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Automatic Heart Sounds Segmentation based on the Correlation Coefficients Matrix for Similar Cardiac Cycles Identification

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***Abstract*— This paper proposes a novel automatic heart sounds segmentation method for deployment in heart valve defect diagnosis. The method is based on the correlation coefficients matrix, calculated between all the heart cycles for similarity identification. Firstly, fundamental heart sounds (S1 and S2) in the presence of extra gallop sounds such as S3 and/or S4 and murmurs are localized with more accuracy. Secondly, two similarity-based filtering approaches (using time and time-frequency domains, respectively) for correlated heart cycles identification are proposed and evaluated in the context of professional clinical auscultated heart sounds of adult patients. Results show the superiority of the novel time-frequency method proposed here particularly in the presence of extra gallop sounds.**

***Index Terms*—Heart sounds, automatic auscultation, heart cycle**

1. Introduction

Heart Sounds can be recorded and represented as Phonocardiogram signals for possible automatic auscultation, particularly in primary health care. Their segmentation is still a challenging phase before the interpretation and objective diagnosis. Phonocardiogram interpretation is mostly based on the envelogram calculated using the Shannon Energy [1, 2, 3, 4], because it emphasizes the medium intensity signals and attenuates the high and low intensities signals. This tends to make medium and high intensity signals nearly similar in amplitude. This in turn makes the PhonoCardioGram (PCG) easier for visual localization of the Fundamental Heart Sounds (the first and the second heart sounds, S1/S2, or Fundamental Heart Sounds, FHS) and murmurs detection and classification. However, in some cases, the Shannon energy envelogram may display high amplitudes of extra sounds known as gallops, such as S3 and S4. These may lead to confusion with the peaks of the FHSs.

This paper addresses the problem of accurate automatic segmentation of the FHSs from a phonocardiogram signal for real-time applications, without the use of a reference signal such as an Electrocardiogram (ECG). The main contributions of this work are:

- Firstly, a novel automatic segmentation method of heart sounds is proposed. In this method the extra heart sounds, such as S3, S4 and murmurs are filtered prior to the envelogram calculation and an adaptive threshold is used for accurate boundaries localization of the FHSs.
- Secondly, a new method in time-frequency domain for the identification of similar cardiac cycles is proposed and compared to the standard time domain method. It computes the Short-Time Fourier Transform (STFT) for every heart period that got segmented in the first step, then compute the correlation coefficients matrix between all the heart periods. The identification of a highly correlated set of cardiac cycles (periods) which includes a reference period can be used for further analysis and diagnosis.

The paper is organized as follows: Section 2 describes the proposed segmentation process for accurate FHS boundaries localization from PCGs. In Section 3 two methods are proposed for similar heart cycle identification, in the time and time-frequency domains. Both methods use a-priori a synchronisation process of heart cycles before the calculation of the correlation coefficient matrix between them. The second method uses the Short Time Fourier Transform (STFT) to compute feature vectors which are used for the correlation coefficient matrix calculation. Results and discussion are given in Section 4 and Section 5 concludes the paper.

2. Segmentation of Heart Sounds

Segmentation aims to determine the boundaries of cardiac cycles from contiguous heart sound signals. This makes it the subject of many studies since it is considered as the most difficult step in heart sounds analysis due to interferences from murmurs, extra peaks and noises. Most approaches are based on the envelogram analysis for FHS, S1 and S2 sounds localization [5, 6, 7]. These approaches calculate the energy envelope of the original heart sound signal and use a threshold value (THV) to detect peaks of the envelope signal. Following this step, localization is done for which peaks correspond to S1 or S2. One cardiac cycle is composed of S1, S2, systole (the silence between S1 and S2) and diastole (the silence between the end of S2 and the start of the next S1).

The peaks are defined as segments of an envelope situated between two consecutive threshold crossings which localize the start and the end of the FHS sounds. Their locations are marked at the highest point of the segment.

Based on the assumption that the systolic phase duration is shorter than that of the diastolic phase [8], the interval between two peaks allows the association of each peak with its corresponding sound (S1 or S2). The heart cycle (period) can

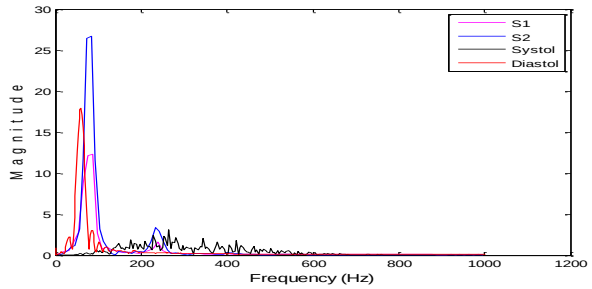

Fig. 1: Spectrum of a PCG period components S1, S2, diastole including S4 and systolic murmur

