Hard and soft computing methods for capturing and processing phonocardiogram

M. Malcangi, M. Riva, and K. Ouazzane

Abstract— Cardiovascular diseases are the biggest cause of deaths worldwide. Heart auscultation based on stethoscope is a noninvasive and a very low cost investigation approach that physician uses to evaluate diseases. To improve auscultation and diagnosis capabilities, a digital stethoscope and a set of digital audio signal processing algorithms have been developed to process adaptively sounds acquired from a couple of microphones embedded in the stethoscope head. Hard computing methods have been applied to the captured digital audio signal to detect cardiovascular diseases. Soft computing inference, such as fuzzy logic, is then proposed to reduce the computational burden of the automatic diseases identification process and to extend the method to the automatic detection of the physiological status of the subject. Finally multimodality and data fusion have been evaluated as methods to improve the diagnostic and identification of the system's capability.

Keywords— Noise cancellation, Automatic diagnosis, Cardiac diseases, Fuzzy classification, Phonocardiogram.

I. Introduction

Healthcare became more and more important in the last years due to economic impact that, mainly cardiovascular diseases, produce on the public medical care system. Early detection of incoming diseases is the best approach to prevent them. Physicians are able to execute a valid prevention of cardiovascular diseases by means of auscultation and interpretation of heart sounds. These capabilities are very effective for a huge number of cardiovascular diseases, and not exhaustive.

Electronic systems can improve the ability of the physician in the detection of cardiac pathologies and shorten the diagnostic procedures. Digitalization of the signals that heart activity generates enables a huge extension of the subjective abilities of the physician to an early detection of an incoming cardiovascular disease.

Many methods have been investigated to extract information from heart activity in order to diagnose cardiovascular pathologies. Some of these are invasive and require very expensive devices while other methods are noninvasive and cheap.

The visual analysis of cardiac cycle is effective but expensive. The Magnetic Resonance Imaging, the Cardiac Computed Tomography or the Echocardiogram give an image representation of the whole heart activities [1]-[6]. The devices required to carry out such measurements are complex and require expert physicians to operate with.

Electrocardiogram (ECG) signal acquisition and processing [7]-[8] is not expensive and it is only partially invasive. The results are immediate and the cost is very limited compared to the visual analysis.

Phonocardiogram (PCG) is an alternative to ECG that offers almost equivalent diagnostic capabilities at a very low cost. The basic diagnostic device is the stethoscope, an instrument that every physician owns. The skills of the physician play a key role for a successful diagnosis. Only heart sounds are captured and amplified to the physician' s hearing level, but no information is extracted from such sounds. All the diagnostic capabilities rely mainly on the physician's skills and their nature is linguistic rather than crisp.

The recent development of electronic stethoscopes [9]-[15] has enabled audio signal recording and processing of the heart and the pulmonary sounds. These new capabilities open a huge spectrum of diagnostic possibilities and potentially overcome the limitations due to the subjective nature of PCG-based diagnosis: automatic and/or assisted diagnosis can be more effective than any other methods and overcome the limitations of the physician's skills.

A key issue to build up a PCG-based automated diagnosis system concerns the acquisition of the heart sound signal and the extraction of an optimal set of features from it. To perform this task the correlation of the audio features to pathologies needs to be achieved. Several relevant approaches are highlighted in the literature, [16]-[20].

The difficulty to perform accurate pathology detection based on the PCG is due to the complexity of the cardiac signal and the acoustic context in which such information occur. Human's heart is like a four chambers pump. The two upper chambers (i.e. atrias) collect blood from veins and the two lower ventricles pump blood into arteries. Two sets of valves prevent the blood from flowing backwards (atria-ventricular/tricuspid and semi-lunar). There are two types of Cardiac sounds:

- sounds (or tones): short lived burst of vibratory energy;
- murmurs: turbulences and ebbs of blood through atria and ventricular valves.

