Real-Time Classification of ECGs on a PDA

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***Abstract*-- The new advances in sensor technology, PDAs and wireless communications favor the development of a new type of monitoring systems that can provide patients with assistance anywhere and at any time. Of particular interest are the monitoring systems designed for people that suffer from heart arrhythmias, due to the increasing number of people with cardiovascular diseases. PDAs can play a very important role in these kinds of systems because they are portable devices that can execute more and more complex tasks. The main questions answered in this paper are whether PDAs can perform a complete ECG beat and rhythm classifier, if the classifier has a good accuracy and if they can do it in real time. In order to answer these questions, in this paper we show the steps that we have followed to build the algorithm that classifies beats and rhythms, and the obtained results, which show a competitive accuracy. Moreover we also show the feasibility of incorporating the built algorithm into the PDA.**

***Index Terms*--ECG classifier, monitoring systems, ubiquitous computing.**

I. INTRODUCTION

PATIENTS with heart rhythm irregularities which are not detected on a normal stationary electrocardiogram (ECG) require some type of monitoring. By looking at the different devices and monitoring systems commercially available and some other research proposals we have made a classification, based on the following features: a) systems that record signals and perform classification off-line; b) systems that perform remote real-time classification; and c) systems that provide local real-time classification. For the last ones, we differentiate them taking into account the level of mobility.

Among the first group of systems and devices the Holters stand out [1]. The use of a holter consists in placing electrodes (leads) on the patient's chest; these leads are attached to the holter. After the patient is sent home and goes back to normal life, a tape records a continuous ECG for 24 or 48 hours. One or two days later, the holter is removed and the tape is analyzed. A physician will see each of the patient's heart beats and if abnormal beats or rhythms occurred during that period, they would be identified by the physician. Nowadays, there are also other more sophisticated recording devices like Medtronic Reveal® Insertable Loop Recorder [2] that allows for up to 14 months recording of ECG episodes. With that device, in case the user experiments a fainting episode, for example after waking, the user can activate a button in a hand-held device and a physician can analyze the stored information a posteriori and determine whether the fainting episode was caused by an abnormal heart rhythm. Although these solutions (holters and new devices) have the advantage that patients can continue living a normal life, they present a serious drawback: if the patient suffers from a serious rhythm irregularity, *only recording is performed and not real-time classification of ECGs: the classification is performed off-line.*

In order to overcome the previous restriction, there are proposals, which belong to the second group, where remote real-time classification is performed while patients continue living a normal life. Vitaphone [3] commercializes a card that can transmit ECG data by infrared to a mobile phone that automatically transmits the ECG to a service center where the ECG analysis can be made. QRS Diagnostic [4] (which acquired Ventracor's Cardiac e-Health Division in 2003) commercializes the EKGCard, that can convert any computer (PC, laptop or PDA) into an electrocardiograph that allows the visualization and storing of ECG data. They also provide analyzer software of the ECG signal that runs only at PCs or laptops but not at PDAs, although the result of the analysis can be made available at the PDA for reviewing purposes. Cardio Control [5] commercializes a product that allows the visualization and recording of ECG signals in a PDA. Those signals can be transferred to a workstation where they can also be analyzed and printed. Additional features like GSM/GPRS transmission to an analyzing unit are also being developed. Active Corporation [6] commercializes the ActiveECG, a device that can be connected to a PDA, store ECG signals and perform a basic cardiac monitoring (identification of QRS, mainly). Pulse Medical Limited [7] commercializes a product, MeditSense, that is a complete 12 lead ECG system designed for mobile and stationary use where ECG data can be recorded in a Tablet PC (not in a PDA). The MeditSense system also provides interpretation of the ECG which can be used as a guide for diagnosis conclusions. MobHealth project [29] has developed a vital signs monitoring system based on a body area network and a mobile-health service platform that can transmit sensor measurements via UMTS o GPRS to a back-end system, where a remote detection of emergencies is

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performed.

Although the previous systems allow for a real-time monitoring of the ECG signal, *they perform a remote real-time monitoring***.** Most of them make use of mobile telephones and/or PDAs (Personal Digital Assistant) to capture the ECG signal and send it to a monitoring center where the real-time classification is performed. They continuously send ECGs through a wireless communication network. In spite of the advantages these kinds of systems provide in relation to recording devices, they still present certain limitations related to the fact that the analysis is not performed in the place where the signal is acquired. In fact, there is a *loss of efficiency* in the use of a wireless network because normal ECGs are also sent (which implies a high cost); and, in case the wireless network is not available at some moment, there might be a loss of ECG signal with the corresponding risk of *not detecting some anomalies* (unless the signal is recorded in the mobile device and sent when the wireless network is available again).

In the third group of systems we consider those that provide real-time classification by using an architecture that includes an intermediary local computer between the sensors and the control center. Those computers perform some *local real-time monitoring* in order to detect some anomalies and send alarms to a control center or a hospital. Among them are research projects like @Home [8], TeleMediCare [9] or PhMon [10], whose aims are to build platforms for real time remote[1] monitoring. These systems include wireless bio-sensors that measure vital parameters such as heart rate, blood pressure, insulin level, etc. The health monitoring system, carried by the patients, controls these sensors and performs some analysis. In the @Home system, the patients are equipped with ambulatory sensors that acquire health care data (ECG among others). These data are transmitted using wireless communication (Bluetooth or DECT[2]) to a patient's local PC station. In that PC, there is analyzing software that can trigger an alert if some thresholds defined by physicians are reached. The TeleMediCare system consists of some intelligent bio-sensors (ECG included) that have a wireless communication module (Bluetooth) which communicates with a Local Patient Computer. This computer samples, stores, processes and analyses patient data through pre-defined procedures and can forward alerts to a Control Center. The PhMon system (Personal Health Monitoring System with microsystem sensor technology) allows to measure all the patient's relevant vital parameters either continuously or at determined time intervals without restricting the patients mobility. Among the considered sensors we can find ECG sensors connected via Bluetooth with a base station (a smartphone or a PDA). In that base station an analysis is performed and, in case a critical vital parameter is acknowledged, the patient is informed. Moreover, the base station, via a mobile communication network, keeps in contact with a central electronic patient database and a medical call center where the acquired signals and vital parameters are reviewed by doctors. However, we have not been able to find precise descriptions of the kind of ECG analysis performed in any of these systems.

