Assessment of Arrhythmias for Heart Failure Management

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***Abstract*— Heart Failure Management is one of the product concepts developed under the FP6 MyHeart project funded by European Union. By providing a periodic monitoring of vital signals and other parameters, which are locally processed and analysed on a personal digital assistant, it is possible to continuously evaluate the cardiac condition, symptoms progression and arrhythmic events, enabling an early detection of heart failure decompensation.**

This work presents the approach followed for the assessment of cardiac arrhythmias, with clinical relevance for heart failure management. The framework includes algorithms for atrial fibrillation and ventricular arrhythmias detection (PVC-premature ventricular contractions, VT-ventricular tachycardia and VF-ventricular fibrillation), that are currently incorporated into the patient station of the heart failure management system.

I. INTRODUCTION

Roughly 45% of all deaths in Europe are due to cardiovascular disease (CVD) and more than 20% of all European citizens suffer from a chronic CVD, such as myocardial infarction, arrhythmias and congestive heart failure. Despite the advances in the treatment of heart failure (HF), it is observed that the mortality rate continues to be high. Nowadays, close to 50% of deaths in HF are thought to occur suddenly [1]. The principal cause of mortality in HF is not absolutely clear, but the presence of cardiac arrhythmias suggests a reserved prognosis. Atrial fibrillation (AF) and ventricular tachyarrhythmia (VA) are the most significant rhythm disturbances found in ventricular dysfunction (decompensation) both in terms of the number of patients affected and the associated mortality and morbidity [2].

AF is a common arrhythmia with a prevalence of approximately 0.4-0.1% in the general population. Prevalence increases with age and is estimated to be present in 5% of those older than age 65, and 10% of those older than 70. AF is associated with an increased risk of stroke and mortality, as well as congestive heart failure [3]. The prognostic significance of ventricular arrhythmias in the patient with decompensated left ventricular function has been examined in a number of studies. Data from the GISSI-2 study [4], examining 8676 post myocardial infarction patients, showed that ventricular arrhythmias were more frequent when signs or symptoms of left ventricular damage were present. The presence of frequent premature ventricular beats (PVC) was found to be an independent risk factor for total mortality and sudden death at 6 months.

Being part of the Heart Failure Management (HFM) product concept of the MyHeart project, this work focuses on the developed ECG analysis algorithm platform designed to detect and to characterize arrhythmic states of the heart (AF and VA) with high accuracy. Moreover, the feasibility of incorporating the designed algorithms into a personal data assistant (PDA) is also a fundamental aspect, since it is the form factor of the patient station of the HFM system. In the current setup of the HFM system, algorithms run off-line, i.e. once signal acquisition has finished. However, both due to technical reasons as well as due to user motivation issues, it is important that the user is able to obtain a timely response from the system and, therefore, the computational efficiency of the algorithms is imperative. Thus the goal of this paper is twofold: on the one hand, to introduce the designed ECG analysis algorithm platform and, on the other hand, to demonstrate the feasibility to run the algorithms in a patient station implemented using a PDA.

Based on the analysis of the ECG, several algorithm strategies have been proposed and implemented, enabling to distinguish between sinus normal rhythms (SNR) and VT/VF [5], as well as to distinguish between VT and VF [6]. Several authors have investigated template-matching algorithms to distinguish SNR from VT and SNR from VF [7]. For discrimination between VT and VF several detection methods have been developed, such as rate and irregularity analysis, correlation waveform analysis, spectral analysis and time-frequency analysis (including wavelets) and algorithms based on complexity measures [7]. Neural networks and fuzzy systems have also been applied to VT and VF detection, and are recognized as powerful and promising techniques for arrhythmia discrimination [8]. Regarding PVC detection, measurements of average wave amplitudes, time duration and wave areas, have been adopted to extract a set of characteristic

ECG parameters [9]. Once this set of features has been evaluated, several techniques for classification are then applied, such as probabilistic approaches, heuristic models, knowledge-based systems or neural networks [10].

Although several cardiac arrhythmias classification methods have been proposed, it is observed that usually they focus on one specific problem, i.e. AF, PVC, VT or VF detection, and only few methods consider the problem of ECG analysis as a global/integrated procedure. In this work, an integrated framework for life threatening arrhythmias (LTA) assessment is proposed. The approach is able to simultaneously handle the detection of AF, PVC, VT and VF.

