A Robust Method for S1/S2 Heart Sounds Detection Without ECG Reference Based on Music Beat Tracking

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Abstract— We present a robust method for the detection of the first and second heart sounds (s1 and s2), without ECG reference, based on a music beat tracking algorithm. An intermediate representation of the input signal is first calculated by using an onset detection function based on complex spectral difference. A music beat tracking algorithm is then used to determine the location of the first heart sound. The beat tracker works in two steps, it first calculates the beat period and then finds the temporal beat alignment. Once the first sound is detected, inverse Gaussian weights are applied to the onset function on the detected positions and the algorithm is run again to find the second heart sound. At the last step s1 and s2 labels are attributed to the detected sounds. The algorithm was evaluated in terms of location accuracy as well as sensitivity and specificity and the results showed good results even in the presence of murmurs or noisy signals.

Keywords—heart sound; detection; beat tracking; onset detection function

I. INTRODUCTION

Heart sound auscultation, i.e. the use of a stethoscope by a trained physician for listening to the sound the heart produces, is one of the most reliable and successful means of early diagnosis of heart dysfunctions. There have been increasing efforts towards finding successful automated heart sound classification algorithms and a key contributing factor to that success is robust and reliable detection of the elements that make up a heart sound. These elements are the first heart sound (s1), the systolic period (sp), the second heart sound (s2) and the diastolic period (dp), in this time sequence (Figure 1). The s1 and s2 are often described as the *lub* and *dub* that make up the *lub-dub* heart sound most people are familiar with, and the systolic and diastolic periods are the pauses between them.

There are two distinct approaches to s1/s2 detection depending on whether or not the ECG is used as a reference (i.e. key ECG features that occur at the same time as features in heart sounds are detected instead).

The first one relies on the temporal correspondence between ECG features and the s1 and s2 [8]. The heart sound and ECG must be recorded simultaneously and because ECG analysis methods are well established, finding the location of ECG features is straightforward. The second approach, referred as independent segmentation [4,5,6,7], identifies the s1 and s2

heart sounds without any supplementary information or signals except from the heart sound itself.

Figure 1. A normal heart sound and a zoomed in view at a beat cycle

The work presented here tackles the second situation. There are several advantages to using independent segmentation, the most important being that patient comfort is not compromised, since only an electronic stethoscope is needed, and it eliminates the need for additional hardware like an ECG machine.

Several methods can be found in the literature where independent segmentation techniques are applied, based either on heart sound envelopogram (envelope calculated using the normalized average Shannon energy) [3], or on frequency domain analysis [4,5,6,7]. These methods perform well (92 to 94% correct detections), however they either have been developed for a particular situation (only on non pathological situations, or a specific pathology), or suffer from a degradation in performance in the presence of heart murmurs (pathological noises produced by turbulent flow of blood), or noisy environments.

Music analysis is an area where there is much interest in research and looking at the main characteristics of the heart sound, namely the periodicity and shape, has lead us to the idea that the concept of beat tracking used in music analysis can be successfully modified and applied to heart sound segmentation. In music, beat tracking is the computational equivalent of tapping one's foot in time to music, and heart sounds present themselves like an ideal candidate since they are repetitive in nature and far less complex than music.

II. METHOD

We propose a robust method, which does not suffer from performance degradation regardless of the situation at least

from the specificity and selectivity point of view, for heart sound segmentation and s1/s2 detection, without ECG reference, based on a music beat tracking algorithm introduced by Davies and Plumbley [1]. Our method first calculates an intermediate representation of the input signal by using an onset detection function based on complex spectral difference. The beat tracking algorithm is then used to determine the location of one of the two heart sounds. Once the first sound is detected, inverse Gaussian weights are applied to the onset function on the detected positions and the algorithm is run again to find the second heart sound. Because the order in which the s1 and s2 heart sounds are detected is not predictable, at the last step s1 and s2 labels must be correctly attributed to the detected sounds. This decision is made by analyzing the length of the intervals between the two sounds. We shall use the notations s' and s'' to denote the two heart sounds, relating to the order in which they are detected.

Within the first stage of the detection algorithm, the input signal is converted into a more useful and compact representation than the time domain. Audio beat tracking algorithms refer to this representation as an *onset detection function* [3]. We have chosen the complex spectral difference as being the most suitable for our purpose because by working in the complex domain, detection can be made either as a result of energy change in the magnitude spectrum or a modification in phase values in the phase spectrum.