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Sounds are generated by contractions of cardiac valves and by potential cardiac action . Murmurs are caused by defect at birth or acquired impediments.
Two primary sounds, named S1 and S2, are audible in all subjects (Fig. 1). The first (S1) is generated by the deceleration of blood during heart contraction (systole). It is a complex sound which consists of four distinct components:

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

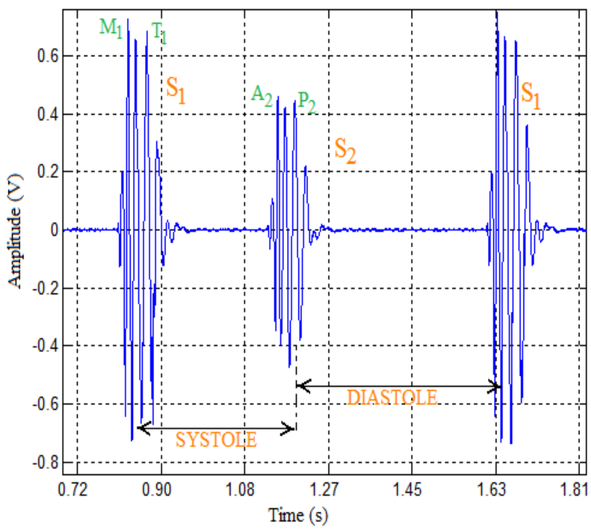

Fig. 1 S1 and S2 tones in the PCG trace of a normal subject.

The second tone (S2) is generated by the decontraction of the heart (diastole). It is a complex sound that consists of two components namely the aortic (A2) sound and the pulmonary (P2) sound. The time delay between these two sounds is less than 50 ms. A2 and P2 have the same frequency content but differ in amplitude. A third tone (S3) is generated when the ventricular pressure is lower than the atria pressure during the diastole. A fourth tone (S4) is generated at the end of diastole when atria contractions make the blood to flow into relaxed ventricles. S1 and S2 are normal tones whereas S3 and S4 are pathologic tones.
Murmurs are classified as:

- systolic
- diastolic
- continuous

These are described in terms of intensity, duration, and placement in the cardiac cycle. Each class includes a deeper classification level related to the time when they occur. Murmurs are sounds due to turbulences that modify the normal (laminar) flow of the blood that occurs when some cardiac diseases affect the subject. Such kind of sounds is like vibrations with frequency spectrum in the range 10 to 1500 Hz.

Cardiac sound frequencies are audible and they range from 20 to 1000 Hz. These frequencies are audible but the background noise and audio artifacts limit the intelligibility. Then, background noise reduction is very important for the development of a reliable cardiac sounds recording.

II. Methods

To develop a system for capturing and processing phonocardiogram signal targeted to the automatic diagnosis of cardiovascular diseases and/or to support the physician in the auscultation activity, a number of tasks need to be carried out, which are;:

- cardiac sounds capturing and noise reduction
- automatic signal quality estimation
- automatic audio feature extraction and processing
- automatic pathologies diagnosis by inference

The frequency range of the cardiac signal is limited below 1 kHz [11] as shown in Fig. 2. In this frequency range, adaptive methods for noise reduction can be very effective.

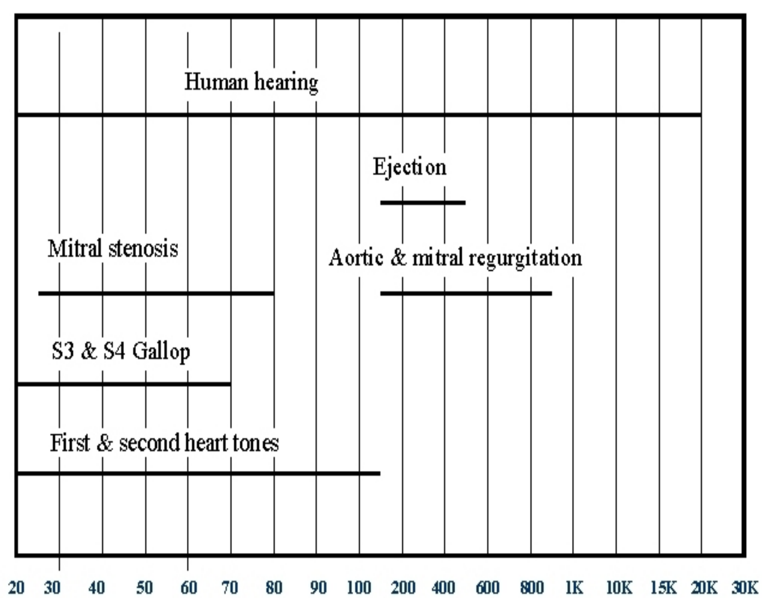

Fig. 2

Fig. 2 Frequency range of the main cardiac sounds are all under 1 kHz: S1 and S2 are under 100 Hz, very close to low frequency audibility threshold.