The paper is organized as follows: in the section 2 an outline of the modules that compose the integrated arrhythmia analysis method is presented. In section 3 some results using public ECG databases are presented and, finally, in section 4, some conclusions are drawn.

II. METHODS

In the HFM product concept of MyHeart, vital signals (ECG and trans-thoracic impedance) will be measured according to a defined daily monitoring protocol. According to the acquisition protocol, 10 minutes of ECG will be collected per day (5 minutes at rest and 5 minutes after a physical exercise) using the wearable MyHeart sensors. The system integrates a patient station in the form factor of a PDA that implements the patient user interface and where algorithms will perform local signal analysis. As has already been mentioned, the proposed algorithm platform is only based on the analysis of characteristics of the ECG signal. To extract these characteristics, pre-processing and segmentation of ECG is essential. Once these stages have been completed, feature extraction methods are applied. The final step consists on the classifier implementation, training and validation.

The functions implemented as part of the framework's toolbox were divided into three main modules (see Fig. 1): fiducial point detection, AF detection and ventricular arrhythmia (VA) detection. Moreover in VA detection three different aspects have been considered: PVC, VA and VF.

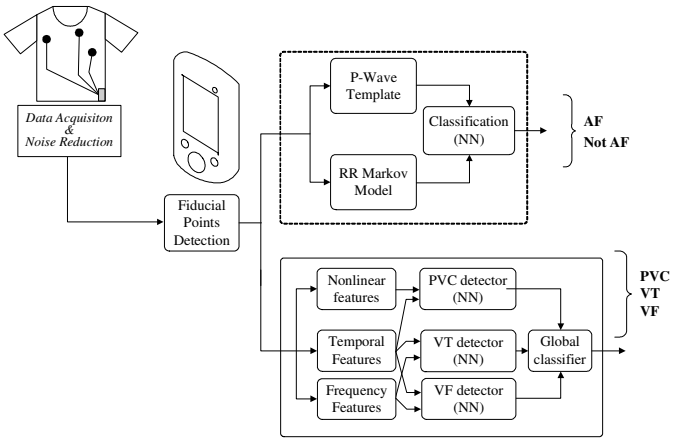

Fig. 1 Architecture of the LTA assessment algorithm.

A. The ECG analysis platform

The main modules of the proposed LTA assessment scheme are depicted in Fig. 1. The input consists of the discrete ECG signal (obtained from wearable sensors) followed by the usual pre-processing techniques, i.e. standard filters for noise reduction and baseline removal. It should be stressed that, in order to enable real-time processing, the ECG is evaluated using a sliding window strategy in all modules that compose the platform. Two distinct outputs have been considered: one for AF assessment and another for VA assessment (PVC, VR or VF).

The proposed approach assumes that the fundamental differences in the physiologic origins of sinus rhythm and AF/PVC/VT/VF can be discriminated via time analysis of the ECG's morphology and spectral components. The set of applied discriminating features have been determined using a correlation analysis procedure of the most significant features found in literature as well as new features developed during this work. These features are provided as inputs to a hierarchical NN module enabling the discrimination of specific arrhythmias. In this classifier configuration, each module discriminates only between two classes. As is well known, the achievable accuracy of a given classifier is highly dependent on the number of classes present in the input data. Clearly, with only two classes each classifier is able to provide a superior classification result, due to the lower complexity of the mapping function to be identified. This fact has justified the design of different neural network classifiers with specialized tasks (PVC, VT, VF and AF). Finally, the outputs of each neural network are used as inputs to a global classifier, based on an ANFIS structure, which provides the global result of the ECG analysis algorithm platform.

B. AF detection

In order to detect AF events two features have been considered as inputs to a neural network classifier: P-waves existence and heart rate variability assessed using a Markov model. These two features are fed into a feedforward neural network classifier to categorize each window of ECG data into two classes: with/without AF.

