Cardiac Sounds Segmentation Algorithm for Arrhythmias Detection by Fuzzy Logic

M. Fanfulla, M. Malcangi, M. Riva, D. Della Giustina, F. Belloni

***Abstract*—**The heart auscultation is the main investigation approach used to evaluate the possibility of a diseases. In order to improve the automatic diagnosis capabilities of auscultations, signal processing algorithms are developed. A basic task for the diseases diagnosis from the phonocardiogram is to detect the exact timing location of the events presents in the cardiac cycle, especially in pathological cases. In this paper is presented a new technique for segmentation and identification of cardiac sounds able to operate even in the case of cardiac anomalies, and without any additional reference signal such as electrocardiogram signal. A framework to arrhythmias detection based on the heart rate variability, is presented. The advantage in term of low computational burden inherited from the characteristics of fuzzy logic has been tested with a set of normal and abnormal heart sounds achieving satisfactory results.

***Keywords*—** Arrhythmia, Automatic diagnosis, Cardiac diseases, Fuzzy classification, Heart sound segmentation, Phonocardiogram.

I. Introduction

IN today medical prevention, the early diagnosis of cardiac diseases is one of the most important topics.

The recent availability of intelligent electronic systems, supporting the automatic detection of cardiac pathologies, represents indeed a very useful way to shorten and make more reliable diagnostic procedures. There are many methods to extract information about pathologies.

The visual analysis of heart beats can give evidence of particular anomalies. Techniques like the Magnetic Resonance Imaging, the Cardiac Computed Tomography or the Echocardiogram allow to give an image of the heart and cardiac valves activities [1]-[6] showing many detailed information on possible symptom of diseases. Though very exhaustive, such techniques require sophisticated, expensive and cumbersome equipment. Therefore, these analyses can be performed in medical facilities only by trained specialist technicians.

Moreover, results are not immediate and therefore these exams do not fit both for domestic and emergency context.

Other techniques [7]-[8] rely on the "electrical characterization" of the heart. The analysis of the electrocardiogram (ECG) signal requires not expensive equipment to be performed and test results are instantaneously available, making such a medical procedure the first choice for screening examinations.

An alternative approach is based on direct auscultation of heart sounds by means of stethoscopes. Phonocardiogram (PCG) requires very affordable equipment and skills common to all physicians. Such a technique is almost cost free and gives immediate results, even though not completely exhaustive. Its main drawback is that diagnoses are based on the experience and abilities of the physician, making the result not objective.

The availability of electronic stethoscopes [9]-[15] opens the way to an automatic analysis of cardiac sounds, which may overcome the limitation of the subjective diagnosis. An effective automated diagnosis can be based upon the extraction of features from the heart sound and upon their correlation to specific pathologies. Several approaches were described in literature.

In [16], combined analyses in the time domain and in the frequency domain are performed by evaluating how the energy distribution of the signal over frequency bands changes in time: pathological sounds can be distinguished from normal sounds. In [17] the authors propose an artificial neural network able to classify some types of murmurs. An analysis based on wavelet decomposition of the signal is proposed in [18]. The choice of a particular mother wavelet allows investigating mitral insufficiency from PCG. A third order statistical analysis is proposed in [19] as useful method to extract information from the acquired heart sounds. An algorithm for the non linear modeling of the cardiovascular apparatus, which generates cardiac sounds, starting from the time series data acquired with PCG is presented in [20]. Model parameters are tuned with an improved genetic algorithm and murmurs can be identified within the heart beat.

The most part of researches are addressed to discriminate only specific pathologies. So, general rules to diagnose anomalies from the sound analysis are not given, as well as

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M. Fanfulla, M. Riva, F. Belloni, D. Della Giustina are with Università degli Studi di Milano, Department of Physics, via Celoria 16, 20133, Milano, Italy (email:riva@unimi.it,federico.belloni@unimi.it,davide.dellagiustina@unimi.it matteo.fanfulla@studenti.unimi.it).

M. Malcangi is with Università degli Studi di Milano – DICo (Informatic and Communication Department), via Comelico 39, 20135, Milano, Italy (email: malcangi@dico.unimi.it)

none objective parameters to support an automatic diagnosis are clearly put into evidence.

This work is focused on the segmentation of cardiac sounds, which is presented as the key point to perform a pathology-independent analysis. This paper presents also some preliminary results on automatic diagnosis of heart diseases. The paper is organized as follows: Section 2 describes main heart sounds and their generation mechanisms; Section 3 discusses the extraction of analytical parameters from the signal and the segmentation algorithm; Section 4 reports some experimental results obtained through software implementing the described procedures.

II. Heart Sound Description

The difficulty to perform an accurate pathology detection based on the PCG is due to complexity of the cardiac signal and to the acoustic phenomena occurring during the heart activity. The following notes do not represent a complete and extended medical discussion about this issue, whose deepening is well beyond the scope of this paper, but they want describe how the sounds are related to their physical causes.