Bai et al. describe another interesting proposal for a portable ECG (and also blood pressure) telemonitoring system [11]. In a previous version of the system [12] there was a PC-based home monitor that was able to acquire, digitize and analyze the ECG signals transmitted by an ECG detector; and also to send alerts to a monitoring center at the hospital via the public telephone network (PSTN) whenever an abnormality of the ECG exceeded an alarm threshold. Aiming at a more cost-effective solution, the PC-based home monitor was replaced by a portable device (with the main board of an IBM 486 compatible PC) to ensure that the ECG analyzer algorithm could run. For this proposal there exists information about the ECG analysis performed: their on-line arrhythmia analysis algorithm is an on-line wavelet-based ECG that can recognize the following abnormalities: asystole, missed beats, bradycardia, tachycardia and premature ventricular contraction.

In those systems that promote an intermediate level, some local real-time classification is performed and therefore communication costs are reduced, because only anomalous ECG signals are sent but not whole ECG signals[3]. For the solutions that make use of PCs in order to perform local real-time classification and make use of wireless communications between sensors and those PCs, the mobility area of the patients is not very large: it is almost reduced to their homes.

We advocate for a solution where a PDA performs local real-time classification and detects the ECG anomalies "in situ". This solution allows a real-time classification anywhere and at any time where the PDAs can analyze ECG signals, detect anomalies, and make use of wireless communications like GSM/GPRS/UMTS in order to send those anomalous situations to the control center. Some known restrictions of PDAs like low battery life and small size of memory will require some ad-hoc solutions. Recharging the PDA battery would restrict the mobility area of the patient during that period (but that could be made while the user is at home). Moreover, other proposed solutions have the same problem. For example, solutions where mobile phones are used to transmit continuously the ECG signal. With respect to the limited size of memory, when the PDA memory is full and it is necessary to keep its content, then that content should be sent to another computer using the best type of connection available at that moment (Bluetooth or cable if it is possible or GSM/GPRS/UMTS in other case).

After an exhaustive search we did not find any work that builds a complete[4] ECG beat and rhythm classifier in a PDA, nor an *open source* complete classifier that we could try to install and deploy in a PDA. For this reason we have designed

[1] "Remote" monitoring from the viewpoint of the hospital.

[2] Digital Enhanced Cordless Telecommunications

[3] Supposing that tariffs based on "data transmitted" are applied (like in GPRS or UMTS), and not tariffs based on "connection time" (like in GSM).

[4] By a *complete* ECG beat and rhythm classifier, we refer to a classifier for all the beat and rhythms types found in the MIT-BIH database.

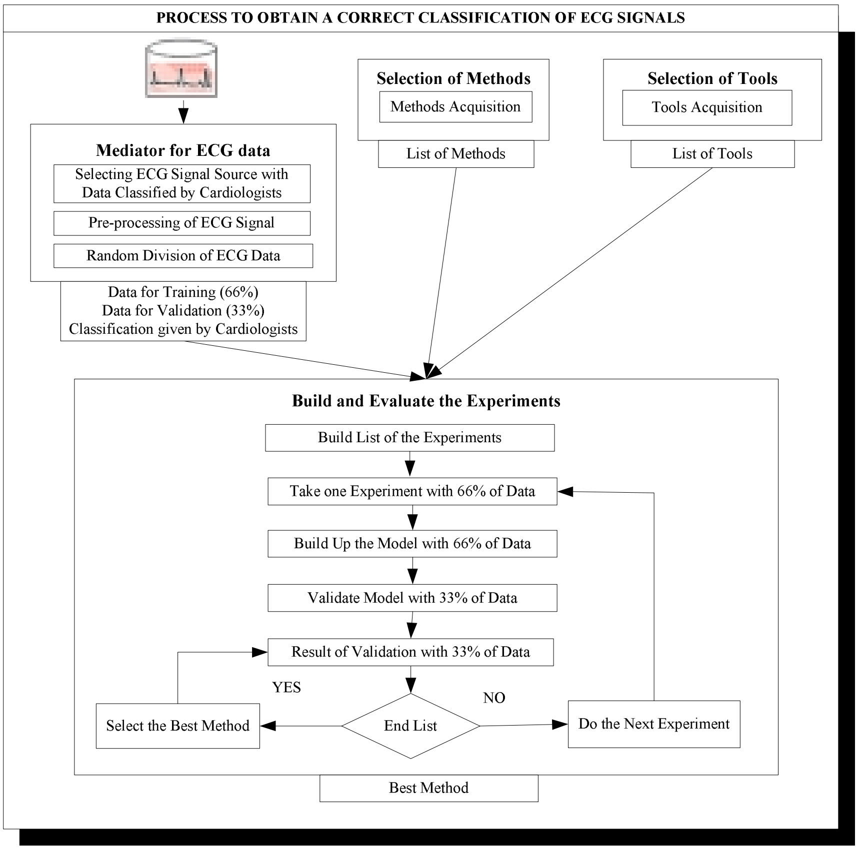

Fig. 1. Process to obtain a correct classification

and implemented one. The goal of this paper is twofold: on the one hand, to try to find a good classifier[5] for beats and rhythms and, on the other hand, to demonstrate that it is feasible to implement it into a PDA. In order to obtain the most accurate beat and rhythm classifier, we have used several tools and methods, in machine learning area. Among those methods we can mention: decision trees [13], nearest neighbor methods [14], neural networks [15], and boosting methods [14].

In the rest of the paper we describe the steps followed to build the most accurate classifier. Then, we present a comparison with other classification works. Later, we show some details of the implementation and experiments on a PDA. And finally, we present our conclusions and future work.

II. Selecting an Accurate Classifier of Beats

In this section we explain the process that we followed in order to select a heart beat classifier that provides competitive results. In figure 1, there is an overview of this process, which consists of building and evaluating several experiments using some available *tools*, which apply some known *methods* over a set of known ECG *data source*. As it is not possible to evaluate all the possible tools and methods with all the existing ECG data sources, we explain the steps arranged in the next subsections.

A. Mediator for ECG data

First, we had to select an appropriate ECG source from which the data used in the experiments could be extracted. Moreover, building tools that would permit to manage the data stored at any source in a common way (for this reason we call to the module Mediator for ECG data) was also relevant at this step. To select the ECG source we use PhysioNet [16] that provides a set of databases that group records of one or more digitized ECG signals, as well as a set of their corresponding beat and rhythm annotations. Some of those databases are: 1) *Long-Term ST Database*. Each record contains ST episodes, rhythm changes, and signal quality changes. 2) *European ST-T Database*, which is used to test the ST segments and the T waves. 3) *MIT-BIH Noise Stress Test Database*, which contains typical noises in ambulatory ECG recordings. 4) *ANSI/AAMI EC13 Test Waveforms*, which is used to test various devices that measure heart rate. 5) *MIT-BIH Arrhythmia Database*, which is used to study the different types of arrhythmias. As this is the appropriate database for our case we have selected it.