In order to calculate the onset detection function, a moving window of size N and step $N/8$ is used, creating a 12.5% overlap at each step. In order to minimize frequency leakage a Hamming window has been chosen. At step k , the onset detection function $\Gamma(k)$ is calculated as the sum of the Euclidean distance between the current frame spectrum $S_m(k)$ and previous frame spectrum $S_m(k-1)$ for all frequency bins m

$$\Gamma(k) = \sum_{m=1}^M |S_m(k) - S_m(k-1)|^2 \quad (1)$$

Also, to allow operation regardless of sampling frequency the onset detection function is calculated in such a way that a fixed time resolution per detection function sample is obtained. Several window sizes have been tested, and an optimum result has been obtained for values of

$$N \cong Fs / 12 \quad (2)$$

samples. Larger window values tend to favor false negative detections, while smaller values lead to false positives. An example of heart sound and corresponding onset detection function is shown in Figure 2 (a) and (b).

The beat tracking algorithm used here works in two steps: it first extracts the beat period and then finds the correct beat alignment. The onset detection function DF is divided into overlapping analysis frames with a step equal to half the frame size. For each frame, an autocorrelation function is calculated and filtered through a comb filterbank. Then to achieve well defined peaks and discard the least significant ones, it is passed through an adaptive moving mean threshold and half wave rectified.

Figure 2. (a) DF onset detection function; (b) Heart sound recording and first detected heart sound – s' ; (c) W_i applied for all s' positions; (d) DF' onset detection function; (e) Heart sound recording and second detected heart sound – s''

The beat period is identified as the index of the maximum value. After the beat period is calculated for all the recording, the locations of the first heart sound are determined using dynamic programming and the same comb filtering technique mentioned above. We will not go into further details as the beat tracking method is described thoroughly in [1].

Since s1 and s2 are the main features in the heart sound that generate onset, by applying the beat tracking algorithm, we expect that the detected beat position will correspond to one or the other of the two. Once one of the two heart sounds, s' (figure 2b), is detected throughout the recording, inverse Gaussian weights are applied to the onset detection function (figure 2c), centered on each detected location. A weighting vector W_i of length D , is constructed for every detected s' according to

$$W_i(x) = 1 - \delta e^{-\frac{(x-\mu_i)^2}{2\sigma^2}}, x = 1..D \quad (3)$$

where μ_i , the median, is the position of the i^{th} detected s' in DF samples, σ is the variance of the distribution, and was found to yield the best results for values around $T/5$, where T is the average detected beat period in DF samples. δ is a scaling factor and D is the length of the onset detection function. A value of 0.95 has been used for δ , however this can vary and it represents how much DF is attenuated at the current beat location. Larger values tend not to have any

influence on the detection but smaller values affect performance. The weighted detection function DF' will be obtained by successively applying W_i to DF (figure 2d). After calculating DF' , the beat tracking algorithm is ran one more time, this time using DF' instead of DF and the locations of the second heart sound, s'' are determined (figure 2e). The order in which s_1 and s_2 are detected cannot be predicted because the beat tracker will detect either of them with equal probability on the first run, so correct labels must be assigned to s' and s'' . For that purpose, the average distance between an s' and the following and preceding s'' will be used. If we consider τ_1^i as the distance in samples between s'_i and the preceding s'' , τ_2^i as the distance between s'_i and the following s'' , and $i = 1..I$ with I being the total number of detected s' except for the first and last, then the sign of $\tilde{\tau}$ defined as

$$\tilde{\tau} = \frac{1}{I} \sum_{i=1}^I \tau_1^i - \tau_2^i \quad (4)$$

will dictate the label of s' and s'' . If $\tilde{\tau}$ is positive then s' will be labeled as s_1 and s'' as s_2 . The opposite will happen if $\tilde{\tau}$ is negative.

Because the detection is made in the frequency domain and the resolution is given by the onset detection function moving window step size, from equation (2) we will end up having a time domain resolution of $N/8 = F_s/12 * 1/8 = F_s/96$ samples. In order to further improve the results, for every detected s_1 and s_2 we added supplementary local peak detection, within the interval $\pm F_s/48$ samples, centered on the detected s position.

III. EXPERIMENTAL RESULTS

The method presented here has been tested in terms of sensitivity, specificity and detection accuracy expressed in milliseconds and also as a percent of the beat period. 18 heart sound recordings were analyzed, containing normal (N) and pathological sounds (the pathologies are: Aortic Stenosis – AS, Aortic Insufficiency – AI, Mitral Regurgitation – MR, Mitral Valve Prolapse – MVP, Pulmonic Stenosis – PS, Tricuspid Stenosis – TS).