Human heart can be modeled as a four chambers pump with two superior atria that collect blood from veins and two inferior ventricles which pump blood into arteries [21]. Its right side (called right heart) is connected to the pulmonary circuit, while the left side (left heart) is connected to the systemic circuit. Two sets of valves prevent the blood from flowing backwards. They are classified as atria-ventricular valves (atria-ventricular and tricuspid) that regulate the blood flow between atria and ventricles, and semi-lunar valves (aortic and pulmonary) that separate the left heart from the aorta and the pulmonary artery.

Cardiac sounds are generated by a plurality of complex mechanisms. In particular, they include:

- sounds (or tones): short lived burst of vibratory energy caused by contractions of cardiac valves and by the cardiac action potential;
- murmurs: that are caused by turbulences and ebbs of blood through atria and ventricular valves, usually due to inborn or acquired impediments.

More in detail, two more intense sounds are audible in all subjects (Fig. 1). The first tone (S1) is generated by the deceleration of blood due to closure of atria-ventricular valves when ventricular blood pressure exceeds the atria one during heart contraction (systole). S1 has four different components coming one after the other:

- low frequency vibrations originated by muscular contraction of the left ventricle;
- high frequency vibration at the closure of mitral valves (M1);
- high frequency vibration due to tricuspid valve closure (T1);
- a low frequency and low intensity vibration caused by the ejection of blood.

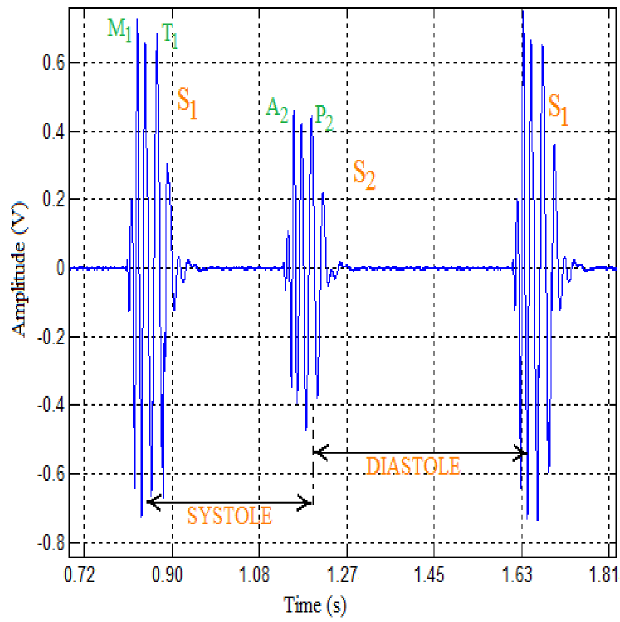

Fig. 1 A normal PCG trace.

The second tone (S2) is generated by the decontraction of the heart (diastole), which closes the semi-lunar valves. S2 is constituted by two components, aortic (A2) and pulmonary (P2), both lasting less than 50 ms and with almost the same frequency content, but different amplitude (due to pressure differences between aorta and pulmonary artery).

An additional tone (S3) is generated if ventricular pressure results lower than the atria during the diastole, so that mitral valve opens causing the rapid flowing of blood from it. S3 is usually considered normal in pre-pubescent and pubescent subjects, while it is considered pathological in adults.

At last, a fourth tone (S4) can be heard at the end of diastole if atria contractions make the blood to flow into relaxed ventricles. This tone is considered pathological.

Blood has a laminar flow through the heart, but some cardiac diseases can cause turbulences with associated vibrations called murmurs. Frequency spectrum of murmurs is usually within the range from 10 Hz to 1500 Hz. They are described and catalogued on the base of their intensity, duration or their placing within the cardiac cycle. Making reference to this last criterion, a common classification differentiates among systolic, diastolic and continuous murmurs. Within each class, there are further and more specific distinctions among murmurs occurring at the beginning, during or at the end of each phase.

III. Methods for Automatic Analysis

A. *Sound Quality Requirements*

The possibility to indentify pathologies depends on the quality of the sound which can be reduced by high levels of external noise. Electronic stethoscopes with high rejection to environmental noise [9]-[15] should be employed to maximize the reliability of diagnoses. Software filtering algorithms can be also applied to further enhance signal to noise ratio.

It is good practice to evaluate sound quality when an electronic stethoscope is employed. A simple procedure consists in analyzing incoming data, isolated in long-time frame of 5-10 seconds, searching for some information. If the stethoscope head is not in contact with the patient body, no sound is detected and so, no analysis is required for this frame. No further examinations are required also when the stethoscope head rubs against the patient's skin for a long time and the subsequent noise masks the signal.