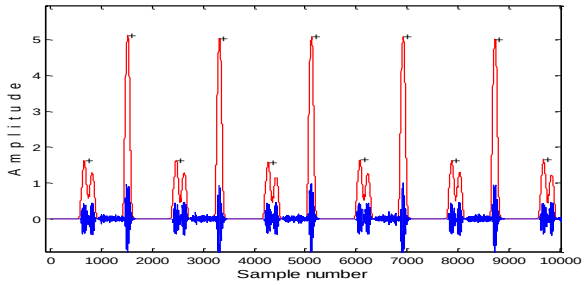

Fig. 2: Energy envelope (red) and PCG(blue) including S4 and systolic murmur before FHS filter .

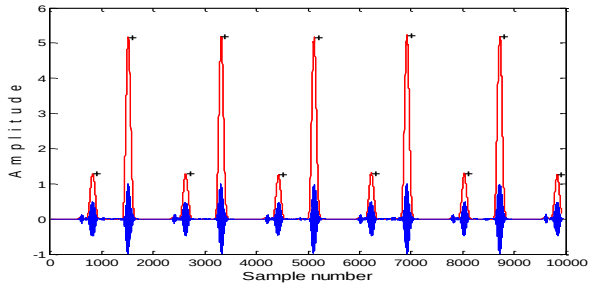

Fig. 3: Energy envelope (red) and PCG (blue) including S4 and systolic murmur after FHS filter.

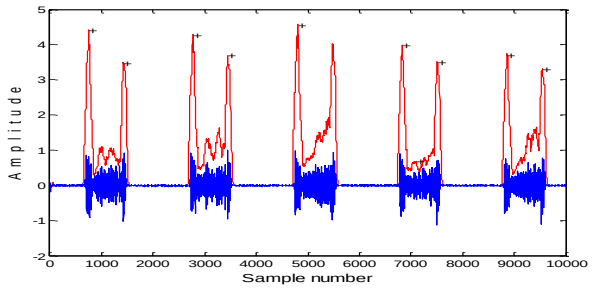

Fig. 4: Energy envelope (red) of Mitral regurgitation PCG (blue) before FHS filter.

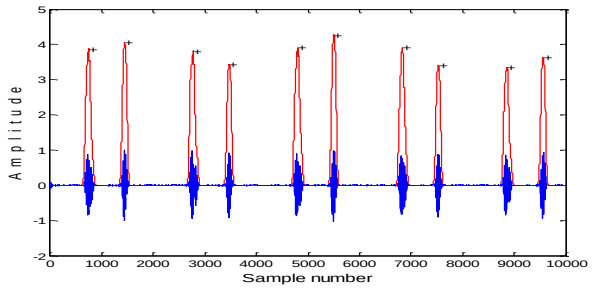

Fig. Enery envelope (red) of Mitral regurgitation PCG (blue) after FHS f ilter

be defined as the interval between the two beginning points of two consecutive S1 sounds.

In the case of an abnormal PCG including extra sounds such as S3, S4 and murmurs, other peaks appear in the envelope, leading to a false classification of FHSs. It is clear that there is no way to complete the cardiac sound analysis until the right THV is achieved.

In order to remove the unwanted peaks, as a pre-processing stage for segmentation, some approaches have used peak conditioning [9, 10]. These methods consist in analyzing the peaks parameters such as peak width, peak start point, peak end point and interval between peaks, then rejecting the Peaks which do not correspond to the FHSs. Another method [2] uses the Discrete Wavelet Transform (DWT) for heart sound signal decomposition. This method uses db6 wavelet with 5 levels, and according to the characteristics of the frequency spectrum of S1 and S2, a reconstructed signal from the d4 and d5 details and a4 approximation is selected for segmentation.

All these approaches are based on the assumption that the FHS peaks are higher than that of the other ones. However, in some cases, PCGs may display high amplitudes of S4 or S3 which may lead to confusion with the FHS peaks.

Also, when using the DWT method, it is difficult to find an exact decomposition level to separate the gallops from the FHSs. To solve all these problems, we propose the following processing steps:

- Signal normalisation.
- FHS filtering to eliminate the S3, S4 sounds and murmurs.
- Calculation of the filtered PCG envelogram.
- Calculations of the heart cycle period using the autocorrelation function of the envelogram.
- Adaptive thresholding segmentation based on the heart cycle period for FHSs localization.