P wave detection: The absence of P waves during the fibrillation process before the QRS complexes is an important characteristic of AF episodes. Although ECG segmentation methods can be very accurate in the detection of ECG fiducial points, it is observed that these algorithms tend to breakdown for the detection of P waves during AF episodes. To avoid these misclassification errors, a template-based approach is proposed. First a model is extracted by averaging all annotated *P* waves found in the *QT* Database from Physionet (see Fig. 2). The existence of a P wave is assessed by the correlation coefficient between the P wave candidate and the P wave template.

Heart Rate variability: The second feature relates to the variability of the RR interval. Basically, the R-R interval sequence is modelled as a three-state Markov process being each interval classified as one of the three states S, R, L (short,

regular or long). Intervals are called short if they do not exceed 85% of the mean interval duration, long if they exceed 115% of the mean interval duration, and regular otherwise. Thus, the R-R interval sequence can be assumed as a stationary first-order Markov process, characterized by its state transition probability matrix [7]. In our approach, the regularity of the heart rate is characterised by the probability of transition from state R to itself, since this transition is more likely to occur when the RR intervals present approximately the same length. Since PVCs induce large variability in heart rate, they are excluded from the computation of the transition matrix in the Markov model (see Fig. 1).

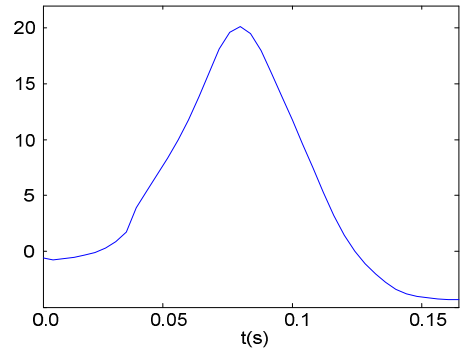

Fig. 2 P wave model extracted from the Physionet QT Database.

C. PVC detection

The proposed PVC detection module considers, for each beat classification, a comparative analysis using the ECG signal in close proximity to the current beat. It has been established that every analysis window must contain at least 10 beats. In order to meet this constraint for real time applications the length of the present analysis window is estimated based on the heart rate frequency observed in the previous window.

For each beat in a given time window a set of 13 features (f_i, i=1...13) is extracted (for a complete review, the reader is referred to [12]). Some of the features are directly related to well defined characteristics of PVCs: *R* wave length, area and centre of mass of *QRS* complex, *T* wave deflection and amplitude, *P* wave absence and *RR* interval variability (Fig. 3).

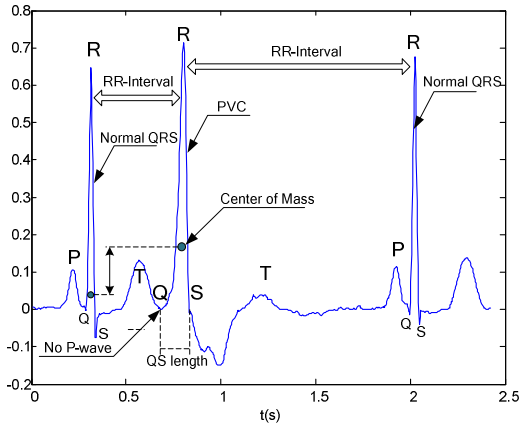

Fig. 3 Features extracted directly connected to ECG characteristics.

The remaining features have been defined using feature extraction methods based on the morphological derivative, spectral and information content.

Morphology Information: Two features are based on the ECG signal's morphological derivative. It is observed that PVC complexes exhibit lower slop before or/and after each *R* peak. The slop from the *Q* peak to the *R* peak can be measured by calculating the morphological derivative's peak amplitudes in this segment (QR_{amp}, see Fig. 4).

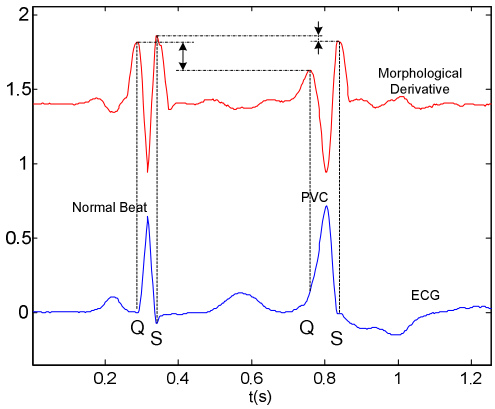

Fig. 4 Comparison of amplitude differences between normal beats and PVCs morphologic derivatives.