[5] Although the classifier obtained in this paper is good enough to be incorporated into any cardioanalyzer software, we think that a classifier to be deployed in a PDA should concentrate in classifying more accurately the high-risk arrhythmias. That can save some life if they are sent as soon as possible by GPRS/UMTS to a control center.

TABLE I
BEAT TYPES

F	Fusion of ventricular and normal beat	N	Normal beat
L	Left bundle branch block beat	E	Ventricular escape beat
R	Right bundle branch block beat	|	Isolated QRS-like artifact
j	Nodal (junctional) escape beat	"	MISSB
f	Fusion of paced and normal beat	!	Ventricular flutter wave
A	Atrial premature beat	J	Nodal premature beat
a	Aberrated atrial premature beat	e	Atrial escape beat
V	Premature ventricular contraction	/	Paced beat
S	Supraventricular premature beat		

TABLE II
TABLE OF RHYTHM TYPES

N	Normal sinus rhythm	VFL	Ventricular flutter
PREX	Pre-excitation (WPW)	AB	Atrial bigeminy
SBR	Sinus bradycardia	VT	Ventricular tachycardia
NOD	Nodal (A-V junctional) rhythm	B	Ventricular bigeminy
P	Paced rhythm	T	Ventricular trigeminy
IVR	Idioventricular rhythm	AFL	Atrial flutter
AFIB	Atrial fibrillation	BII	II heart block
SVTA	Supraventricular tachyarrhythmia		

The MIT-BIH database contains forty-eight 30-minute registers (enumerated from 100-124 and from 200-234 with some missing in between). In the first interval of registers, several typical clinical cases can be found. In the second one, we can find several complex anomalies like nodal rhythms, ventricular and supraventricular.

These registers were collected from men and women between the ages of 23 and 89. All registers, were first acquired analogically, and later transformed into digital signals, with a frequency of 360 Hz, using 11 bits and a resolution of approximately 5 mV. Afterwards, the registers were analyzed by two independent cardiologists which classified them using the nomenclature for type of beats and rhythms that appear in tables I and II respectively.

In figure 2 it appears the data that are significant to classify beats. The right input format is composed of the peaks and limits of P, QRS and T waves, the PR and QT intervals, the size of the P, QRS complex and T waves, their frequency, and also the ST and PQ segments.

In order to obtain values like those that appear in the bottom of figure 2, we have used the ECGPUWAVE tool [17] that extracts the wave events of an ECG signal. Besides, we built an automata that divides the signal into a sequence of beats.

Once we got the data in the right format, the pre-processed data obtained from the ECG source had to be divided in two random groups: one for training (66% of the data) and another one for validation (33% of the data). The data in the first group were used as input data from which the chosen tool and method build up the classification model. The data in the second group were used to validate that model.

B. Selection of Tools and Methods

We selected two well-known machine learning tools in order to perform the experiments: 1) *Weka* [18] is a large collection of machine learning algorithms that solve real data mining problems and contains tools for classification, clustering, association rules, regression and visualization.

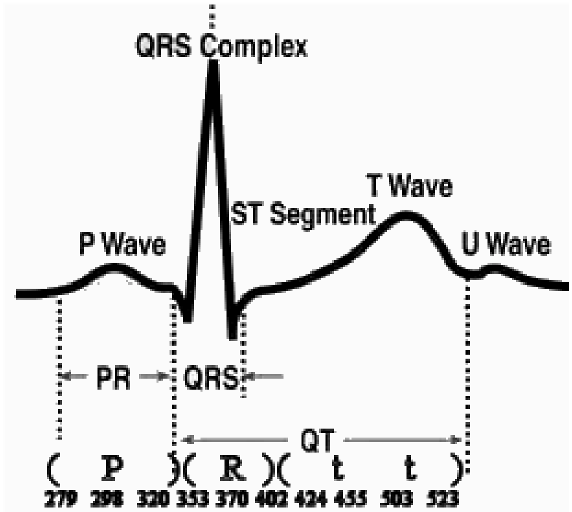

Fig. 2. Parts of a beat

TABLE III
LIST OF EXPERIMENTS AND THEIR VALIDATION RESULTS

Tool	Method	Algorithm based on	Validation	CPU Time
Weka	j48.Part	C4.5(decision trees)	92.73 %	8m 11s
Weka	IB1	nearest neighbor classifier	92.26 %	12m
Weka	NeuralNetwork	uses backpropagation	91.61 %	2h 10m
Weka	LogitBoost	for boosting any classifier	91.53 %	8m 20s
Weka	kstart.KStart	entropic distance measure	90.59 %	50m
Weka	KernelDensity	kernel density classifier	90.54 %	7m 43s
Weka	DecisionTable	decision table	90.51 %	3m 28s
AnswerTree	DecisionTree	decision tree	89.05 %	4m
Weka	OneR	1R	83.86 %	3s
Weka	NaiveBayes	Bayesian classifier	70.12 %	5s
Weka	DecisionStump	decision stump	67.55 %	4s
Weka	AdaBoostM1	Boosting a classifier	59.52 %	1s
Weka	Bagging	bagging a classifier	59.52 %	1s
Weka	ZeroR	using a 0-R classifier	59.52 %	1s
Weka	VFI	Voting feature interval	49.92 %	1s
Weka	HyperPipes	hyperPiper classifier	15.16 %	1s

It was selected because: a) Weka is an open source software issued under the GNU General Public License, b) it has a great acceptance among the machine learning community and c) it is written in Java. Some methods offered by Weka can be seen in table III. 2) *AnswerTree* [19] represents the classification by means of a decision tree that contains a set of rules and parameters that characterize and define it. Although AnswerTree is a proprietary software, we chose it because it has been developed by an industry leader in data mining technology: SPSS Inc. AnswerTree only offers the method decision tree, as can be also seen in table III.

There are different methods [14] in the machine learning area that can be applied to classify beats and rhythms. These methods are general-purpose and can be applied in any classification task. Although we have tested sixteen methods (see second column of table III) only the four most accurate in our case are enumerated here: 1) *j48.part* method that implements the C4.5 algorithm, based on decision tree techniques [13]. These kinds of methods approximate discrete-valued target functions. The learned functions are represented by decision trees, but they can also be represented as a set of *if-then* rules to improve human readability. 2) *IB1* method that implements the simple but powerful nearest neighbor algorithm [14]. These kinds of methods work by measuring the distance of a given point in the feature space to the nearest point of known class, and assigning the unknown point to that class. 3) *Neural Network* method that uses back propagation to classify instances [15]. The methods based on *neural networks* are computational models that share some of the properties of brains: they consist of many simple units working in parallel with no central control. The connections between units have numeric weights that can be modified by the learning element. 4) *LogitBoost* method uses a regression scheme as a learning base [14]. *Boosting methods* work by sequentially applying a classification algorithm to reweighted versions of the training data (increasing the weight of misclassified cases) and then taking a weighted majority vote of the sequence of classifiers.