2.1. Signal normalisation

The original digital signal recorded by an electronic stethoscope is defined by *x(n)*, and its normalized version is given by the following equation :

$$x_{norm}(n) = \frac{x(n)}{max(|x(i)|)} \quad (1)$$

where $max(|x(i)|)$ is the maximum of the absolute amplitude of *x(n).*

2.2. FHS filtering

In order to limit the appearance of S3, S4, and murmurs in the energy envelope, a digital filter is applied to the normalized PCG, discarding all the peaks except those of the FHS parts. This filter is chosen according to the frequency characteristics of the heart sound components, observed in [11]. The ranges of frequencies are for S1 and S2 50-110 Hz, for S3 and S4 40-80 Hz and for the murmurs 100-600Hz. The selected filter band can be 95Hz -100Hz (Figure1) which is enough to maximize the distance between the fundamental heart sounds and the background noise, including S3, S4 and murmurs. Figure 2, Figure 3, Figure 4 and Figure 5 show two different examples of FHSs Filtering.

2.3. *Heart cycle period (heart beat)*

The normalized filtered signal $x_{norm}(n)$ is divided into packets with duration of five seconds in order to adapt the method to the real cardiac auscultation, where about five seconds is enough for a valve auscultation with almost invariable beat rates[12]. Also, the advantage of this division is the minimization of the computing time. The energy envelope is calculated for each packet so as to produce a better representation than the original sound signal. Several kinds of envelopes are calculated by Hilbert transform [7, 13], Shannon Energy [2, 3], homomorphic filtering [6], Shannon energy envelope of the local spectrum calculated by the S-transform for each sample of heart sound signal [8], and cardiac sound characteristic waveforms [1, 5].

In our case the envelope is calculated with the continuous average energy of x_{norm} defined by the following formula [14, 15]

$$E(k) = \frac{1}{N}.\sum_{n=k}^{N+k-1} {x_{norm}}^2(n) \qquad (2)$$

Where N is the number of samples within 50 ms of the moved window for every sample k of the normalized signal (i.e. , a shift of 1 sample which makes the signal overlapped by 98% of the moved window).

The Rate *Rate (beats/s)* of the heart sound is computed after the calculation of the autocorrelation function of the continuous average energy using the following equation:

$$R(m) = \sum_{m=1}^{M} E(k) \times \bar{E}(k-m) \qquad (3)$$

$k=1, 2, 3,..,M$, where M is the number of samples.

Note that the autocorrelation function is symmetric, and has several peaks. The highest one is located in the middle of the function curve. The interval between each peak pair correspond to the period of the signal *x(n)*.

In our work, the period (*Period)* is defined as the interval between the position of the highest peak of autocorrelation function, defined as $peak\,(first)$ and the second one in a window of 1.5 seconds, defined as $peak\,(second)$. This window is chosen according to the physiological observations reported in [12], showing that for normal heart rates of adult patients (60 to 100 beats per minute) a value of 1.5 seconds is enough to find all possible periods. In the case of an out of range of normal heart rate, all the five second block must be rejected, and then another five second block auscultation is repeated.

$$Period = interval\,(peak(first), peak(second)). \qquad (4)$$

$$Rate_{(beat/s)} = 60/\,period \qquad (5)$$

2.4. *Adaptive Thresholding segmentation and FHSs localization*

The threshold is represented by a straight line across the energy signal (envelope). Calculating the maximum values between the intersection points gives the positions of peaks which represent the FHS (S1 or S2) sounds.

Some authors use the selected THV manually [1, 3], and then submit to subjective acceptance. If these values are not acceptable, they must change the THV and proceed to follow the same process. For an automatic process, we propose a novel adaptive THV based on the beat rate value. The initial threshold value is fixed to 10% of the envelope maximum value.

We define *Peak(i)* as the indices vector of the *i* peaks, and *Md(i)* as the interval between each pair of *peak(i)* and *peak(i+2), i=1 to P-2*, where *P* is the number of detected peaks using the initial threshold value. After every iteration, there are three possibilities:

- The case where the mean of *Md*(*i*) is equal to the duration of the period calculated in 2.3, in this case the threshold is correct .
- The case where the mean of *Md(i*) is less than 5 % of the period calculated in 2.3, new peaks are recalculated with a new threshold increased with 1% from the previous value.
- The case where the mean of *Md(i*) is greater than 5% of the period calculated in 2.3, new peaks are recalculated with a threshold decreased by1% from the previous value.

An iterative process is executed until the right threshold level is reached where all FHS peaks are localized.

2.5. *FHS Sounds Boundaries*.

