.6%.

Further studies are needed for a clinical validation of the methods presented in this paper by increasing the number of patients and randomly choosing the single 4 (or 1) s intracardiac electrogram intervals for an improved statistical analysis. Other developments proposed by Jones et al.[19] include the possibility of improving the morphological algorithms by means of an automatic adaptation of the thresholds defining middle amplitude range or B_T.

Morphological analysis was found to be complementary to the cycle-length method in that it added different information about the signal. In particular, while the cycle-length method revealed clear differences between SR and AF or AFL, the morphological analysis exploited to a greater extent the differences between AF and SR or AFL. Their combination, as demonstrated in this paper, allowed for very good performances.

At first glance, our results appear to be very good compared to those obtained from algorithm implemented in commercially available dual-chamber ICDs (ventricular fibrillation sensitivity around 100% with a specificity between 67 and 87%)[20,21]. However, a real comparison is not easy because we have considered electrograms collected during electrophysiological studies in resting patients; furthermore we have very carefully selected stable rhythms and we have eliminated all recordings with any type of artifacts.

For the above reason we consider the present results as very promising on the basis of the performances obtained along with the possibility of implementing such methods on future implantable devices, whose automaticity levels are destined to increase.

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