The mean value

$$\bar{\epsilon} = \frac{1}{n} \sum_{i=1}^n \epsilon_i \quad (5)$$

and also the standard deviation

$$s = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (\epsilon_i - \bar{\epsilon})^2} \quad (6)$$

were calculated for each recording.

To determine the optimal parameter set $(\delta; \sigma)$ we repeatedly analyzed all the recordings and calculated the average absolute error. The parameter set that produced the smallest detection errors was $(\delta = 0.95; \sigma = T / 4.3)$ and it

was used for all the simulations that are presented from this point forward.

Table 2 shows the obtained average detection errors expressed in ms and also in percent of the beat period. Positive values indicate early detection and negative values indicate late detection. Overall the absolute value mean error was of 14.2ms for s_1 and 34.4ms for s_2 (1.74% of the beat period for s_1 and 2.37% for s_2).

It can be observed that because the method is based on onset, the algorithm has a tendency of detecting s_1 and s_2 earlier than they actually occur thus the majority of the values in milliseconds have positive values. In terms of sensitivity and specificity the results obtained were very good, and even more important with no false negative detections across all recordings (Table 1). The false positive detections appeared in all situations at the beginning of the recording and are attributed to the fact that the detection method needs a short period of time to “latch on” to the beats.

TABLE 1. Sensitivity and specificity the results for each recording

Recording	Total beats	extra s_1	extra s_2	missed s_1	missed s_2	s_1 sensitivity [%]	s_1 specificity [%]	s_2 sensitivity [%]	s_2 specificity [%]
1	25	0	0	0	0	100	100	100	100
2	6	0	1	0	0	100	100	100	85.7
3	22	0	1	0	0	100	100	100	95.7
4	25	0	0	0	0	100	100	100	100
5	23	1	1	0	0	100	95.8	100	95.8
6	25	0	0	0	0	100	100	100	100
7	17	0	1	0	0	100	100	100	94.4
8	34	0	1	0	0	100	100	100	97.1
9	37	1	1	0	0	100	97.4	100	97.4
10	8	0	1	0	0	100	100	100	88.9
11	20	0	1	0	0	100	100	100	95.2
12	24	0	1	0	0	100	100	100	96.0
13	10	0	0	0	0	100	100	100	100
14	19	0	1	0	0	100	100	100	95.0
15	24	1	1	0	0	100	96.0	100	96.0
16	19	1	1	0	0	100	95.0	100	95.0
17	13	0	1	0	0	100	100	100	92.9
18	17	0	1	0	0	100	100	100	94.4

By comparing these results with those obtained in literature, it can be seen that although high accuracy (less than 10 ms) is not obtained overall, it is compensated by the very good results in terms of correct detection: the selectivity and specificity are close to 100% or even 100% if the above mentioned situations are ignored. By comparison, in [5] the reported selectivity and specificity were around 91% and the reported average detection accuracy was of approximately 4.2 ms.

The greatest advantage of our method is that because it is based on periodicity, transient noises that are generated either by physiological or environmental factors can have little influence, if any, on the detection results. To show this we ran the algorithm on the same recordings contaminated with noise. We used additive pink noise, with normalized amplitude equal to 20% of the recording amplitude. The results, presented in table 3 clearly show that as we expected, there is little difference between the two situations and the detection still performs good.

TABLE 2. Average detection errors expressed in ms and also in percent of the beat period for every recording; positive values indicate early detection and negative values indicate late detection