Analogously, the slop after the *R* peak can be represented by the amplitude of the *RS* peak segment (RS_{amp}). An approximation to the normal beat *R* wave left and right slops can be estimated by calculating the averages of *QR* and *RS* amplitudes. Let these be $\overline{QR_{amp}}$ and $\overline{RS_{amp}}$, respectively. The relations between QR_{amp} and $\overline{QR_{amp}}$, and the relation between RS_{amp} and $\overline{RS_{amp}}$, provide two original features, equations (1) and (2):

$$f_1(i) = QR_{amp}(i) \times \log \frac{QR_{amp}(i)}{\overline{QR_{amp}}}, \qquad i = 1,...,nbeats \tag{1}$$

$$f_2(i) = RS_{amp}(i) \times \log \frac{RS_{amp}(i)}{\overline{RS_{amp}}}, \qquad i = 1,...,nbeats \tag{2}$$

Spectral Information: Chick *et al.* [10] proposed that the *QRS* complexes' morphology differences between PVCs and normal beats might be evaluated using frequency spectrum signatures. Namely, PVC spectrums tend to be more concentrated in lower frequencies, while spectrums from normal beats tend to be more dispersed. The following features are based on this observation. The entropy of each normalized QRS spectrum assesses the concentration of each spectrum. The logarithmic comparison between the entropy (H) and the average of all entropies ($\overline{H}$) leads to the feature presented in (3). Another feature is calculated using the *Kullback–Leibler* divergence (D_{kl}) between every normalized

spectrum (S_p) and the average of all spectrums ($\overline{S_p}$). This feature expresses the similarity between each spectrum and a spectrum that is an approximation of a normal *QRS* complex spectrum, according to (4).

$$f_3(i) = H(i) \times \log \frac{H(i)}{\overline{H}}, \qquad i = 1,...,nbeats \tag{3}$$

$$f_4(i) = D_{kl}\left(S_p(i), \overline{S_p}\right), \qquad i = 1,...,nbeats \tag{4}$$

$$D_{kl}\left(P(X), Q(X)\right) = \sum_{x \in X} P(x) \log\left(\frac{P(x)}{Q(x)}\right) \tag{5}$$

D. VT and VF detection

The selection of the most relevant features for VT and VF discrimination was performed through a correlation analysis procedure. This approach took into consideration a set of available features found in literature and developed within this work and their dependency with respect to the desired task. Concerning temporal domain markers, five morphological features were chosen. These represent information about the shape of the ECG signal:

a) PTABT (percentage of time above or below thresholds) is defined as the relative amount of time of beat peaks, which are above a high threshold or below a low threshold [13]. This parameter is a characteristic of the temporal ECG morphology: a normal ECG presents a very small PTABT and a ventricular tachycardia/fibrillation exhibits a larger value of PTABT.

b) Another feature was based on an algorithm presented by Jekova and Krasteva [14]. Following this approach, a particular band pass digital filter is applied to the original signal. Then, from the filtered signal a set of time domain parameters are extracted, enabling the rhythm classification.

c) A feature comparable to the heart rate was extracted. This feature employs a nonlinear transform, derived from multiplication of backward differences, providing an estimation of extreme variations in the ECG [15].

d) Another feature was obtained from a two dimensional phase space reconstruction diagram, a tool able to identify chaotic behaviour of signals. Fundamentally, if the signal is non-chaotic (normal sinus rate), the curve in the phase space diagram showing a regular form is concentrated in a restricted region of the plot. However, a chaotic signal (VT/VF) produces a curve that is uniformly distributed over the entire diagram.

e) For detection of abnormal signal amplitudes and slopes, appropriate markers were implemented. These markers were evaluated inside a specific window (10 seconds) by assessing the portions of small and high derivatives in the ECG signal: i) the number of points close to the baseline where the derivative is small (signal is almost horizontal) and ii) the number of points where the derivative is high (signal is almost vertical). The baseline (*bLine*) as well as the respective derivative (*dLine*) was found. The number of points close to the baseline (*horizontalP*) and the number of points, where the derivative is high (*verticalP*) were computed using (6) and (7):

$$\begin{aligned} &If\ \left(dLine(i) < lowT\right) AND\ \left(ecg(i) - bLine(i) < baseT\right) \\ &\quad horizontalP = horizontalP + 1 \end{aligned} \tag{6}$$

$$\begin{aligned} &If\ \left(dLine(i) > highT\right) \\ &\quad VerticalP = verticalP + 1 \end{aligned} \tag{7}$$

Variables *lowT*, *highT* and *baseT* define three thresholds, which are established based on the amplitude of the ECG signal. The number of points (*horizontalP* and *verticalP*) is evaluated for every window and allows the estimation of the time interval where the signal is almost horizontal or vertical.