A. *Cardiac sound capture and noise reduction*

The captured sound in the acoustic sensor in the head of a traditional stethoscope is a combination of the heart sound and the noise convolved by the band-pass filtering action of the head. The signal processing model (Fig. 3) of this process is

$$y = x_h \times h_b + x_n \times h_b, \quad (1)$$

where,

x_h is the heart sound signal,
x_n is the noise
h_b is the impulse response of the band-pass filter.

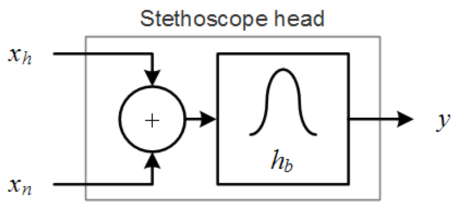

Fig. 3 Signal and noise add and convolution in the head of a traditional stethoscope.

The simpler filtering solutions would work if most part of the energy of the background noise is associated with high frequencies. Optimum filtering techniques must be considered (Fig. 4).

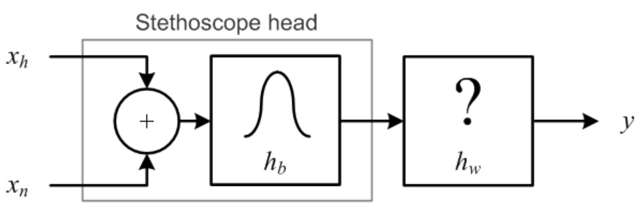

Fig. 4 Filtering scheme for noise reduction at stethoscope head level.

These algorithms move the noise reduction problem to a dynamic identification problem, but methods like standard Wiener filtering technique [12] which is based on a single-channel acquisition are not applicable here as the noise reduction is strictly linked with a signal distortion that makes the traditional diagnosis impossible. If h_w is the impulse response of the optimum Wiener filter, the output signal is $y = h_w \times (x_h + x_n) \times h_b$. This differs from the expected signal $x_h \times h_b$. The distortions could be reduced using a multiple-channel algorithm [13], but in both, single and multiple channels' cases, the noise has to be estimated in the operative conditions, i.e. when the stethoscope head is applied on the patient's body, without detecting the heart beat. As this condition cannot be satisfied, standard and multi-channel Wiener filtering methods cannot be successfully applied.

The approach proposed in [30] uses a stethoscope head equipped with two small pipes. The first pipe directly connects to the stethoscope head, the second is just beside, as shown in Fig. 5.

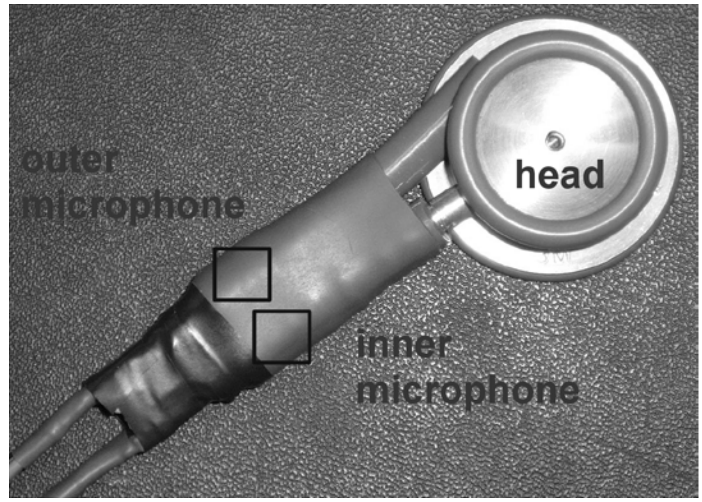

Fig. 5 Double microphones modified head stethoscope.

A microphone has been integrated at the end of each of the two pipes close to the stethoscope head, an inner one to sense sound and the outer one to sense noise (the audio level of the heart sound is considered negligible outside the head). This microphones placement does not allow the application of the direct difference filtering model (Fig. 6); the noise is not exactly the same at both microphone ends, due to head and to the interaction with the patient's body.