C. Build and Evaluate the Experiments

For each tool-method combination that appears in table III an experiment was run taking the training data set as input, which is automatically selected by the tool (Weka or AnswerTree). The result of each experiment was a classification model, which was later validated against the validation data set also obtained previously.

The fourth column in table III shows the result of the validation: an accuracy percentage that indicates the amount of beats identified as x by the physician and classified as x. This type of evaluation is known in the machine learning community as *hold-out validation* [14]. Although the final classifier was built with the whole set of cases of the database, its recognition accuracy was measured by training the classification method in 2/3 of the cases and evaluating this trained classifier in the rest 1/3 of the cases[6]. Finally, the fifth column in table III shows the CPU time needed in the computer used (Pentium IV, 512MB RAM, 2,4GHz), to induce and validate the methods, that is, only for the learning phase.

D. Choosing the Most Accurate Classifier

The goal of running the experiments was to obtain the most accurate classifier. Thus, we decided to use decision trees (method j48.part) to classify beats because it carried out all the criteria that we considered relevant: 1) *Good results*: the decision tree obtains the best results classifying the beats with a 92.73% accuracy (i.e. the beats identified as x by physician and classified as x by the decision tree). 2) *Adequacy of representation language*: it is possible to represent the classifier as a tree and as a set of rules which are easily understood by people; 3) *Flexibility*: the rules may be easily modified; and finally 4) *Efficiency*: the time needed to induce is fast.

[6] In the machine learning area, it is common to validate by using that data partition (2/3 for training and 1/3 for validation) [28]. Moreover, we have also made the validation by using ½ data for training and ½ for validation and we obtained almost the same results.

TABLE IV
BEAT TRAINING

=== Run information ===
Scheme: *weka.classifiers.j48.PART -C 0.25 -M 2*
Relation: test.txt Instances: *64260*
Attributes: *13* Test mode: evaluation on training data

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TABLE V
SELECTED ATTRIBUTES

Evaluator: weka.attributeSelection.*InfoGainAttributeEval*
Search: weka.attributeSelection.*Ranker* -T -1.7976931348623157E308 -N -1
Relation: test.txt Instances: *64260*

=== Attribute Selection on all input data ===
Search Method: Attribute ranking
Attribute Evaluator (supervised, Class (nominal): NOT_LAT:
Ranked attributes:

1.0246	4	EndWaveR-WaveR	0.5246	7	WaveR
0.5155	1	Age	0.46	9	Interval_RR
0.2378	3	WaveR–BeginWaveR	0.46	12	Freq
0.1836	5	BeginWaveT-BeginWaveR	0.1598	11	Interval_QT
0.1301	8	Interval_PR	0.1123	10	wave_T
0.0487	2	Sex	0.0395	6	Nott

Selected attributes: 4,7,1,9,12,3,5,11,8,10,2,6 : 12

Although, we had already selected the beat classifier we continued working with the idea of improving the results of classifying beats and we started another training process focusing now on the next parameters of the scheme j48.part: 1) *Determining how deeply to grow a decision tree.* There are several approaches that we also apply: to limit the number of the level of depth or to limit the number of the descendents in each node, etc. 2) *Reducing error pruning.* We used the so called reduced-error pruning proposed by Quinlan [20-21], that considers each of the nodes in the tree as a candidate for pruning. 3) *Choosing an appropriate attribute selection measurement.* A statistical property called “info-gain” [20-21] was used to measure how well a given attribute separates the training data set according to its target classification. 4) *Handling training data with missing attribute values.* In certain cases, the available data may be missing for some attributes (for example the absence of P Wave).

If we observe table IV, we can see the scheme: j48.part with the values of two parameters -M 2 that indicates that the minimum number of descendents per node considered is 2; and -C 0.25 that indicates that 0.25 is the threshold of confidence for pruning.

TABLE VI
RESULT OF VALIDATION OF THE DECISION TREE

=== Summary ===

Correctly Classified Instances	21003	96.128 %		
Incorrectly Classified Instances	846	3.872 %		
Kappa statistic	0.934	Total Cost	1248	
Average Cost	0.057	Mean absolute error	0.0045	
Root mean squared error	0.058	Relative absolute error	7.606%	
Root relative squared error	33.66%	Total Number of Instances	21849	

=== Confusion Matrix ===

a	b	c	d	e	f	g	h	i	j	K	l	m	n	Clas
1507	2	3	4	0	1	27	0	0	0	0	4	0	0	a=R
0	1392	9	5	0	7	113	5	3	33	7	0	0	0	b=V
5	5	1574	6	1	1	7	1	0	0	0	0	0	0	c=L
2	1	3	105	2	2	0	0	0	0	0	0	0	0	d=!
2	0	0	0	31	0	0	0	0	0	0	0	0	0	e=E
4	4	0	0	0	193	49	0	0	0	0	0	0	0	f=A
35	73	2	0	0	21	13228	3	44	28	7	0	0	0	g=N
0	0	0	0	0	0	5	2333	22	0	0	0	0	0	h=/
0	0	0	0	0	0	17	37	298	0	0	0	0	0	i=f
1	17	0	0	0	1	46	0	0	210	0	0	0	0	j=F
0	5	0	0	0	0	17	0	0	0	19	0	0	0	k=a
2	1	0	0	0	2	3	0	0	0	0	8	0	0	l=J
0	0	0	0	0	0	2	0	0	0	0	0	1	0	m=j
0	0	0	0	0	0	2	0	0	0	0	0	0	0	n=S

The next rows indicate the data source (test.txt), the number of instances (64,260), the number of attributes used (13), the type of test used (evaluation on training data) and the incorporation of the cost matrix. For the selection of the attributes we used the info-gain value associated to each of them and we decided to choose the best ranked 13 attributes. In the last row of table V, we show the list of the selected attributes among the whole set of cases, where number 4 is the first selected taking into account the info gain; number 7 is the second and so on.

The cost matrix in table IV represents the weights used to penalize bad classifications. The main diagonal of a normal cost matrix contains only zeros (0), because it corresponds to the case of correct classifications. Every cell that is not in the main diagonal of a normal cost matrix usually should contain ones (1). The 0 and 1 are values used in the zero/one loss approach where the general idea is that in many contexts, the costs of all errors are equal. But in our context to confuse a high risk arrhythmia that requires medical assistance in less than 3 minutes with a low risk arrhythmia may have serious consequences. Therefore to improve the classification we used information about the specific domain and we have introduced the values 2 in the following cases: 1) The rows and columns with !-label, E-label and F-label are penalized because the sequence of the first label are associated with Ventricular Flutter arrhythmia (VFL) and the sequence of the two last are associated with Idioventricular rhythms (IVR), which both are associated to the high-risk arrhythmia that requires a medical assistance in less than 3 minutes. 2) The row and column V-label are penalized because the sequences of these labels are associated with the Ventricular Tachycardia (VT) that requires a medical assistance in less than an hour.