Global classifier

A global classifier implemented using an ANFIS (*Adaptive-Network-Based Fuzzy Inference System*) scheme forms the final stage of the proposed algorithm platform. This classifier performs the decision-making, based on the outputs of the simple two-class NN classifiers applied for each ventricular arrhythmia, deciding on whether the current signal is a normal or abnormal signal, i.e. if it is NSR, PVC, VT or VF.

For this classifier, hybrid learning algorithm was implemented, combining the subtractive clustering technique with the least-squares method. Subtractive clustering has been utilized to partition the training sets and to generate the structure, i.e., to determine the number of rules and membership function parameters (the membership functions of the input fuzzy sets were selected in the form of Gaussian functions). The parameters (weights) associated with the membership functions were tuned using the least square method.

III. VALIDATION

In a first phase, all the functionalities related to database access, signal processing, network and ANFIS training, as well as validation results were implemented in Matlab. In a second phase the Matlab code was manually ported to C language, integrated and tested in the portable device (PDA).

A. Training and Validation

In order to train and to validate the module developed for AF detection, a comparative study using the MIT Atrial Fibrillation database has been employed. This database includes twenty-three ECG recording of paroxysmal AF patients, i.e. containing AF episodes and NSR. Five recordings (ID: 05091, 07162, 07859, 08405 and 08455) have been excluded from the analysis, due to the fact that they exhibit mainly very short duration AF episodes. Using the remain eighteen records, a total ECG signal duration of 7937 minutes have been used to validate the module, including 246600 heart beats of AF episodes and 435600 heart beats of NSR episodes.

The PVC detection algorithm validation has been performed using 46 of 48 MIT-BIH database records. Non MLII lead configurations records have been removed from the training and testing datasets, preserving coherence in the

morphological characteristics of ECG records. 1965 PVCs and 11250 normal *QRS* complexes from the aforementioned dataset, compose the training dataset. Validation was performed using all 46 dataset records (6595 PVCs and 95893 normal beats).

To validate the VT/VF module of the algorithm, the following public databases were employed: MIT-BIH Arrhythmia Database (MIT) [16], MIT-BIH Malign Arrhythmia Database (MVA) [17] and Creighton University Ventricular Tachyarrhythmia Database (CVT) [18].

In a first phase, NN and ANFIS structure were trained and validated independently for each database. In a second phase, the training was performed taking into account simultaneously all available databases. In both cases the training data was carefully selected in order to include representative examples of the arrhythmias under study. The validation was performed using randomly data from these databases. The NNs were trained using the Levenberg-Marquardt algorithm and the number of hidden neurons was determined experimentally. The ANFIS structure and training was performed through a hybrid learning algorithm. The subtractive clustering method with *ra*=0.2 (neighbourhood radius) was used to partition the training sets and generating the FIS structure.

B. Results and discussion

The achieved results by the algorithm platform regarding sensitivity and specificity for each of the arrhythmia assessment tasks are presented in Table II through Table IV. Table I presents the achieved processing times using a QTeK-S200 PDA.

TABLE I – AVERAGE PROCESSING TIME OF 10 SECONDS OF ECG ON A S200 PDA FROM QTEK.

Module	Time (Seconds)
Segmentation	4.8
AF Detection	7.9
PVC Detection	0.4
VA Detection	16.7

TABLE II – RESULTS ON AF DETECTION.

	Se(%)	Sp(%)
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TABLE III – RESULTS ON PVC DETECTION.

	Se(%)	Sp(%)
Proposed Algorithm	96.35	99.15
Jekova *et al.* [19]	93.30	97.30
Christov *et al.* [20]	96.90	96.70
Christov and Bortolan [21]	98.50	99.70

TABLE IV- VT/VF CLASSIFICATION PERFORMANCE.