Even short-time spikes (e.g. $1000/f_s$ samples) can reduce the quality of sounds. In this case, the problem can be fixed by pre-processing data with interpolation algorithms.

Some parameters are typically used to investigate the quality of the signal: Root Mean Square (*RMS*), Volume Dynamic Ratio (*VDR*), Zero Crossing Rate (*ZCR*) and Silence Ratio (*SR*). Their expression are reported in (1)-(4), taking into account that $x(n)$ denotes the nth sample of the input data, $w(n)$ is a window of N samples and x_j is the jth frame. Hamming window is a common choice.

$$RMS = \sqrt{\frac{1}{N}\sum_{n=1}^{N} x_j^2(n)} \tag{1}$$

$$VDR = \frac{\max(RMS_j) - \min(RMS_j)}{\max(RMS_j)} \tag{2}$$

$$ZCR = \frac{1}{2N}\sum_{n=2}^{N}\left|\operatorname{sgn}(x_j(n)) - \operatorname{sgn}(x_j(n-1))\right| \tag{3}$$

$$SR = \frac{SF}{J} \tag{4}$$

RMS provides information about the energy of the signal, while *ZCR* gives the rate at which the signal crosses the null value and so it is linked to the energy distribution through frequencies. *SR* is calculated through *SF* that represents the number of frames with root mean square value less than 10% of the *max*(*RMS*). All the conditions above described are reported in Table I.

Table I. low sound quality conditions and solutions.

Source	**Solution**
background noise	HW and SW S/N enhancement
no event/long-time spikes	Ignore time frame
short-time spikes	Interpolation algorithm

B. Signal Segmentation

Segmentation (or end-point detection) of the cardiac audio signal, i.e. the subdivision of the entire signal into single beat periods with the identification of S1 and S2, is the first fundamental step towards the automatic diagnosis of the heart sounds [22]-[24].

Defining a general procedure to perform heart cycle isolation is not a trivial task. In fact, sounds with heterogeneous characteristics have to be faced. Fig. 2 shows some relevant cases: a murmur, a third tone and a tone-masking phenomenon.

S1 and S2 locations are not easy to find, because of the additive noise introduced by pathologies alter the normal sound morphology.

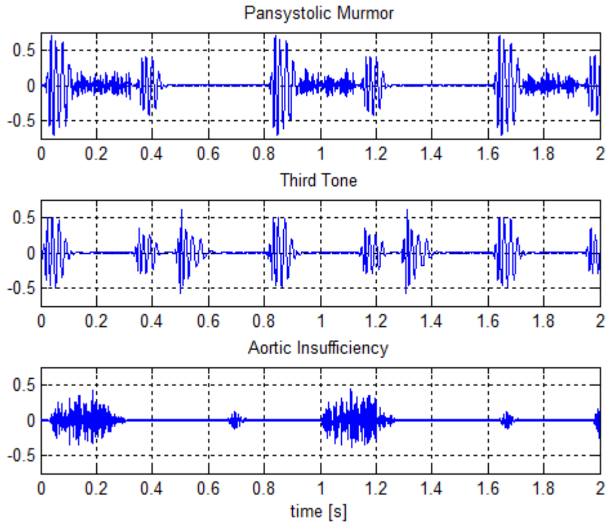

Fig. 2 Three different types of heart pathologies: pan-systolic murmur, third tone, and aortic insufficiency.

Several methods have been proposed to segment normal heart sounds or specific pathology sounds. A peak identification is employed in [25] to tell apart S1/S2 from other peaks and murmurs. Then, period identification is performed counting the occurrences of systole/diastole alternation. The algorithm supposes systolic period to be shorter than diastolic period. [26] adopts a segmentation method based on the multi-band wavelet energy approach. Also this method relies on the same relationship between systolic and diastolic periods as the previous one.

In the presented approach, *RMS* is the basic feature used in signal segmentation. Some authors [27] prefer to employ normalized average Shannon energy, because it enhances the frequency range where normal sounds (S1 and S2) are located. As a general consideration, complex methods require more computational power and are not always deployable on real-time processors. This is also the reason why authors chose to focus on a so simple index.

At first, it is necessary to erase sounds due to anomalies and pathologies, which can mask the actual tones. A sixth order low pass Butterworth filter with poles at 100 Hz is applied to the signal. The effect of the filter applied to signals reported in Fig. 2 is shown in Fig. 3. Pathologies which result in a continuous sound, like patent ductus arteriosus, are already flagged as anomalies during the evaluation of signal quality, since characteristics of their *RMS* are quite similar to those of a persistent rub of the stethoscope head against the patient's body.