In some methods [1, 3], the S1 and S2 boundaries are localized by the intersection points of the energy curve with the threshold line. Some pathological PCGs need to be segmented by a high-level threshold because of some residual S3, S4 or murmurs amplitudes even after FHS filtering. In this case the localization of the boundaries is not accurate (see an example in Figure 6). For accurate boundaries localization of FHSs we propose a limits recalculation of each FHS segment where, once the threshold is chosen in 2.4, we look for the start and the end of each S1 and S2 sounds. We then

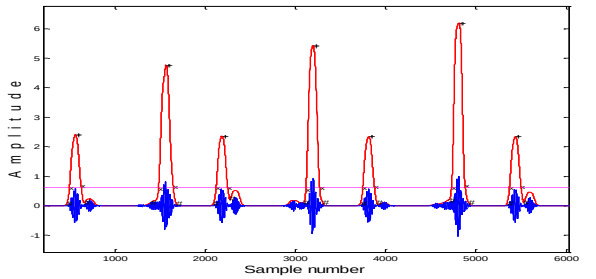

Fig. 6 With threshold crossing, S1 duration = 141 samples, S2 duration S2 = 117 samples, and with the new accurate boundaries, S1 duration = 173 samples, S2 duration = 154 samples. (x) Threshold crossing, (#) new FHS boundaries.

localize the lowest point of the envelope curve of FHS before the curve changes its sense in case of an extra-peak or still monotone in case of systolic/diastolic silence.

After localization of all the peaks and their durations, it remains to identify which peaks are S1 or S2.

Knowing that the systolic duration is shorter than that of the diastolic one, it is easy to localize the position of S1 and S2 in the original continuous heart sound. All these localized points are stored in a matrix to be used in the extraction of the periods, where we can extract each segment such as S1, S2, systole, diastole or the entire period which represents the cardiac cycle. Table1 shows an example of the segmentation results for some 5 seconds of a heart sound.

Table 1

Segmentation results of one packet (5seconds)

	Heart cycle 1	Heart cycle 2	Heart cycle 3	Heart cycle 4	Heart cycle 5
Start S1(s)	0.2825	1.0895	1.894	2.6985	3.5035
End S 1(s)	0.404	1.2085	2.016	2.8205	3.6255
Start S2(s)	0.6	1.4045	2.2095	3.016	3.8215
End S2(s)	0.731	1.5355	2.34	3.1445	3.9495
End of diastole(s)	1.089	1.8935	2.698	3.503	4.31
S1duration (s)	0.1215	0.119	0.122	0.122	0.122
S2 duration(s)	0.131	0.131	0.1305	0.1285	0.128
systole duration (s)	0.196	0.196	0.1935	0.1955	0.196
diastole duration (s)	0.358	0.358	0.358	0.3585	0.3605
Period(s)	0.8065	0.804	0.804	0.8045	0.8065

3. Filtering Of Similar Heart Cycles

Filtering of similar heart cycles consists in identifying the correlated periods from the non-correlated ones, and then removing the unwanted periods from the periods set. for thispurpose , two identification approaches are proposed.

3.1. Similar heart cycles Identification in the Time Domain.

3.1.1. Correlation Coefficient

The similarity between two heart periods *x* and *y* can be deduced by using the pearson's correlation coefficients r_{xy}. It is a scale-free measure of linear association between the two heart periods, and is given by the formula:

$$r_{xy} = \frac{cov(x,y)}{\sigma_x \sigma_y} \ , \quad -1 \leq r_{xy} \leq 1 \qquad (6)$$

σ_x is the standard deviation of period *x*.

σ_y is the standard deviation of period $ycov(x,y)$ is the covariance between two heart periods *x* and *y* defined as:

$$cov(x,y) = E[(x - E[x])(y - E[y])] = \frac{1}{N-1}\sum_{i=1}^{N}(x_i - \mu_x)(y_i - \mu_y) \qquad (7)$$

Where μ_x and μ_y are the averages of *x* and *y* respectively.

It is well known that if the value of r_{xy} is close to 1 then the periods *x* and *y* are similar and positively correlated. That means the high values of *x* are associated with the high values of y and the low values of *x* are associated with the low values of *y*. If r_{xy} is close to 0 there is no correlation between *x* and *y*. If r_{xy} is close to -1 then the periods *x* and *y* are negatively correlated (the low values of *x* are associated with the high values of y and vice versa), which means the two period x and y are similar but there are an offset of 180° between them.

3.1.2. Heart cycles calibration

After the segmentation of the PCG into separate periods (cardiac cycles), it is clear that the segments do not have the same length, which can be clearly seen in the example reported in Table 1. Before the calculation of the cross-correlation function between two heart periods, all the periods are calibrated to the same length, which is the lowest period length value. To achieve this, the corresponding late samples of the diastole components are removed.