Database	MIT	MVA	CVT	All
Se (%)	99.7	90.7	91.8	89.3
Sp (%)	98.8	95.0	96.9	94.1

**AF

The achieved results regarding PVC detection performance are presented and compared in Table III with state of the art algorithms. The values shown for the later are those reported by their respective authors. The sensitivity and specificity achieved by the proposed algorithm are 96.35% and 99.15%, respectively. Comparing these values with those of the algorithms reported in literature, it is observed that the proposed algorithm reveals very accurate classification results. Christov and Bortolan [21] present higher sensitivity (+2.15%) and slightly higher specificity (+0.55%) than the proposed algorithm. However, it should be noted that the algorithm proposed by these authors is based on two ECG leads and 26 features, while the proposed algorithm is based on only one ECG lead and a much lower number of features. Another advantage of the proposed PVC detection module is that it is more patient invariant than other state-of-the-art PVC algorithms, since it uses features that rely on local relative comparisons of ECG properties instead of global absolute values. As can be inferred from table I, the achieved solution enables real-time processing for PVC detection, since on average, the method requires 0.4 sec. of processing time in the PDA for each 10 sec. window of ECG signal.

The performance of the algorithm for VT and VF (MIT/MVA/CVT) detection are presented in Table IV. As can be observed, the detection results are higher when considering independently each database. Applied to all databases the method has a sensitivity of 89.3% and specificity of 94.1%. This has mainly to do with dubious annotations in some signals of the publicly available databases. For instance, in fig. 5, two ECG signals from the MVA (record 421) and CVT databases (record 07) are shown. One has been annotated as a VT (fig. 5 a)), while the other one has been annotated as a sinus normal rate (fig. 5 b)). Obviously, recognition of signals of this kind is a challenge to the algorithm and should be dealt with in further studies.

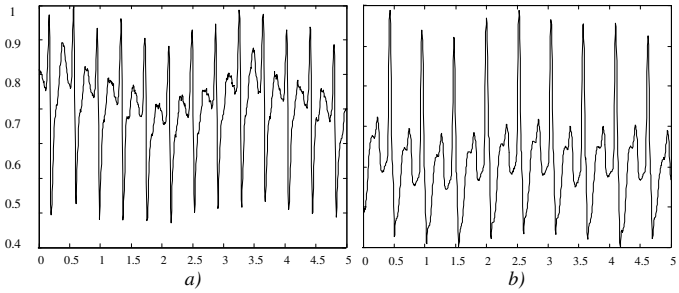

Fig. 5. Examples of incorrectly classification ECG signals.

ANÁLISE DO TEMPO

IV. CONCLUSIONS

In this paper the integrated ECG analysis algorithm platform developed for the HFM product concept of MyHeart was introduced. The proposed architecture is modular and enables the simultaneous detection of the most significant cardiac arrhythmias in heart failure management, i.e. AF, PVC, VT and VF detection. It should be stressed that all modules of the algorithm have been designed to operate on short signal windows (typically in the order of 10 seconds). This has the potential to enable real-time operation, which is a significant aspect for many home monitoring eHealth applications. This

is a significant result, since most of the few available integrated analysis algorithms require significant durations of ECG to perform arrhythmia analysis.

The results obtained, by implementing the algorithm in a PDA with a standard CPU, demonstrate that it is possible to run the algorithms in real-time, if required. In our current implementation this is clearly not possible (nor was it the goal of the application), since processing time is larger than the analysis window duration. However, it should be stressed that there is a considerable margin for code optimization (e.g. in our implementation floating point arithmetic was used instead of fixed point or integer arithmetic), which could enable real-time realization if required.

The validation of the algorithms was based on public databases. Classification results show that the proposed approach can be used to discriminate between different types of arrhythmia with state of the art accuracy. However, to evaluate effectively the developed algorithms, their performance has to be tested in real conditions. Under these circumstances, some modules have to be probably improved, to maintain/increase the obtained sensitivity and specificity and to assure robustness to changes in real measurements conditions (including noise and misunderstand events). This will be performed in a very near future using the data collected during the observational study that is planned for the HFM concept of MyHeart.