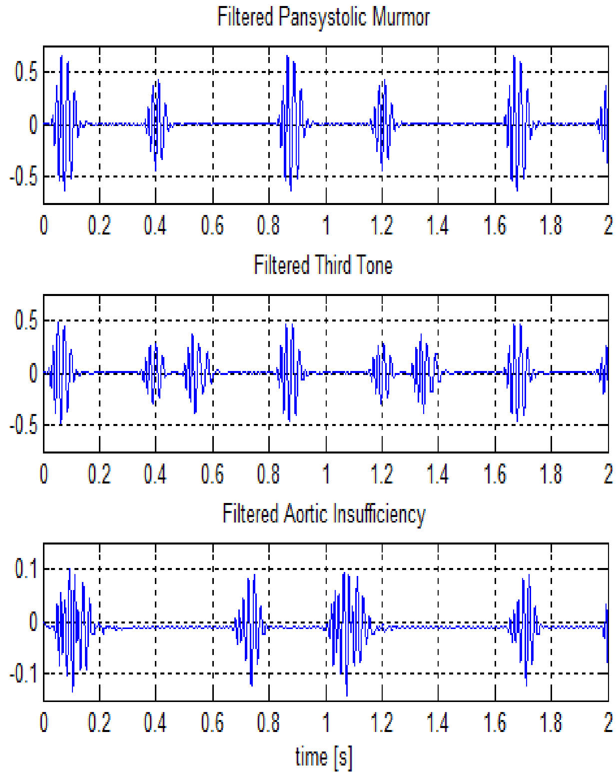

Fig. 33 Pan-systolic murmur, third tone, and aortic insufficiency after filtering.

Then, the algorithm seeks for points of the *RMS* satisfying the condition:

$$RMS > \gamma \cdot \max(RMS) \tag{5}$$

where γ is a pre-fixed threshold. Short time spikes of the original signal have smaller energy if compared to that of actual tones. A right choice of γ allows to reject these contributions.

Time intervals $\Delta T_{i,i+1}$ between two adjacent points over threshold $\gamma \cdot max(RMS)$, are calculated. If the condition:

$$\Delta T_{i,i+1} > \delta \tag{6}$$

is satisfied, both peaks are kept. On the contrary, the smallest one is discarded. This step allows to reject adjacent peaks inherent to the same tone. In (6), δ is a fixed time interval chosen considering that the human heart beat can have frequency in the range 40 beats/min – 200 beats/min.

Once tones are isolated, they can be identified. There are three possible cases:

1. presence of S1 and S2 only
2. presence of S1, S2 and a further tone
3. presence of S1, S2 and two other tones

An algorithm has been designed in order to parse the signal. Fig. 4 shows a flow chart of the segmentation process. For each tern of tones (i, i+1, i+2) the relative distances $\Delta T_{i,i+1}$ and $\Delta T_{i+1,i+2}$ are calculated. In the following, the hypothesis that systolic period is shorter than the diastolic one is assumed [25]-[27].

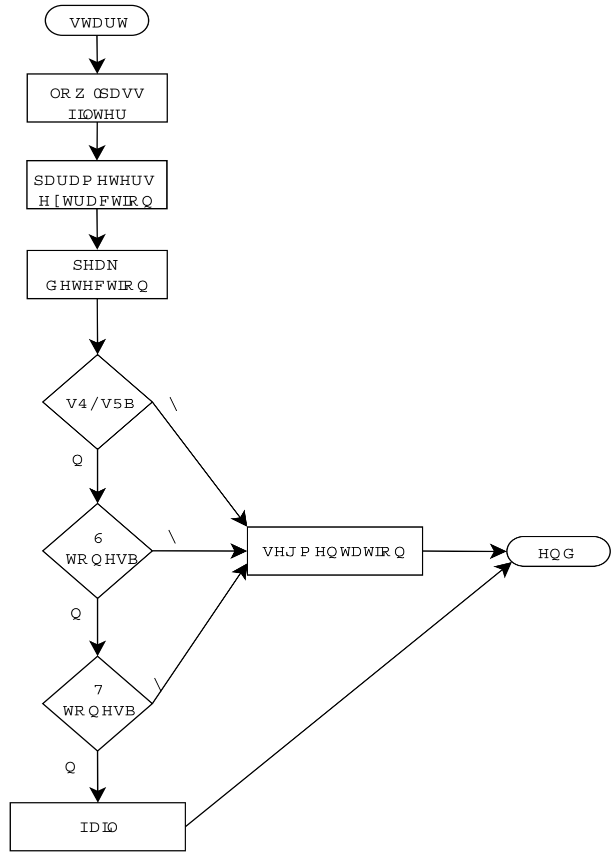

Fig. 4 Flow chart of end-point detection algorithm.