In table VI, we show the new validation results obtained by using hold-out validation and the Weka tool. At the top of that table, we show the percentage of correctly classified beats (96.128%), immediately afterwards we show the percentage of incorrectly classified beats (3.872%). The confusion matrix is also shown, where the horizontal axis represents the classification made by the physician, whereas the vertical axis represents the classification made by the selected rules.

Once the most accurate beat classifier and a set of rules associated with it were obtained, it was necessary to determine an accurate rhythm classifier.

I. SELECTING THE MOST ACCURATE RHYTHM CLASSIFIER

In the specialized cardiologic literature [1] descriptions of arrhythmias can be found. Although, they are not very explicit, it is possible to represent them using a computer language. However, in order to select the most appropriated set of rules we used the following approach: 1) we rewrote the rules, corresponding to the arrhythmia descriptions found in the literature (we call it Cardiologic Rules); 2) in parallel, we obtained the arrhythmia rules by using techniques based on decision trees (we call it Inferring Rules); and last, 3) we used the combination rules that classify arrhythmias and provides competitive results. We are going to explain those steps.

A. Cardiologic Rules

In the specialized literature we can find for example the next definition for Ventricular Tachycardia (VT): “The VT is the result of a series of rapidly firing electrical impulses arising from within the ventricles”. In other words, VT is a sequence of rapid ventricular impulses or beat (V). That rhythm definition can be directly translated into a rule. However, there are other ambiguous and contradictory rhythm definitions. For example, the definition of the Atrial Fibrillation arrhythmia (AFIB) is: “The atria may beat irregularly and very rapidly, between 350 and 600 times per minute. This causes the ventricles to beat irregularly in response as they try to keep up

TABLE VII
RHYTHM TRAINING

Scheme: weka.classifiers.j48.PART -C 0.25 -M 2
Relation: test.txt Instances: 64260
Attributes: 56 Test mode: evaluation on training data

Evaluation cost matrix:

N	P	B	VT	T	NOD	IVR	AFIB	AFL	VFL	SVTA	
0	1	1	2	2	2	2	1	1	2	1	N
1	0	1	2	2	2	2	1	1	2	1	P
1	1	0	2	2	2	2	1	1	2	1	B
2	2	2	0	2	2	2	2	2	2	2	VT
2	2	2	2	0	2	2	2	2	2	2	T
2	2	2	2	2	0	2	2	2	2	2	NOD
2	2	2	2	2	2	0	2	2	2	2	IVR
1	1	1	2	2	2	2	0	1	2	1	AFIB
1	1	1	2	2	2	2	1	0	2	2	AFL
2	2	2	2	2	2	2	2	2	0	2	VFL
1	1	1	2	2	2	2	1	1	2	0	SVTA

TABLE VIII
CHOSEN RULES

Rhythm	Cardiologic	Inferring	Chosen Rule
B	89 %	82 %	Cardiologic
VT	47 %	44 %	Cardiologic
N	96 %	84 %	Cardiologic
VFL	94 %	94 %	Cardiologic
IVR	82 %	81 %	Cardiologic
SVTA	90 %	82 %	Cardiologic
T	94 %	54 %	Cardiologic
AFIB	40 %	54 %	Inferring
P	95 %	95 %	Cardiologic
NOD	54 %	52 %	Cardiologic
PREX	69 %	91 %	Inferring
SBR	100 %	100 %	Cardiologic
AFL	20 %	32 %	Inferring

with the atria". In other words, AFIB is a sequence of rapid atria beat (A) with some isolated ventricular beat (V). The sequence is very fast 350-600 times per minute. Moreover, the definition of the Atrial Flutter (AFL) arrhythmia is: "The atrial contractions are less rapid than in the AFIB, however, usually between 200 and 400 beat per minute, and are regular." In other words, it is a rapid sequence (200-400) of atrial beat (A). In any case, we have translated these definitions into rules.

B. Inferring Rules

In order to make the experiments that permitted us to select the accurate classifier, we needed to group the previously classified beats into groups of four beats. These groups were the input to the decision tree that classifies the different rhythms.

In this case, we only show the selected rhythm classifier. Thus, if we look at row 1 of table VII we can see the schema used: j48.part with parameters -C 0.25 and -M 2. The next rows show the data source (test.txt), the number of instances (64,260), the number of attributes used (56) and the type of test used (evaluation on training data). This training process was built considering the parameters explained in subsection 2.D. In the cost matrix the incorrect classifications of arrhythmias VFL, IVR, VT, T and NOD are penalized in their rows and columns. Te reason is that they require a medical assistance in less than 3 minutes (VFL and IVR) or less than an hour (VT) or that the other arrhythmias (T and NOD) show that the user has a high-risk of suffering a heart attack.

TABLE IX
RESULT OF VALIDATION

Correctly Classified Instances 62389 86.91 %
Incorrectly Classified Instances 9840 13.09 %

=== Confusion Matrix ===

a	b	c	d	e	f	g	h	i	j	k	l	Class
1934	91	2	0	0	12	25	3	0	0	0	465	a = B
16	**70**	0	0	0	2	11	1	0	0	0	66	b =VT
0	2	**204**	0	0	0	0	0	0	0	0	11	c =VFL
0	17	1	**101**	0	0	0	0	0	0	0	5	d =IVR
0	0	7	0	**353**	0	0	0	0	0	0	21	e =SVTA
6	14	0	0	0	**913**	14	0	0	0	0	293	f =T
38	84	0	0	0	156	**5622**	21	0	0	0	3506	g =AFIB
0	12	0	0	0	0	4	**7532**	0	0	0	380	h =P
0	0	0	0	0	0	0	0	**36**	0	0	14	i =NOD
0	0	0	0	0	0	0	0	0	**255**	0	117	j =PREX
0	0	0	0	0	0	0	0	0	0	**594**	17	k =SBR
256	474	53	164	0	903	1480	168	2	251	6	**47387**	l =N

C. Combining Rules

In order to select the best set of rules that classified rhythms we evaluated the Cardiological Rules and Inferred Rules independently. From left to right, table VIII shows: the type of rhythm, the accuracy percentage of Cardiologic Rule and Inferring Rule respectively and finally the type of rule chosen. The percentage indicates the rhythms identified by the physician as x and classified by the set of the rule as x rhythms; that is, correct classification percentage.