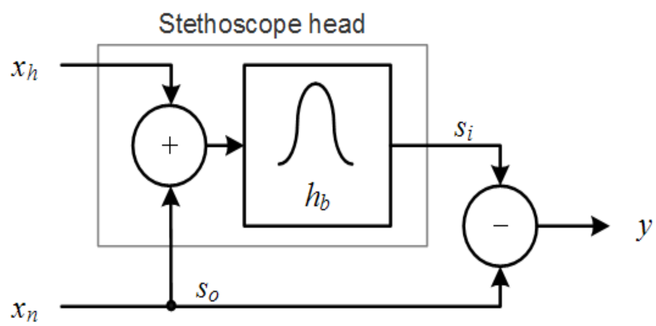

Fig. 6 Direct difference method for noise reduction.

Physical system response h_{wd} (Fig. 7) needs to be estimated, considering that its time-variant dynamics depends on:

- type of stethoscope head
- patient's build and posture
- position and pressure of the head over the patient's body
- possible presence of clothes

Adaptive filtering is then needed to perform optimal noise reduction to capture noise free audio signal at stethoscope head level. The filtering model needs to minimize the equation:

$$\mathrm{E}(h_{wd}) := \left\| s_i - s_o \times h_{wd} \right\|^2 \qquad (2)$$

Where,

s_i is the signal from the inner microphone,
s_o is the signal from the outer microphone.

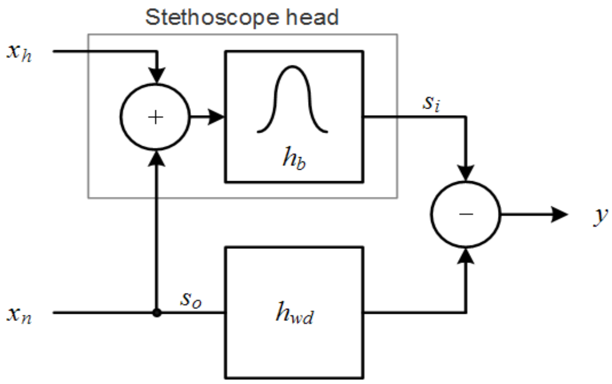

Fig. 7 Weighted difference method.

The discrete form of (2) is as follow:

$$\mathrm{E}(h_{wd}) = \sum_{k=1}^{m} \left[s_i(k) - \sum_j s_o(k-j) h_{wd}(j) \right]^2 + \sum_{k=1}^{n} a(k) h_{wd}^2(k) \qquad (3)$$

$$a(k) > 0, \text{ for all } k$$

where,

n is the number of coefficients of the filter,
m is the number of the processed incoming samples.

The minimum of (3) is unique and is the solution of the linear system $h_{wd} \cdot A = B$ where;

$$A_{ij} := \sum_{k=1}^{m} s_o(k-j) s_o(k-i) + a(i)\delta(j-i) \qquad (4)$$

$$B_{1i} = \sum_{k=1}^{m} s_i(k) s_o(k-i)$$

for $i, j = [1, n]$

After the transfer function h_{wd} is estimated, the noise reduction could be effectively executed with the processing model of Fig. 7.

B. Audiosignal quality evaluation

Audio noise reduction at stethoscope head level is a necessary step but not sufficient to ensure that the audio signal quality is good enough to accomplish optimally the feature extraction process. The ability to identify automatically the cardio vascular pathologies evaluating the phonocardiogram depends on the quality of the sound. Such ability can be significantly reduced by high levels of external noise [9]-[15].

The proposed procedure to evaluate the signal quality consists of long-term signal analysis; 5-10 seconds windowed segments of the audio signal coming from stethoscope head are processed to extract the following features:

Root Mean Square (*RMS*)

$$RMS = \sqrt{\frac{1}{N} \sum_{n=1}^{N} x_j^2(n)} \qquad (5)$$

Volume Dynamic Ratio (*VDR*)

$$VDR = \frac{\max(RMS_j) - \min(RMS_j)}{\max(RMS_j)} \qquad (6)$$

Zero Crossing Rate (*ZCR*)

$$ZCR = \frac{1}{2N} \sum_{n=2}^{N} \left| \mathrm{sgn}\left(x_j(n)\right) - \mathrm{sgn}\left(x_j(n-1)\right) \right| \qquad (7)$$

Silence Ratio (*SR*)

$$SR = \frac{SF}{J} \qquad (8)$$

Where,

$x(n)$ is the nth sample of the input data;
$w(n)$ is a window of N samples;
x_j is the jth frame;
SF is the number of silent frames.