If the condition:

$$\varepsilon \cdot \Delta T_{i,i+1} = \Delta T_{i+1,i+2} \tag{7}$$

with $1 < \varepsilon < 2$ is fulfilled, it means that the tone i is a S1, i+1 is S2 and i+2 is S1, otherwise i is a S2, i+1 is S1 and i+2 is S2. For each i, spanning from 1 to n – 2, where n is the number of peaks, this calculation is performed and results are stored into a matrix $n \times n$ – 2. Matrix elements outside the principal diagonal are set to null value.

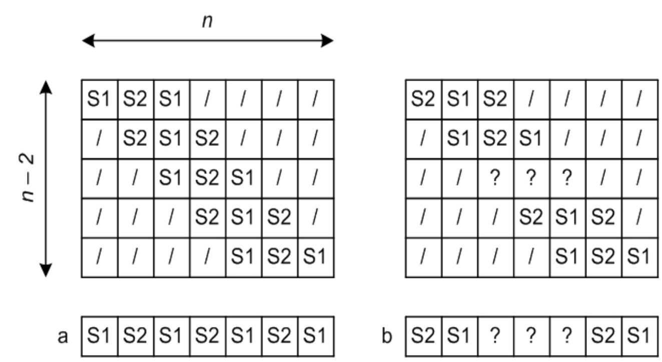

Fig.5 Labeling process applied to a normal sound and to a sound with a third tone.

If each column contains the same values (excluding null values), each peak can be identified properly (Fig. 5a).

Otherwise, if this proportion is not always respected, as in the case of Fig. 5b, it is not possible to label peaks. A more general procedure, involving groups of four peaks have to be adopted in this case.

C. Diagnosis of a Simple Pathology

This paper presents only the automatic detection of murmurs. With this term, authors mean components with lower energy (i.e. *RMS*) and higher frequency (i.e. *ZCR*) than a normal tone, as previously shown in Fig. 2, and located between tones.

Fig. 6 shows an example of cardiac sound with evidence of such a pathology together with its *RMS* and *ZCR*. An algorithm which correlates these parameters to diagnose murmurs was designed and implemented.

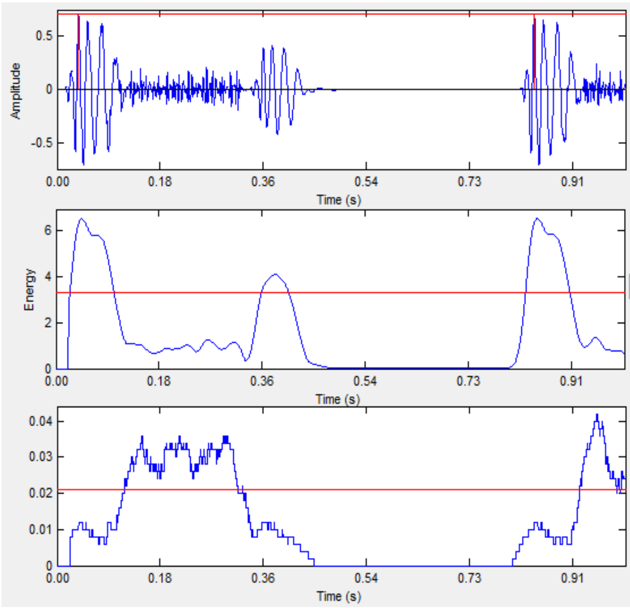

Fig. 6 Cardiac signal with systolic murmur and its associated *RMS* and *ZCR*.

In particular, a portion of the signal is flagged as murmur if:

$$RMS < \varsigma \cdot \max(RMS) \quad (8)$$

$$ZCR > \eta \cdot \max(ZCR) \quad (9)$$

Segmentation allows the simple distinction between systolic and diastolic murmurs. A more complete tool, based on an inferential fuzzy engine, is under development.

IV. Experimental Results

The previously described algorithms are implemented into a software tool, whose graphical interface is shown in Fig. 7. It allows to load files containing cardiac sound acquired with any electronic stethoscope (.wav). The signal is displayed together with the calculated parameters, for a visual comparison. All calculated data can be saved into binary files for further processing.

A set of 48 cardiac signals with different pathologies, chosen among those disposable in [28]-[34], was analyzed and segmented. The success rate in the identification is 89.5%. These tests were performed with: γ= 0.2, δ= 0.15 s, ε= 1.3.