Notice that, we chose the rules that had a higher percentage, and in case that both types provided the same percentage we chose the cardiologic rules because they are clearer for physician and they are focused on the specific rhythms.

D. Validation of the Beat and Rhythm Classifier

The validation results of the rules that classify the heart rhythms are shown in table IX. It must be noticed that the rhythm classifier is using the beat types identified by the beat classifier as input (and not the beat type annotations found in the MIT-DB). First, we summarize the features of the validation; next, we present a confusion matrix. At the top of table IX we show the percentage of correctly classified rhythms (86.91 %), immediately afterwards we show the percentage of incorrectly classified ones (13.09 %).

The main diagonal shows the number of correctly classified rhythms. For example, in class c=VFL (row 3) there are 204 rhythms classified correctly, but 13 are classified wrong. Moreover in class d=IVR (row 4) there are 101 rhythms correctly classified but 23 incorrectly.

E. High-Risk Arrhythmias and Episodes

Although the obtained results were relevant, with the goal of improving them we followed the next approach.

First, with the help of some cardiologists, we made the next classification of rhythms, depending on their risk of suffering a heart attack (from highest to lowest):

1. *Heart attack:* requiring medical assistance in less than 3 minutes. There are two arrhythmias: VFL and IVR.
2. *Very high risk of heart attack:* requiring medical assistance in less than an hour. There is only one: VT.

TABLE X
EPISODES

Risk-Group	TYPE	Nro- episodes	Action
1	IVR*(Idioventricular rhythm)*	2	Notify
1	VFL*(Ventricular Flutter)*	6	Notify
2	VT*(Ventricular Tachycardia)*	49	Notify
3	NOD*(Nodal Rhythm)*	6	Notify
3	T*(Ventricular Trigeminy)*	74	Notify
4	AFL*(Atrial Flutte)*	3	NO Notify
4	AFIB*(Atrial Fibrillation)*	79	NO Notify
4	PREX*(Pre-excitation)*	45	NO Notify
4	SVTA*(Supraventricular tachyar.)*	17	NO Notify
4	B*(Ventricular Bigeminy)*	182	NO Notify
4	P*(Paced Rhythm)*	64	NO Notify
4	SBR *(Sinus Bradycardia)*	2	NO Notify
5	N*(Normal sinus rhythm)*	389	NO Notify

TABLE XII
COMPARISON AMONG BEAT CLASSIFIERS

Work Reference	**#Beat**	**% TP**	**Method**
Prasad	13	96.77%	Wavelet and Neural Network
Prasad /USCL	5	98.02%	Neural Network
Prasad /FTNN	3	98.00%	Fourier Transf Neural Net
Prasad /DWT1	10	97.00%	Discrete Wavelet Trans
Prasad /DWT	13	96.79%	Discrete Wavelet Trans
Prasad /FHhd-HOSA	7	96.06%	Fuzzy and Neural Network
Prasad /MOE	4	94.00%	Mixture-of-Experts
Prasad /DFT1	10	89.40%	Discrete Fourier Transform
Osowski	12	95.91%	HER/HOS
Lagerholm	all MIT	98.50%	Clustering
Cardident	all MIT	87.00%	Algoritmo CSL
MOLEC	**all MIT**	**96.128%**	**Decision Tree**

TABLE XI
RHYTHM VALIDATION

	1	2	3	4	5	Total	Correct	Wrong	%
1	8	0	0	0	0	8	8	0	100 %
2	0	48	0	1	0	49	48	1	97.95 %
3	0	0	76	1	3	80	76	4	95 %
4	0	30	23	339	0	392	339	53	86.47 %
5	3	84	40	0	262	389	262	127	67.35 %

TABLE XIII
COMPARISON AMONG RHYTHM CLASSIFIERS

Work Reference	**VFL**	**VT**	**IVR**	**NOD**	**T**	**N**	**DB**
Dingfei Ge	98.6%	97.78%	-	-	-	93.2%	Own-Record
Ayesta / SPDR	81.9%	94.6%	-	-	-	100 %	MIT-DB
Ayesta /RT	81%	90%	-	-	-	-	MIT-DB
Ayesta /SPRT	93%	96%	-	-	-	-	MIT-DB
Ayesta /X-S Zhang	100%	100%	-	-	-	100 %	Own-Record
Ayesta /Regresion	100%	100%	-	-	-	-	Own-Record
Ayesta /CWA	100%	50%	-	-	-	-	Own-Record
Ayesta /ALPF	91%	75%	-	-	-	-	Own-Record
Ayesta /ANN	59.1%	91.2%	-	-	-	99.3%	Own-Record
MOLEC/Rhythm	**94%**	**54%**	**82%**	**72%**	**94%**	**96%**	**MIT-DB**
MOLEC/Episodes	**100%**	**97.95%**	**100%**	**95%**	**95%**	**67.35%**	**MIT-DB**

3. *High risk of heart attack:* arrhythmias that precede a heart attack: NOD and T. They are arrhythmias that show that the user is going to suffer from arrhythmias of type 1 or 2.
4. *Moderate and low risk of heart attack:* abnormal rhythms that must be attended, but not necessarily notified immediately to the hospital. There are several: AFL, AFIB, PREX, SVTA, P, B and SBR.
5. *Normal sinus rhythm (N)* is the correct function of the heart.

We considered the groups 1, 2 and 3 as high-risk arrhythmias, that is, arrhythmias that should be notified to the hospital when they are detected by the system.

Second, we defined *episode* as a sequence of consecutive beats that appear in a record of the MIT-BIH database, and that are associated with the same rhythm annotation (given by the cardiologists). One example of Bigeminy episode (B) can be a sequence of twelve beats (NVNVNVNVNVNV). In the MIT-BIH database there are 918 episodes. In table X, for each type of rhythm it appears the number of episodes found in the MIT-BIH database, the risk group and the action that should be taken. Moreover, an episode of risk group 1, 2 or 3 is successfully classified by the system if there is at least one group of four consecutive beats in that episode that is classified in that risk group (1, 2 or 3). Notice that, the monitoring system will classify the rhythm as soon as a relevant group of beat of the rhythm is detected. At that point, an alarm could be sent to the hospital. An episode of risk group 4 is successfully classified by the system if there is at least one group of four consecutive beats in that episode that is classified in that risk group 4. In that case, no alarm could be sent to the hospital.

However, for the case of risk group 5 (normal sinus rhythm) an episode of that group is successfully classified if all beats in that episode are associated with normal sinus rhythms. But, we do not consider that the normal sinus rhythm episode is not successfully classified if the first beats of that episode are associated with the rhythm of the previous episode, or if the last beats of that episode are associated with the rhythm of the next episode. In that case, we consider that the monitoring system is still detecting the previous rhythm or anticipating the next one.