3.1.3. Heart cycles synchronisation

If two PCG periods are identical and not synchronous, their correlation coefficient will be close to zero. For this reason we must synchronize all the PCG periods to the same period, which will act as a reference period for all the periods set.

To synchronize each pair of heart cycles, time-difference estimation via generalized cross-correlation is used.

Let R_{12} be the cross-correlation of two heart cycle PCG_1 and PCG_2,

$$R_{12} = E(PCG_1(t) \times PCG_2(t - \tau)) \qquad (8)$$

We assume that *PCG2* is similar to *PCG1* but shifted by t_1.

$$PCG_2(t) = PCG_1(t - t_1) \qquad (9)$$

Substituting equation (9) into (8), we get:

$$R_{12}(\tau) = E(PCG_1(t) \times PCG_1(t - t_1 - \tau)) \qquad (10)$$

$$R_{12}(\tau) = R_{11}(\tau - t_1) \qquad (11)$$

The properties of the autocorrelation function show that, when$(\tau - t_1) = 0$, R_{12} is at its maximum value. Therefore, the interval between the corresponding τ of the maximum value of $R_{12}(\tau)$ and the middle locations of the cross-correlation function indicate the time delay (offset time) between the two heart cycles PCG_1 and PCG_2, as shown in Figure 7.

If two heart cycles are synchronous, the maximum of the amplitude correspond to the middle location of the cross-correlation function. And if there is a delay between them, generally due to the non-regularity of the diastole duration, the maximum is shifted either to the left or right of the middle point of the cross-correlation function. This difference is taken as the value of the offset. Figure 8 shows an example of two heart cycles corresponding to a normal heart before and after synchronisation in time domain.

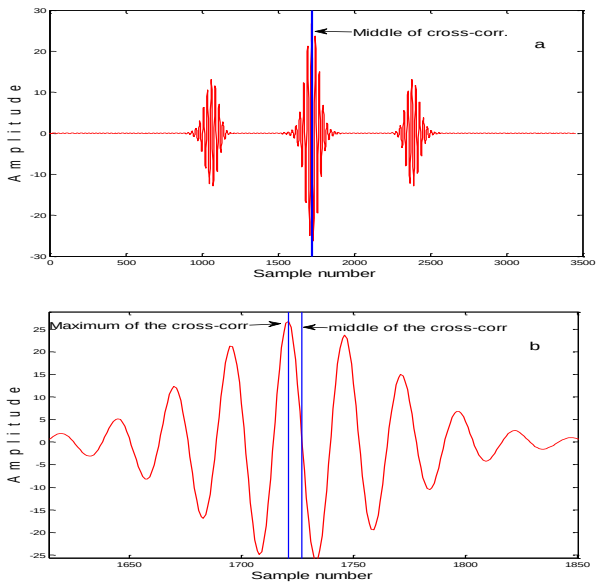

Fig. 7: (a) Cross correlation function. (b) Zoom of the offset defined by the interval between the maximum location of the cross-correlation function and its middle location.

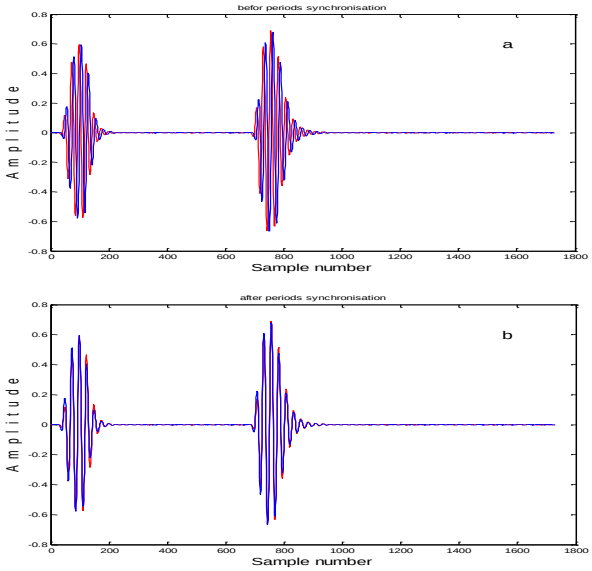

Fig. 8: (a) Two heart cycles (red) and (blue) before synchronisation, (b) after cross-correlation synchronisation.

3.1.4. Identification of similar heart cycles

In order to extract the correlated periods (heart cycles) from the set of the periods extracted by the segmentation process (section 2), the values of all the correlation coefficients between each pair are calculated with (6 and 7) and stored in a matrix *M*, with size *HC*×*HC*, where *HC* is the number of heart periods. From this matrix and after taking the absolute value of each element the mean of the rows is computed, and all the unwanted periods which have their row mean lower than a threshold value can be removed.