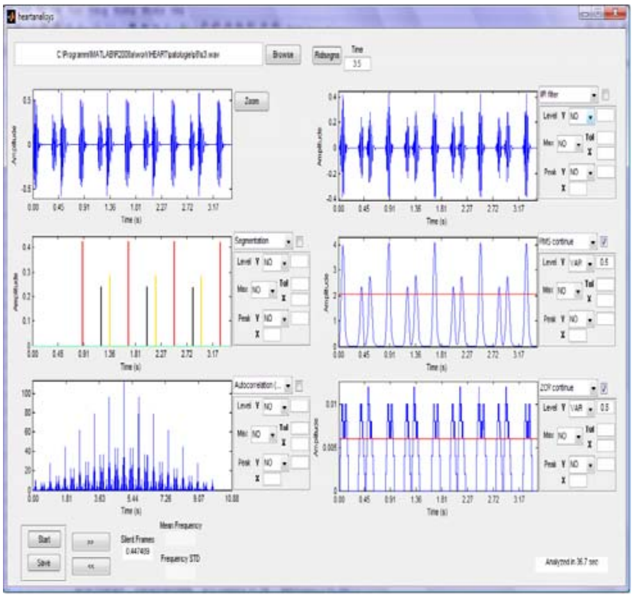

Fig. 7 Main window of the analysis software.

The murmurs diagnosis algorithm was tested as well. In the case the pathology was actually present, its identification rate is 93.3%. In the case there was not any murmur, right diagnosis was reached in the 82.1% of cases. Tests were performed with $\zeta = 0.5$ and $\eta = 0.5$.

V. Methods for Arrhythmias Classification

Arrhythmia is a term that indicates any cardiac rhythm that deviates from normal sinus rhythm.

This disease may be due to a disturbance in impulse formation or conduction but it is not always an irregular heart activity. In fact respiratory sinus arrhythmia is a natural periodic variation corresponding to respiratory activity.

Arrhythmia may occur with premature or retarded beats or a regular sequence of beats at a reduced (bradycardia) or accelerated (tachycardia) frequency. Their impulse formation can be sinus or ectopic (premature beat that is perpetuated in time), the rhythm regular or irregular and the heart rate fast, normal, or slow.

Then the detection of abnormal cardiac rhythms and automatic discrimination from the normal heart activity became an important task for clinical reasons.

A. Time Domain Analysis

One of the advantages of the method proposed in this work is that the simple use of heart rate features can lead to the identification of arrhythmic cardiac recordings and the procedure does not depends on the type of arrhythmia.

One of the most markers of individual's health condition noted by specialists for assessing the heart activity and discrimination of cardiac abnormalities is the Heart Rate Variability (HRV), that represents the automatic activity and its influence on the cardiovascular system. With HRV we refers to the beat-to-beat heart rate alterations that symbolizes the amount of fluctuation around the mean value of the rhythm. Usually the variability of heart rate can be estimated by calculating an index using statistical operations on the RR-intervals, or by spectral analysis on an array of RR-intervals, where RR-intervals are typical values of an ECG analysis (Fig. 8).

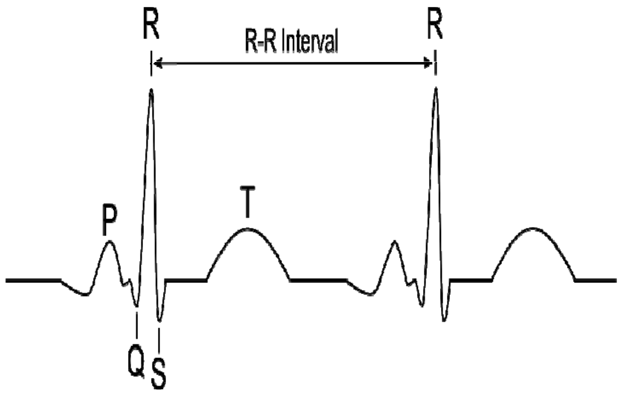

Fig. 8 A sketch of ECG signal.

These values can be used in an investigation based on PCG too. In fact, the ECG heart rate is measured only by observing the duration of time intervals respect R waves (corresponding to ventricular depolarization) subsequent. This distances within the PCG are nothing but various cardiac cycles bounded by adjacent first tones and obtained using the heart sound segmentation algorithm previously described. Therefore we will refer to the various indices calculated with the typical ECG nomenclature.

There are two types of statistical indexes of heart rate variability that can be calculated. The indices beat-to-beat (short-term variability) representing fast variations of heart rate and the indices of long-term variability relative to slower fluctuations. Both these parameters are calculated from RR-intervals that fall in a narrow time window.

Variation in heart rate may be evaluated by various methods. Maybe the simplest to perform are time domain analysis (the type adopted in this work) on the segmented dataset. Time domain analysis results in markers obtained from the tachogram. With these methods both the instantaneous heart rate at any point in time and the differences between successive normal intervals are determined.

From the original RR-intervals standard parameters are calculated:

- Mean of all RR-intervals in each segment.
- The standard deviation of all normal to normal RR-intervals (SDNN), i.e. the square root of variance. This is the simplest feature that can be extracted from the tachogram, however it should be noted that total variance of HRV increases with the length of analyzed recordings. Thus in practice it is inappropriate to compare SDNN measures obtained from recordings of different durations.
- The standard deviation of successive differences between adjacent normal to normal RR-intervals (SDSD).
- The root mean square of successive differences of all normal to normal RR-intervals (RMSSD).
- The percentage of intervals presenting time duration difference between adjacent normal to normal RR-intervals greater than 50 ms (pNN50).