In table XI, we show the number of episodes correctly classified. This form of validating the rhythms based on episodes instead of validating the current rhythms for each beat is not only more realistic but also shows a much better performance for the high-risk arrhythmias than it was shown in table VIII. All episodes of high-risk 1 were correctly classified (in table VIII the accuracy percentages for VFL and IVR were 94% and 82% respectively); 97.95% of episodes of high-risk 2 were correctly classified (the accuracy percentages for VT was 47% in table VIII); 95% of episodes of high-risk 3 were correctly classified (the accuracy percentages for NOD and T were 54% and 94% in table VIII). On the contrary, the accuracy percentage for normal sinus rhythms was 67.35% instead of 96% (see table VIII) which means that more false alarms would be sent to the hospital. The number of false alarms can be reduced by adding harder constraints to the rules for VT and T arrhythmias. For example, by considering that a T arrhythmia occurs when the beat sequence VNNVNNVNN is found instead of the sequence VNNVNN, then the percentage for normal sinus rhythm would be much better (75.06% instead of 67.35%), but on the contrary, the accuracy percentage for high-risk arrhythmias would be worse (100%, 97.95%, 86.53% instead of 100%, 97.95%, 95%). Moreover, by considering also that a VT arrhythmia occurs when 3 consecutive V beats appear (instead of 2), then the percentage for normal sinus rhythm would be much better (86.68% instead of 67.35%), but on the contrary, the accuracy percentage for high-risk arrhythmias would be worse (100%, 90%, 86.53% instead of 100%, 97.95%, 95%). In summary, the classifier could be setup in order to augment or reduce the number of false alarms.

II. Comparison with other Classification Works

In this section we compare the results obtained using our beat and rhythm classifiers (labeled with MOLEC[7] in tables XII and XIII) with the results claimed by other research works. Making such a comparison is not an easy task because it depends on many factors like the ECG databases used and the number of beat and rhythm types to be classified[8]. Taking into account that we selected the MIT-DB ECG database, we searched some works that build beat and rhythm classifiers by using that database.

In table XII, we show some details about works that define beat classifiers. For each one of them, it appears a work reference, the number of beat types to be classified, the percentage of true positives (%TP) and the classification method used.

Prasad et al. [22] propose a method that is capable of distinguishing the normal sinus beat and 12 different abnormal beats with an accuracy percentage of 96.77% (see row 1). In the same paper, they present a comparison with other works that we also present in table XII (rows 2 to 8). Osowski et al. [25] present an expert system (see row 9 in table XII), based on the application of Support Vector Machine for reliable heart beat recognition on the basis of the ECG waveform. Two different preprocessing methods (HERmite characterization and High Order Statistic) have been integrated into the expert system to improve the overall accuracy of heart beat recognition (95.91%) by 12 different types of beats. None of the previous works try to classify all the 17 beat types in MIT-DB. Lagerholm et al. [24] have devised a procedure for clustering all the MIT-DB beat types into classes. The method entails HERmite function representation and self-organized neural networks for the purpose of beat clustering. Decomposing the beats into five Hermite function turns out to be sufficient for achieving good classification accuracy (98.5%). They claim that they need less than 1 minute to classify a 30-minute ECG signal, but we do not know whether the method could be applied with good results in real-time (and, in particular, running in a PDA). CARDIDENT [23] is a system of on-line detection, classification and identification of the most important waves of the beat: the QRS complex, with the aim of classifying the different types of heart beats.

[7] MOLEC stands for “Monitorización On-Line de Enfermos del Corazón” (On-Line Monitoring for Heart Patients)

[8] It is obvious that the problem of classifying data into N different classes is more complex than classifying data into M classes when N>M.

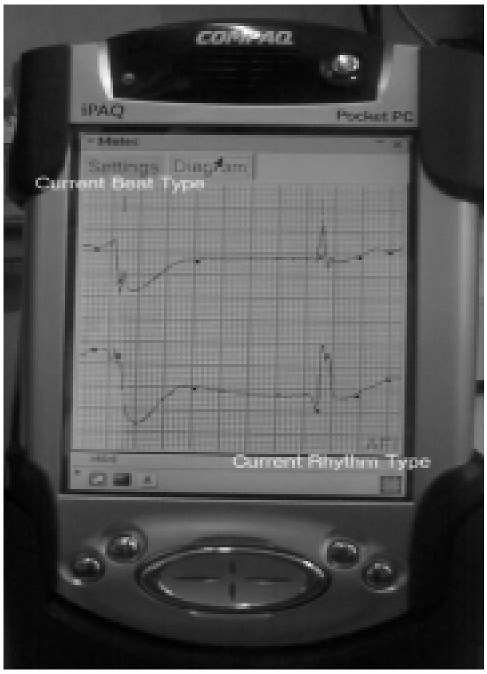

Fig. 3. ECG visualization in MOLEC

CARDIDENT classifies all the MIT-DB beat types with an error of 13% and a sensibility of 87%. MOLEC only reaches an error of 3.581% classifying beats and it also classifies rhythms.

In table XIII, we show some details about works that define rhythm classifiers, and in particular, works that classify high-risk arrhythmias. For each one of them, it appears a work reference, and the accuracy percentage for VFL, VT, IVR, NOD and T high-risk arrythmias and the normal rhythm N. Finally, the ECG database used (notice that in this case we are comparing also with other works that use their own ECG records).

Dingfei Ge et al [27] have proposed a simple autoregressive (AR) modeling technique to classify the beat types N, V, S and the rhythms SVTA, VT and VFL, also with data stored in their own ECG records (see row 1 in table XIII). The reported accuracy percentage for VFL, VT and N are 98.6%, 97.78% and 93.2% respectively. Ayesta et al. [26] proposed the method of Sample Percentage in the Dynamic Range (SPDR) for classification of N, VFL and VT (see row 2 in table XIII). In the same paper, they present a comparison with other works that we also present in table XIII (rows 3 to 9). Some of them claim very good accuracy for VFL, VT and N. For example, the work reference in row 5 obtained a perfect classifier for VFL, VT and N by using the CM algorithm but own ECG records as input data. However, Ayesta et al. claim that the CM algorithm works much worse when applied to the MIT-DB database. Therefore, it seems that it may be unfair to compare our classifier with others that do not use MIT-DB but their own ECG records. Our rhythm classifier (see last 2 rows in table XIII) obtains very good results in the classification of high-risk arrhythmias, although the set of rhythm types to be classified is greater than in the previous works. The accuracy percentage for some arrhythmias improves a lot when complete episodes are considered instead of individual beats inside a rhythm. But, on the contrary, the accuracy percentage for N normal rhythm gets lower (from 96% to 67.35%).