The maximum of the rows' mean of the matrix *M* indicates the reference heart period which has the highest degree of similarity of all the periods set. Table 2 and 3 show an example of a matrix calculated before and after cross-correlation synchronisation for five heart cycles; we can see that the coefficients are close to the maximum value (1) in Table 3.

Table 2

Correlation Coefficients Matrix without heart cycles synchronisation

	HC1	HC2	HC3	HC4	HC5
HC1	1.00000	-0.95818	-0.23097	0.68862	-0.86290
HC2	-0.95818	1.00000	-0.04912	-0.45784	0.68516
HC3	-0.23097	-0.04912	1.00000	-0.85889	0.68295
HC4	0.68862	-0.45784	-0.85889	1.00000	-0.95969
HC5	-0.86290	0.68516	0.68295	-0.95969	1.00000

Table 3

Correlation coefficients matrix after heart cycles synchronisation

	HC1	HC2	HC3	HC4	HC5
HC1	1.00000	-0.99877	0.99318	0.98612	-0.99385
HC2	-0.99877	1.00000	-0.99751	-0.97850	0.98871
HC3	0.99318	-0.99751	1.00000	0.96247	-0.97628
HC4	0.98612	-0.97850	0.96247	1.00000	-0.99817
HC5	-0.99385	0.98871	-0.97628	-0.99817	1.00000

Example of a correlation coefficients matrix of five normal heart cycles which are well correlated each other after cross-correlation synchronisation.

3.2. Similar heart cycles identification in the Time-Frequency Domain

In this approach, the identification of similar heart periods is evaluated in the time-frequency domain. Firstly, feature vectors are calculated from the Short-Time Fourier Transform (STFT) for every heart period (heart cycle), and then used for the calculation of the correlation coefficients matrix.

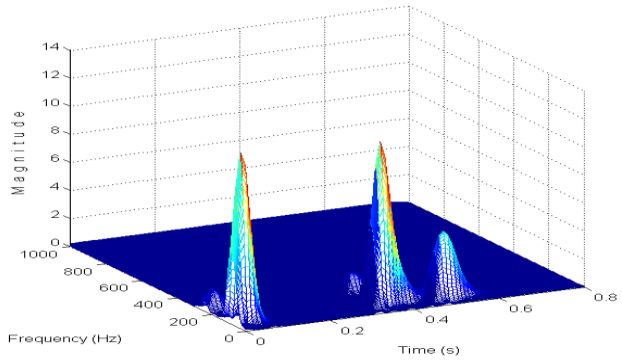

Fig. 9 STFT of one cycle PCG including S3 gallop, with a 50ms window size and a 10 ms overlap

The STFT consists of subdividing each heart cycle into *Nw* equal overlapping time windows (frames) to ensure a good stationarity of thesignal in each frame. Then, in order to reduce the effect of the spectral energy leakage which is due to the time truncation of the signal, each frame is multiplied by a Hamming window defined in equation (12).

$$w(n) = 0.54 - 0.64\cos\left(\frac{2\pi n}{N-1}\right) \qquad 0 \le n \le N-1 \quad (12)$$

where N is the frame length.

Following this, a Fast Fourier Transform (FFT) is applied to each frame. Figure 9 shows an example of the STFT calculated for one heart cycle including the S3 gallop.

The frequency spectrum of each frame is divided into ten (10) equally-spaced frequency bands, and for each band the average of the magnitudes is calculated. The results are stored in a feature vector (see Fig. 11) containing 10 times *Nw* values for each heart cycle, where *Nw* is the number of overlapping time windows (frames) for one heart cycle.

$$\textit{Feature vector size} = 10 \times Nw \quad (13)$$

After calculation of the feature vector for each heart cycle, the values of all pearson's correlation coefficients between each feature vectors pair are calculated whith (6 and 7) and stored in a Matrix M whith HC x HC size,where HC is the number of feature vectors. The identification of the similar heart cycles is deduced with the same method as section 3.1.4.

4. Results and Discussion

The experiment carried out with a Database of 21 clean heart sounds recorded as mp3 files and were converted using Matlab to wave files (duration: 30 seconds, resolution: 16 bits and down sampling frequency: from 44kHz to 2 kHz) which correspond to normal and pathological adult patients with normal heart beats rate [11].

The segmentation method was applied for each heart sound, and it was observed that FHS filtering resulted in a net improvement in segmentation of pathological PCGs by reducing the appearance of gallops and murmurs and allowing an accurate localization of the S1 and S2 sounds. Segmentation results were stored in a matrix that includes time durations and the start and end positions of each segment (S1, S2, systole and diastole) for each detected heart cycle.