RMS provides information about the energy of the signal, Hence it is a reliable indicator of valid amplitude levels; *ZCR* gives the rate at which the signal crosses the null value and therefore it is an indirect indicator of energy distribution through frequencies; *SR* is calculated through *SF* that is the number of frames with root mean square value less than 10% of the *max* (*RMS*).

More features can concur to signal quality evaluation such as stethoscope head off the patient body, head rubbing against the patient's skin, and short-time spikes (e.g. $1000/f_s$ samples).

A frame-by-frame sound quality evaluation has been implemented by a simple fuzzy logic inference engine in order to avoid wrong diagnosis.

C. End-pointing the cardiac cycle

Sound captured and conditioned by the digital stethoscope is a continuous audio stream in which the cardiac sound cycles repeat in a continuous mode. The single period has to be isolated so that the processing and analyzing actions (the beat periods that embed normal tones, their time occurrence and the presence of pathological tones) could be executed correctly. In order to identify the single cardiac beat, end-pointing detecting techniques are applied [21]-[24].

End-pointing the cardiac cycle is relatively simple for a normal subject, but this process becomes very complex for pathological subjects due to extra sounds such as murmur, third tone, and other sounds caused by pathologies mask S1 and S2, which are the two main sound's components that characterize the cardiac sound cycle. Fig. 8 shows some of these masking sounds.

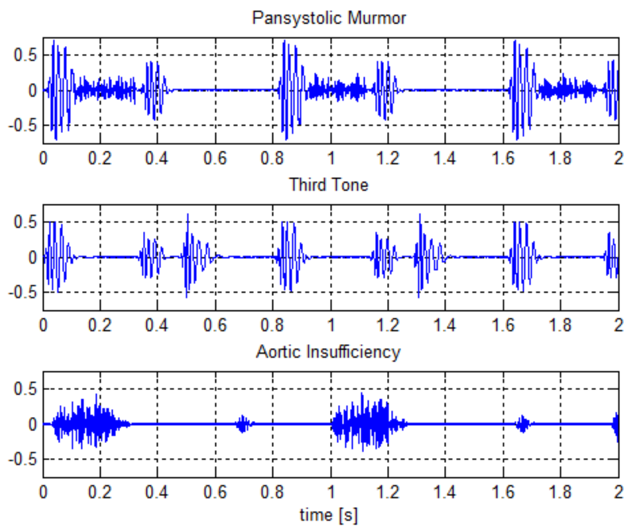

Fig. 8 Three different types of heart pathologies: pan-systolic murmur, third tone, and aortic insufficiency.

Several methods have been proposed for end-pointing cardiac cycles embedded in a continuous audio stream captured by the digital stethoscope. Peak identification is proposed in [25] and segmentation based on the multi-band wavelet energy is presented in [26]. In [15] *RMS* feature is the basic feature used in cardiac audio signal end-pointing. A further improvement of end-point detection algorithm can be achieved [27].

The method based on RMS feature [15] first proceeds to erase sounds generated by anomalies and pathologies. The audio stream is processed by a sixth order low pass Butterworth filter (poles located at 100 Hz). The effect of the filter applied to signals reported in Fig 8 is shown in Fig. 9.

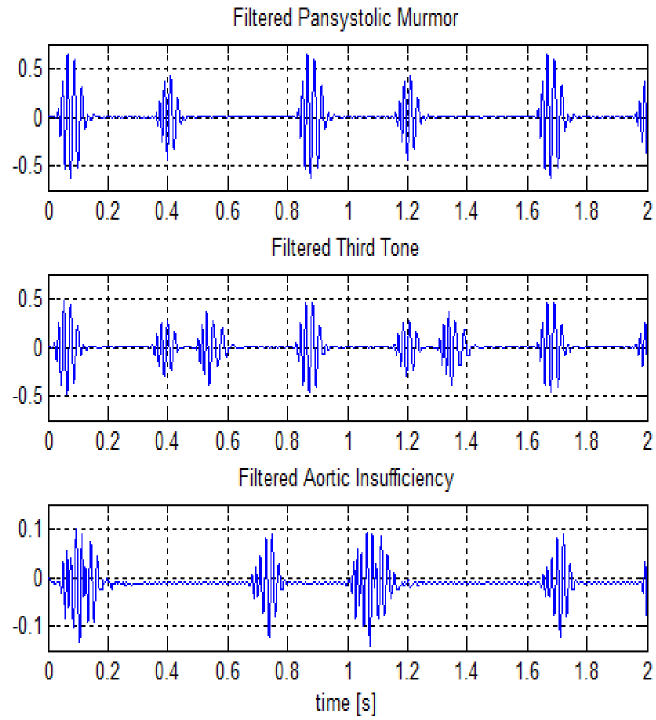

Fig. 9 Pan-systolic murmur, third tone, and aortic insufficiency after filtering.