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REFERENCES

[1] Narang R, Cleland JGF, Erhardt L, Ball SG, Coats AJ, Cowley AJ, Dargie HJ, Hall AS, Hampton JR, Poole-Wilson PA. Mode of death in chronic heart failure: a request and proposition for more accurate classification. Eur Heart J 1996: 17: 1390–403.

[2] W. Arthur, G. C. Kaye, Tachyarrhythmias and Heart Failure, J Clin Basic Cardiol 2001; 4: 115.

[3] D. Bialy, M. Lehmann, D. Schumacher, R. Steinman, and M. Meissner, "Hospitalization for arrhythmias in the united states: importance of atrial fibrillation," J Am Coll Cardiol, vol. 19 (Suppl. A), no. 41 A, pp. 612–627, 1992.

[4] Maggioni AP, Zuanetti G, Franzosi MG, Rovelli F, Santoro E, Staszewsky L, Tavazzi L, Tognoni G, on behalf of the GISSI-2 investigators: Prevalence and prognostic significance of ventricular arrhythmias after acute myocardial infarction in the fibrinolytic era. GISSI-2 results. Circulation 1993; 87: 312–22.

[5] Tomaselli, G., A. Nielsen, W. Finke, L.. Singupta and J. Griffin; "Morphologic Differences of the Endocardial Electrogram in Beats of Sinus and Ventricular Origin", *PACE*, 11, 254-262, 1998.

[6] Throne, R., J. Windle, R. Easley and D. Wilber; "Scatter Diagram Analysis: A New Technique for Discriminating Ventricular Tachy-arrhythmias", *PACE*, vol. 17, 1267-1275, 1994.

[7] Tratnig, R.; "Reliability of new Fibrillation Detection algorithms for automated External Defibrillators", *PhD Dissertation*, Technische Universitaet Graz, 2005.

[8] Ham, F. and S. Han; "Classification of cardiac arrhythmias using fuzzy ARTMAP*", IEEE Trans Biomed Eng 43*, 425-430, 1996.

[9] Hu, N., S. Palreddy and W. Tompkins; "A patient adaptable ECG beat classifier using a mixture of experts approach", *IEEE Trans Biomed. Eng*., 44, 9, 891-900, 1997.

[10] Chikh, M, N. Gbelgacem and F. Reguig; "The use of artificial Neural networks to detect PVC beats", *Lab. de Génie Biomédical. Dép. d'électronique*, Univ. Abou Bekr Belkaïd, 2003.

[11] Moody B. G. and Mark R. G., "A new method for detecting atrial fibrillation using R-R intervals", IEEE Computers in Cardiology 1983; 10:227-230.

[12] R. Couceiro, P. Carvalho, J. Henriques, M. Antunes, On the detection of premature ventricular contractions, IEEE EMBS, 2008 (submitted)

[13] Tian, L. and J. Tompkins; "Time domain based algorithm for detection of ventricular fibrillation", *Proceedings of the 19 Int. Conference IEEE/EMBS Oct 30-Nov 2*, Chicago, USA, 1997.

[14] Jekova I., and V. Krasteva; "Real time detection of ventricular fibrillation and tachycardia", *Physiol. Meas*. 25, 1167–1178, 2004.

[15] Kunzmann U, G. Schochlin and A. Bolz; "Parameter extraction of ECG signals in real-time*". Biomed* Tech (Berl). 4, 2:875-8, 2002.

[16] http://www.physionet.org/physiobank/database/html/

[17] http://www.physionet.org/physiobank/database/vfdb/

[18] http://www.physionet.org/physiobank/database/cudb/

[19] Jekova I., Bortolan G. and Christov I., "Pattern Recognition and Optimal Parameter Selection in Premature Ventricular Contraction Classification", IEEE Computers in Cardiology 2004; 31: 357-360.

[20] Christov I., Jekova I. and Bortolan G., "Premature ventricular contraction classification by Kth nearestneighbours rule", Physiologic Measurements 2006; 24:123–130.

[21] Christov I. and Bortolan G., "Ranking of pattern recognition parameters for premature ventricular contractions classification by neural networks", Physiologic Measurements 2004; 25: 1281-1290.