Beyond these, more complex statistical time domain indices could be considered particularly those calculated from a series of cycle intervals recorded over longer periods suggesting the presence of very slow rhythms with a period greater than one hour too.

B. *Fuzzy Inference Model Description*

When a clinical situation is very complicated, i.e. there are many variables and diagnostic rules, the fuzzy approach is particularly useful. It is easy to check and to modify adding or deleting every fuzzy variable for obtain the better automated analysis.

The fuzzy logic approach makes possible to integrate the notion of membership degree, which represents the amount of membership of an object to specific classes. In the fuzzy representation of any real phenomena the transition from one class is not done abruptly at a precise value but smoothly over an interval. The main idea in fuzzy classifiers is the possibility of belonging to more than one class at the same time which is not possible in hard classifiers.

Fig. 9 shows schematic of the fuzzy classifier developed with Fuzzy Inference System (FIS) in Matlab's editor. It is based on Mamdani's method and inputs to the system are the features discussed in previously section.

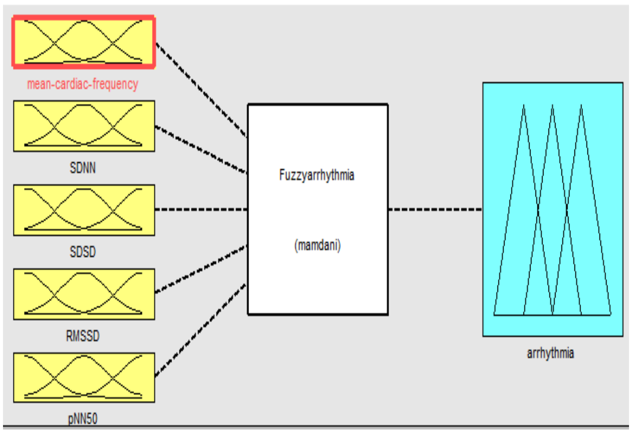

Fig. 9 FIS Editor of the fuzzy model.

For each one, the knowledge of the expert is expressed in natural way using linguistic variables represented by fuzzy sets.

These sets are modeled by a number of membership functions (MF) mapping input space to resulting membership value. Each input feature is represented by linguistic values which distributions are defined by triangular membership functions (Fig. 10). That type of functions has the advantage of making calculations faster but could be adopted more complex functions for better distribution of input values.

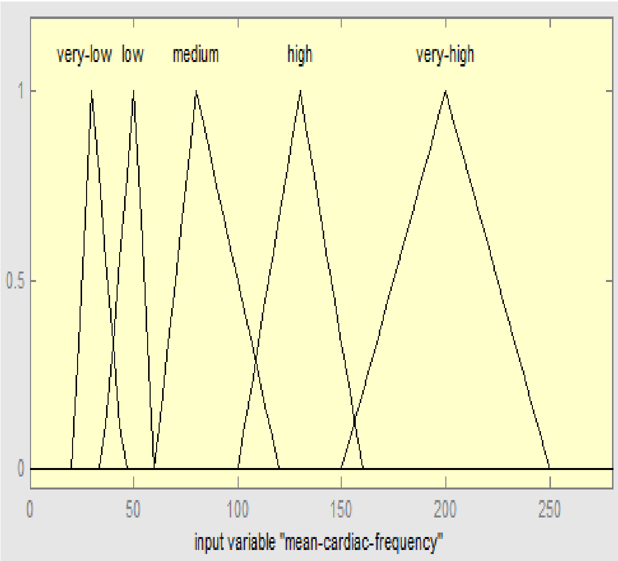

Fig. 10 MF of input variable mean cardiac frequency.

In order to pass arguments to fuzzy system data clustering for all crisp inputs is performed. This is achieved building histograms of the values of each feature for the various arrhythmias considered, so giving clusters of data whose ranges are the input arguments for the membership function curves.

At this point the knowledge base is formed with a set of ''If-Then'' statements called fuzzy rules which performs a combination of different fuzzy sets in order to direct the fuzzy system and through which output is inferred. The defined fuzzy rule base is formed by nine rules and therefore is not complete because with five input features a higher number of combinations that can be made. That does not mean that the model is poorly representative since many feature combinations do not necessarily represent a real case. These rules has been obtained manually with the help of cardiology expert.

Crisp values returned from fuzzy system in defuzzification procedure based on centroid calculation indicate degree of association with the different basic arrhythmias catalogued, that consist on tachycardia and bradycardia with various degree of seriousness and normal rhythm.

Fig. 11 shows trapezoidal shaped membership function used relatively to output.