Then, the algorithm seeks frame-by-frame for *RMSs* satisfying the condition;

$$RMS > \gamma \cdot \max(RMS) \quad (9)$$

where γ is a pre-fixed threshold. A right choice of γ allows rejection of short time spikes.

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

$$\Delta T_{i,i+1} > \delta \quad (10)$$

is satisfied, both peaks are identified, however only the one with a biggest peak is retained.

δ is a fixed time interval chosen considering that heart beat has its frequency in the range 40 beats/min – 200 beats/min.

Once heart sound cycle has been end-pointed the following combination of tones can occur:

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

Fig. 10 shows an example of cardiac sound with evidence of such pathology together with its *RMS* and *ZCR*. An algorithm which correlates these parameters to diagnose murmurs has been designed and implemented [15].

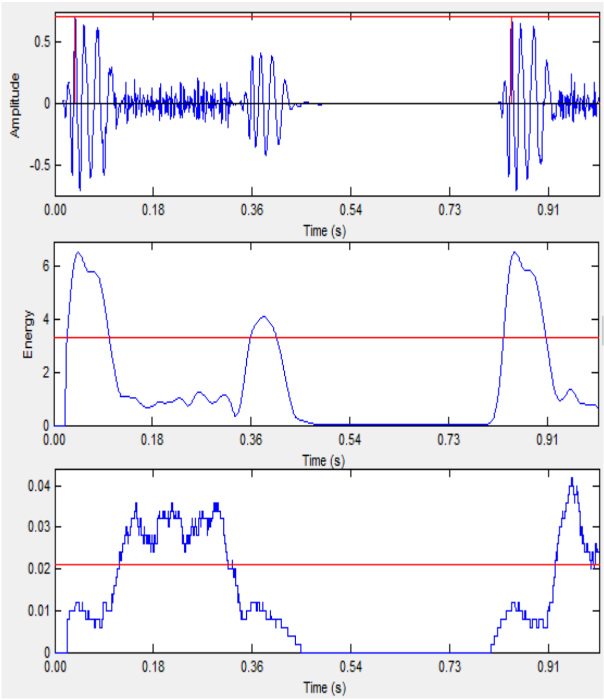

Fig. 10 Cardiac signal with systolic murmur and its associated *RMS* and *ZCR*.

To successfully execute the end-point process, only S1 and S2 tones needs to be visible. All other tones must be cancelled (reduced) as these could significantly mask the cardiac cycle marking tones S1 and S2. Such extra tones and sounds need to be flagged and removed.

As an example, a portion of the signal can be flagged as murmur if:

$$RMS < \varsigma \cdot \max(RMS) \quad (11)$$

$$ZCR > \eta \cdot \max(ZCR) \quad (12)$$

III. Results

All the above signal processing and identification processes have been implemented into an integrated development environment (IDE), whose graphical user interface (GUI) is shown in Fig. 11 [15]. Such environment allows to load files containing cardiac sound acquired with any electronic stethoscope (.wav), to display the audio stream and its feature computed after the end-point process has successfully isolated the cardiac cycles.

To test and validate the procedure, a set of 48 cardiac signals with different pathologies [28]-[34] have been processed with a success rate of 89.5%. The tests have been performed with: $\gamma = 0.2$, $\delta = 0.15$ s, $\varepsilon = 1.3$.