For the identification of highly correlated heart cycles, the two similarity-based filtering approaches that use the correlation coefficients matrix were applied. The first one used the cross-correlation synchronisation in the time-domain and the second one used the STFT function in the time-frequency-domain.

Figure 11 shows five feature vectors of a normal heart sound with an added synthetic noise in the third cycle. This is clearly obtained using the second method as described in section 3.2. The corresponding correlation coefficients' matrix is displayed in Table 4, where we can see low values for the third cycle as compared to other cycles. The corresponding time-domain cycle can be removed from the cycles set in the output of the algorithm as shown in Figure 10.

Figure 12 shows an example of the output of the algorithm for 5 seconds of a real PCG (18) representing a transient split S2. The same results are obtained when using both similarity-based filtering approaches, where one can see in this example that all the heart cycles which have a single S2 are identified, because they are more correlated between them as compared to others.

Results for the entire Data base sounds are summarized in Table 5, where it can be seen in this table that the synchronisation pre-processing of the heart cycles significantly increase the number of the correlated periods in the PCGs (1, 4, 7, 9, 10, 14, 15, 16, 19 and 21) as compared to the results obtained without synchronisation.

Table 4

Correlation Coefficient Matrix

	HC1	HC2	HC3	HC4	HC5
HC1	1.00000	-0.99877	0.94279	0.98611	-0.99385
HC2	-0.99877	1.00000	-0.94687	-0.97850	0.98871
HC3	0.94279	-0.94687	1.00000	0.91364	-0.92670
HC4	0.98611	-0.97850	0.91364	1.00000	-0.99817
HC5	-0.99385	0.98871	-0.92670	-0.99817	1.00000

Example of a correlation coefficients matrix which indicates that the third heart cycle (HC3) has low values of correlation coefficients as compared to others HCs

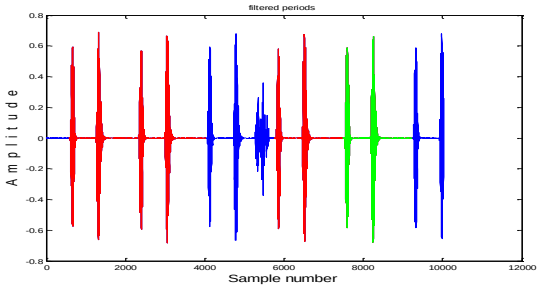

Fig. 10 This is a normal PCG with a synthetic noise added in the diastole of the third cycle, The result of similarity-based filtering in the time-frequency domain indicates the undesirable heart cycle (in blue), correlated periods (in red) and the reference heart cycle (in green).

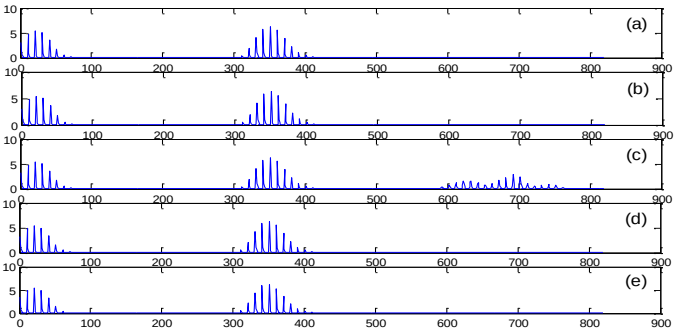

Fig. 11 Five STFT feature vectors a,b,c,d and e representing the heart cycles of the figure 10 where the third one (c) includes a synthetic noise. (The x-axis and y-axis represent 10 times *Nw* and the band magnitude average, respectively).

For the PCGs (3, 5, 11 and 12) where these heart sounds include gallops, either S3 or S4, their non-synchronized cycles due to the S3 or S4 parts were apparent even after the cross-correlation synchronisation process, as seen in Figure 13, which decreases the correlation coefficients values and then reduces the number of correlated heart cycles. For these heart sounds, the alternative time-frequency method improves significantly the number of the correlated cycles.

Table 5 also includes the Early Time Decay, T20, as an indicator of pathology [15, 16]. T20 represents the time for which the sound energy decreases to 20 dB from the total energy. This is calculated for the reference heart cycle of every heart sound as the difference between T20s calculated for S1 and S1 plus systolic segments and T20s calculated for S2 and S2 plus diastole segments. Results show a sensitivity

of 76 %, where a nearly zero value of T20 corresponds to a normal heart sound and a larger value indicates a pathological heart sound. The reason for this is the fact that the five heart sounds (PCGs (1, 6, 7, 8 and 9)) representing 24 % of the Database which have a false indication are noisy recorded from the Database. The calculation of T20 can help in the quantification of murmurs such as mild or significant degree of regurgitation or stenosis. However, it is very sensitive to the background noises that may lead to false indications. Therefore, heart sounds must be as clean as possible before their segmentation process.