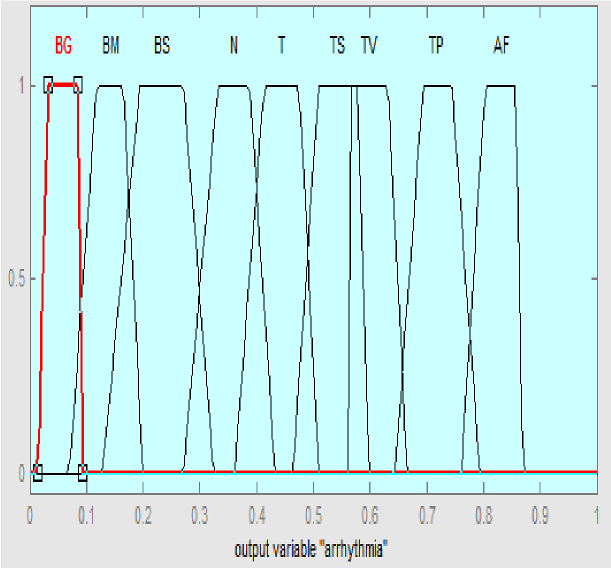

Fig. 11 Output membership function.

VI. Conclusion

A general algorithm for the segmentation of cardiac sounds is presented in the paper. It performs the extraction of features of the signal and allows the identification of heart tones. The segmentation process takes into consideration the root mean square values of the signal and it is based on physiological considerations about the positioning of the different tones within the cardiac cycle. The robustness of the algorithm versus possible short-time spikes and high frequency noises and sounds has been verified. A method for the diagnosis of murmurs has been implemented and experimental results confirm the pertinence of the proposed methods.

The information provided by the end-point detection algorithm successively used to feed an inferential fuzzy system addressed to arrhythmias detection and classification.

Mainly difficulty during design was due to the intuitive nature of the human way of thinking which cannot be easily transformed in a numerical method. Besides, the available amount of data was not large enough to allow the use of automated techniques for computing the membership functions as well as the selection of a combination of fuzzy rules yielding the best classification results. Consequently we relied only on the knowledge of the cardiologist to build the fuzzy model. As a future improvement, tuning of the membership function is likely to better the system performances.

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Federico Belloni received his M.S. degree in Physics in 2003 and Ph.D. in Applied Physics in 2006 from the Università degli Studi di Milano, Italy.

He is currently working as researcher at the Department of Physics in the same University. His areas of research include design, modelling and control of power electronics circuits for space application and distributed power and digital signal processing.

Dr. Federico Belloni is author of technical papers on magazines and conference proceedings. He holds two patents.

Davide Della Giustina received his M.S. degree in Physics in 2007 from the Università degli Studi di Milano, Italy.

He is currently a Ph.D student at the Department of Physics in the same University. His areas of research include the application of discrete time system to control power electronics circuits, and digital electronics for signal processing.

Dr. Della Giustina is a member of AEIT (Italian Association of Electrical Engineer).

Marco Riva received his M.S. degree in electrical engineering and Ph.D. from the Polytechnic of Milan, Italy, in 1994 and 1997 respectively.

He joined the Power Electronics and Electrical Drives Laboratory of the Department of Electrical Engineering in the same University, from 1994 to 1997. In 1998, he joined the Electronic Laboratory of the Università degli Studi di Milano, Department of Physics, as Assistant Professor. His research activity, technical publications and patents are addressed in the field of electronic converters analysis, control optimization and biomedical signal processing.

Dr. Riva is Councillor of AEIT (Italian Association of Electrical Engineer) and member of the IEEE Power Electronics and Industrial Electronics companies, the ANIPLA (Italian Association for Automation) and of the Italian Technical Committee (CEI) for standards in Power Electronics.

Prof. Mario Malcangi received his undergraduate and graduate degrees in Electronic Engineering and Computer Science from the Politecnico di Milano in 1981. He is member of the International Neural Network Society and among the founders of the Engineering Applications of Neural Networks Special Interest Group (SIG). His research is in the areas of multimedia communications, digital signal processing, and embedded/real-time systems. His research efforts are mainly targeted at speech- and audio-information processing, with special attention to applying soft-computing methodologies (neural networks and fuzzy logic) to speech synthesis, speech recognition, and speaker identification for implementation on deeply embedded systems. He teaches digital signal processing and digital audio processing at the Università degli Studi di Milano. He has published several papers on topics in digital audio and speech processing.

Matteo Fanfulla received his B.S degree in Physics in 2007 from the Università degli Studi di Milano, Italy.

He is currently a M.S. student at the department of Physics in the same University. His initial activity concerned in software tool design in support to power electronics applications. Nowadays his areas of research include signal processing for biomedical applications and is also interested in computer science, particularly fuzzy logic modeling.