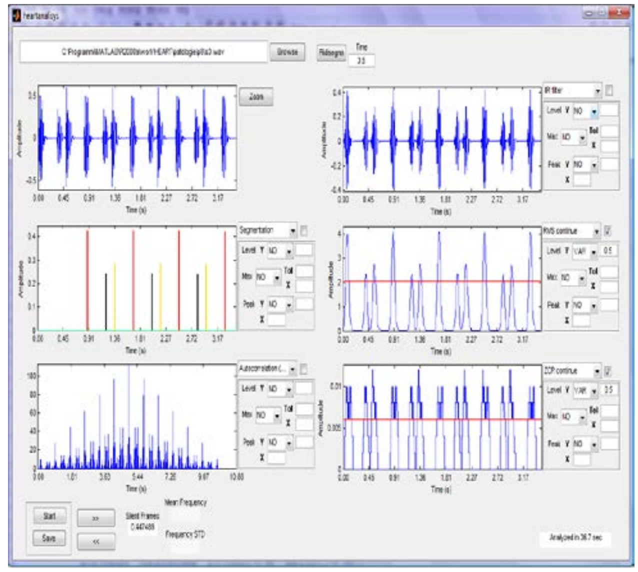

Fig. 11 Main window of the analysis software.

The diagnosis algorithm applied to murmurs has been tested. In the cases where the above pathology is present its identification rate is 93.3%. Tests were performed with $\zeta = 0.5$ and $\eta = 0.5$.

IV. Discussion

Modern signal processing techniques enable powerful diagnosis based on cardiac activity. PCG and ECG embed a huge number of audio and bioelectric features that are typically extracted from the signals. This expanded set of features allows physicians to diagnose various pathologies, but they are too complex to manage manually. Methods for feature representation and evaluation are necessary for supporting medical diagnosis.

The phonocardiogram audio signal contains useful information about the condition of the heart, but physicians need to look at other signals to detect subtle details which are too difficult to evaluate by means of PNG alone. Multimodality and data fusion is a novel approach applied to the process of automatic detection of diseases. Phonocardiogram and electrocardiogram data needs can be captured separately by different modes (audio and electric) and evaluated jointly for achieving improved diagnosis.

Computer based analysis of bioelectric heterogeneous information needs the application of an efficient data fusion approach [35]-[36]. Data fusion is an important methodology to correlate data from multiple sources and to infer about a possible disease or a physiological state of a subject. Fuzzy logic based data fusion is an optimal approach as it enables the emulation of the physician's experience in evaluating multiple and heterogenic information in his diagnosis' action.

Tuning of a fuzzy logic engine is proposed (Fig. 12) to make inferences considering heart rate variability (HRV) from data coming from multiple bioelectric subsystems, the phonocardiogram and electrocardiogram. HRV is a physiological phenomenon that consists of the variability of intervals in the beat rate [37]. It reflects the activity of the autonomic nervous system (ANS), so physicians can make an assessment for the cardiac health, trying to prevent cardiovascular diseases.

The fuzzy engine makes epoch-by-epoch (20 or 60 seconds per epoch) inferences on HRV extracted from ECG and audio features extracted from PCG to evaluate the stress level in a subject.

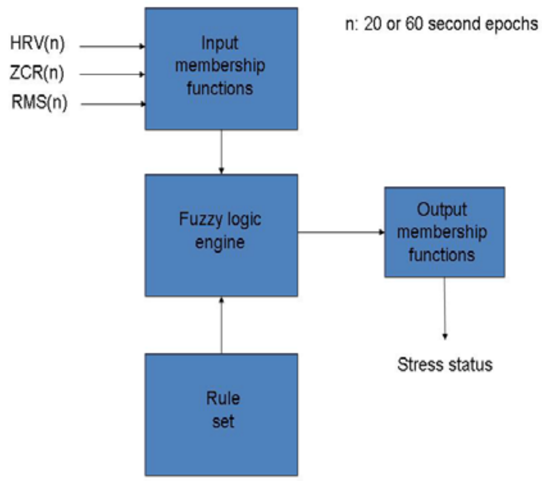

Fig. 12 Fuzzy-logic decision engine to decide about the behavioural state (stress level) of a subject from data detected by PCG and ECG subsystems.

To fuzzify such features, membership functions are modeled based on the distribution of crisp features. Inferring rules are defined and tuned manually and look like these:

…
if HRV(n) is Low and
ZCR(n) is Medium Low and
RMS(n) is Medium Low
then the epoch is RELAXED
…
if HRV(n) is High and
ZCR(n) is High and
RMS(n) is Medium
then the epoch is EXCITED
…

These rules are the strongest in determining the output, but more variants are in the rule set to recover some occurred false detections due to noise and artifacts. The output of the fuzzy logic-based subject physiological status consists of singleton membership functions. "Center of gravity" algorithm is applied to defuzzify the final decision.

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