Table 5

Results of Early Time Decay along with identification of the similar periods in time and time-frequency domains.

PCG(database)	Correlated periods without synchronisation	Correlated periods in time domain	Correlated periods in time-frequency domain	Total of periods	Heart rate beat/m	T20 Sys (ms)	T20 Diast (ms)
1 Normal	11	25	25	25	74.73	0	32.44
2 Split S1	3	14	29	30	85.34	2.99	2.99
3 S4 gallop	9	12	25	25	72.48	0	405.69
4 Mid sys-systolic Click	7	23	23	23	70.44	24.95	0
5 S3 gallop	3	13	23	23	70.32	0	123.75
6 early-syst. murmur	24	21	21	21	63.65	209.58	492.02
7 mid-syst. murmur	16	20	20	20	63.28	232.54	425.15
8 late-syst. murmur	25	21	21	21	63.12	223.05	429.64
9 Holosystolic murmur	16	20	20	21	64.03	243.51	372.76
10 Syst.click with late syst murmur	7	22	22	23	70.48	94.81	0
11 S4 and mid-syst murmur	6	10	23	23	66.69	242.52	469.56
12 S3 with holosyst murmur	3	9	29	29	79.95	211.57	109.28
13 Mitral opening snap with diastolic murmur	2	2	16	25	73.86	0	403.19
14 Normal	7	23	23	23	69.38	0	0.5
15 Early diastole murmur	8	23	23	23	74.96	0.5	0
16 Single S2	7	23	23	23	69.38	0	0.5
17 Split S2 persistent	24	26	26	27	77.77	0	1.49
18 Split S2 transient	5	12	12	25	74.68	0	0.5
19 Ejection systolic murmurs with transient splitting S2	7	27	27	27	79.52	142.22	0
20 Ejection systolic murmurs with persistent split S2 and ejection systolic murmur	4	16	23	23	69.42	241.01	0
21 Ejection systolic murmurs with single s2 and ejection click	8	23	23	23	69.74	47.41	0.5

Similarity-based filtering in the time domain evaluated with a threshold value of 0.9 and Similarity-based filtering in the time-frequency domain evaluated with a threshold value of 0.94.

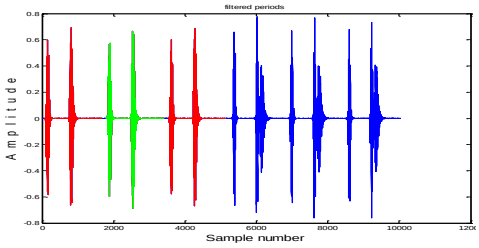

Fig. 12 Example of a transit split PCG (18), correlated periods (in red) uncorrelated periods (in blue) and the reference heart cycle (in green)

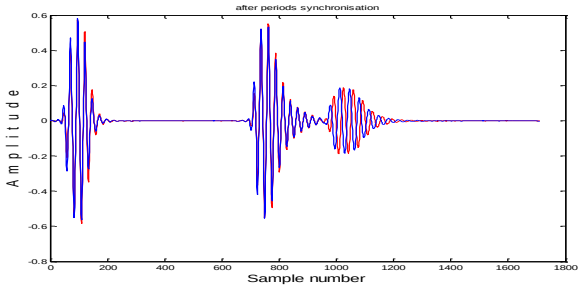

Fig. 13 Two synchronized heart cycles (red, blue) of PCG (5) with unsynchronized S3 (Gallop) part.

5. Conclusion

A segmentation method is proposed for accurate Fundamental Heart Sounds (FHS) boundary localization in the presence of extra sounds such as: gallops, S3, S4 and murmurs. This method uses FHS filtering to remove the extra sounds and murmurs from the PCG, calculates the PCG envelope and uses an adaptive threshold based on heart period duration to localize the segment. Two similarity-based filtering approaches that use the correlation coefficient matrix for the identification of similar cardiac cycles are also proposed. The developed overall algorithm has been evaluated using a professional database including normal and pathological adult heart sounds. The results that have been obtained clearly show a performance superiority of the similarity-based filtering approach in the time-frequency domain as compared to the time domain, particularly in the presence of extra heart sounds such as Gallops, S3 and S4. The identified correlated heart cycles can help physicians and

health professionals in the early detection of valvular diseases during routine auscultation examination, which would otherwise not be easily detectable through subjective auscultation alone.

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