In any case, we can conclude that our beat and rhythm classifier is comparable to any of the classifiers for which we have found accuracy percentages in the literature.

III. Implementation of the Classifier on a PDA

After having developed an ECG beat and rhythm classifier it was necessary to prove if the classifier could be run, in real time, into a PDA, because it is known that the most powerful current PDAs, even with the latest technological advances, are environments with limited computing resources if compared to PCs. Moreover, the processing tasks that a monitoring system implies require a high computation cost: the signal acquisition, processing and visualization (see figure 3).

The signal acquisition[9] implies: the picking up of the sample (in our case with frequency of 360 samples per second that is equivalent to 21,600 samples per minute), the conversion of the digital samples into a format understandable by the rest of the system (signal preprocessor and classifier) and their grouping together into signal packages with a defined size.

The signal processing implies running several threads: the thread that performs the preprocessing and classification, the thread that stores the signal and classification results in a local database; the thread that manages the alarms and finally another thread in charge of the communications between the PDA and a control center. The hard restriction here is that the thread that preprocesses and classifies the signal has to finish before the signal acquisition obtains the next signal package.

In this section, we will answer the next question: which is the appropriate size of a signal package? or, in other words, how often does the signal process have to be executed? We will call “processing cycle duration” to that time. It is obvious that the greater the processing cycle duration is, the greater the rhythm detection delay is. The rhythm detection delay grows with the signal package size because at least four beats are needed in order to classify the rhythm, and some beats may delay until the package is completed according to the processing cycle duration. However, the processing cycle duration cannot be very small because the system would get overloaded: the threads of the signal processing have to synchronize with the thread that performs the signal acquisition. And, moreover, it does not have much sense to start a new processing cycle if a new signal package with at least one beat has not yet arrived: no new rhythm can be detected.

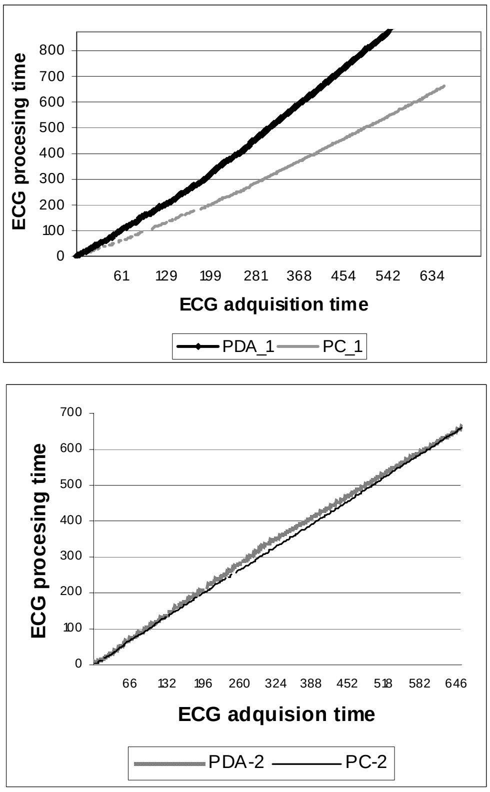

Fig. 4. Time in which an acquired signal starts its processing, for signal packets of one and two seconds

Therefore, in order to establish the optimal processing cycle duration we tested the system performance for processing cycles of one and two seconds respectively. Both types of test were performed in the PDA[10] and in a PC (with the goal of pointing up their different performance). The experiment consisted on: 1) running several threads into each device: a signal acquisition thread and all threads involved in the signal processing and classification, storing and visualization; and 2) measuring when the signal package, provided by the signal acquisition, started its processing in the signal processor and classifier. Notice that only processing times of those threads into PC and PDA had an influence on that time and not communication times from the sensors to PC and PDA.

Figure 4 shows four functions: PC-1, PDA-1, PC-2 and PDA-2. Every point (x,y) of all those functions indicates that the signal package provided by the signal acquisition thread at the second x is processed by the processor thread at the second y. For PC-1 and PDA-1 functions, the processing cycle duration is of 1 second, and for PC-2 and PDA-2 functions it is of 2 seconds. In PC-1 and PC-2, the processing cycle is performed in the PC, and, obviously PDA-1 and PDA-2 in the PDA. As it can be observed in the figures, in both cases the system running in the PC achieves a stable state since the corresponding functions are very close to the diagonal function

[9] For this experiment, we simulate the ECG sensors with software in a PC that sends the ECG data of the MIT-DB to the PDA, via Bluetooth.

[10] The platform used for the implementation of classifier has been the next PDA: an iPaq 3970 with a 400Mhz XScale processor, 64MB SDRAM and 48 MB Flash memory. The PC configuration was Pentium IV (512MB RAM, 2.4GHHz).

(that would mean that the signal packet received at second x is processed by the system at second x). The stability comes from the fact that the difference between the diagonal and the PC-x functions does not grow with time. In other words, the system performs all the tasks before the next signal package has been arrived.

In the PDA case, for processing cycles of one second, this property is not achieved but it was achieved with processing cycles of two seconds. Therefore, the optimal processing cycle duration would be of 2 seconds for the case of the PDA. In that case the average rhythm detection delay would be of 6.66 seconds. In the PC case, the optimal processing cycle duration would be of 1 second being the average rhythm detection delay of 4.43 seconds.

IV. Conclusion and Future Work

Monitoring systems that perform a complete ECG analysis in a local device near the patients are of great interest because they allow to improve the quality of life of persons that suffer from arrhythmias and reduce communication costs. For an anywhere and at anytime monitoring system, used devices have to be actually mobile. That is why we advocate for using PDAs as the core of these kinds of monitoring systems. In this paper, we have presented the steps followed in order to build a complete ECG beat and rhythm classifier for a PDA. The obtained results for the classifier have shown that it is comparable to other ECG classifiers found in the literature. In particular, it provides a very good accuracy for classifying rhythms (100% for arrhythmias that require medical assistance in less than 3 minutes, 97.95% for arrhythmias that require medical assistance in less than an hour and 95% for arrhythmias that usually happen before a worse arrhythmia).

Finally, we have incorporated that classifier into a PDA, and performed a set of experiments that show its feasibility. Moreover, those experiments have shown that the ECG signal processing and the classification can be performed in real-time on the PDA by using a processing cycle duration of 2 seconds, that is, if it is performed every 2 seconds. In that case, the rhythm detection delay would be of 6.66 seconds.

As future work, we plan to incorporate this PDA into a real-time monitoring system that acquires and analyzes ECG of people that may be moving, and sends alarms to a hospital center when high-risk arrhythmias are found.

Acknowledgment

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