Recording	Pathology	BPM	Total number of beats in recording	Mean s1 error [ms]	Standard deviation of s1 error [ms]	Mean s2 error [ms]	Standard deviation of s2 error [ms]	Mean s1 error as % of period	Standard deviation of s1 error as % of period	Mean s2 error as % of period	Standard deviation of s1 error as % of period
1	AI	65	25	8 16	20 33	-0 04	5 31	0 88	2 20	0 00	0 58
2	AI	59	6	-1 00	0 00	-1 00	0 00	-0 10	0 00	-0 10	0 00
3	AS	67	22	-9 09	23 92	3 36	23 86	-1 02	2 67	0 38	2 66
4	AS	75	25	5 96	34 58	48 96	90 92	0 75	4 32	6 12	11 37
5	AS	80	23	-1 04	0 47	144.74	54 89	-0 14	0 06	19 30	7 32
6	AS	79	25	-5 20	3 44	137 60	17 18	-0 68	0 45	18 12	2 26
7	N	65	17	15 29	23 55	5 71	28 37	1 66	2 55	0 62	3 07
8	N	103	34	10 41	22 41	1 44	19 67	1 79	3 85	0 25	3 38
9	N	116	37	1 89	9 09	-0.05	6 19	0 37	1 76	-0 01	1 20
10	N	66	8	4 25	17 59	-3 88	6 42	0 47	1 93	-0 43	0 71
11	MR	61	20	1 95	10 14	-0 90	0 45	0 20	1 03	-0 09	0 05
12	MR	73	24	10 75	27 03	22 50	47 71	1 31	3 29	2 74	5 80
13	MR	54	10	-0 90	0 57	15 00	34 13	-0 08	0 05	1 35	3 07
14	MR	76	19	-53 26	31 31	62 95	42 00	-6 75	3 97	7 97	5 32
15	MVP	72	24	-17 88	64 78	19 17	31 43	-2 15	7 77	2 30	3 77
16	PS	62	19	-101.05	49 22	9 84	39 91	-10 44	5 09	1 02	4 12
17	PS	78	13	4 15	6 59	86 31	8 93	0 54	0 86	11 22	1 16
18	TS	70	17	-0.82	1 13	0 88	6 83	-0 10	0 13	0 10	0 80

TABLE 3. Detection errors for each recording in the original and noise-affected cases; original and noise affected results are placed side by side for a better comparison;

Rec	Mean s1 error [ms]	New values [ms]	Standard deviation of s1 error [ms]	New values [ms]	Mean s2 error [ms]	New values [ms]	Standard deviation of s2 error [ms]	New values [ms]
1	8.16	7.64	20 33	15 73	-0.04	0.36	5 31	5 85
2	-1.00	2.83	0 00	6 01	-1.00	0.33	0 00	3 27
3	-9.09	17.82	23 92	38 38	3.36	15.77	23 86	30 80
4	5.96	60.36	34 58	143 67	48 96	52.24	90 92	90 90
5	-1.04	-1.04	0 47	0 56	144.74	140.78	54 89	54 79
6	-5.20	-5.48	3 44	4 00	137.60	122.84	17 18	16 64
7	15.29	25.53	23 55	36 92	5.71	14.53	28 37	33 47
8	10.41	15.56	22 41	27 16	1.44	7.09	19 67	16 78
9	1.89	11.24	9 09	26 62	-0.05	2.62	6 19	5 73
10	4.25	4.75	17 59	17 85	-3.88	-4.00	6 42	6 30
11	1.95	12.90	10 14	18 98	-0.90	-0.90	0 45	0 45
12	10.75	36.13	27 03	55 92	22.50	36.96	47 71	51 49
13	-0.90	-5.10	0 57	14 03	15.00	6.80	34 13	32 30
14	-53.26	-51.84	31 31	31 95	62.95	33.95	42 00	37 27
15	-17.88	-18.54	64 78	63 73	19.17	19.33	31 43	27 91
16	-101.1	-111.2	49 22	46 54	9.84	-154.4	39 91	105 42
17	4.15	12.23	6 59	17 96	86.31	88.15	8 93	3 69
18	-0.82	-1.71	1 13	2 85	0.88	-0.24	6 83	13 05

In some cases, the detection results are identical, like in the case of s1 for recording 5, where the s1 and s2 have high amplitude peaks. The *DF* samples that are marked as s1 coincide in the two situations (no noise vs. noise), and because they exhibit high amplitudes the local peak detection that follows the beat tracking will return the same position. In terms of specificity and sensitivity the results remain identical with the original simulations.

IV. CONCLUSIONS

We have proposed a robust method for heart sound segmentation and s1/s2 detection, without ECG reference, based on a modified beat tracking algorithm. The particular advantages of using this method are that very good results are obtained in terms of sensitivity and specificity, and the presence of artifacts, noise, or murmurs only marginally affect the performance of the detector.

In terms of computational complexity, we ran the simulations on a 2GHz dual core AMD based machine with 2GB of RAM, using the MatlabR2010b environment and, on average, the analysis of one second of heart sound took 29 milliseconds. This is an important result because due to the small time needed for analysis a real-time version of the detector can be easily implemented.

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