Acoustic Cardiac Signal Analysis : a toolbox

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Abstract—**We present a Matlab framework for heart sound processing and analysis. This framework includes algorithms developed for segmentation of the main heart sound components capable of handling situations with high-grade murmur, and for measuring systolic time intervals (STI). Methods for cardiac function parameter extraction based on STI are also included. Currently, the proposed algorithms are being extended for multi-channel applications. The algorithms outlined in the paper have been extensively evaluated using data collected from patients with several types of cardiovascular diseases under real-life conditions.**

Keywords: Non-cardiac Sound Detection, Heart Sound Segmentation, Heart Murmur, Systolic Time Intervals

I. INTRODUCTION

According to the WHO report on chronic diseases [1] 80% of all deaths worldwide due to chronic diseases occur in middle and low-income countries, being cardiovascular diseases (CVD) by far the most prevalent chronic disease. The first line of defense against CVD is the regular follow-up by primary care physicians. Given the medical, social and economical implications of CVD, a significant research trend is observed in science and technologies to deploy personal health (pHealth) systems for CVD management (e.g. [2]). The goal of these systems is to support physicians and patients in detecting trends and in collecting data for clinical decision support. In order to implement cost effective CVD prevention strategies, pHealth systems as well as physicians require affordable, comfortable and highly discriminative information sources for diagnosis. Traditionally, the electrocardiogram (ECG) and heart sound (HS) auscultation are among the most used signals for CVD diagnosis. These information sources provide complementary information: the ECG enables to assess the electrical activity of the heart, while heart sounds (HS) provide information on the mechanical activity of the heart [3].

Heart sound is a consequence of turbulent blood flow and vibrating cardiovascular structures, which propagate to the chest. These vibrations typically result from myocardial and valvular events that are affected by the function, the hemodynamics and electrical activity of the cardiac muscle. The later have a direct impact on the morphological, spectral and the timing characteristics of the main heart sounds (S1, S2), which have been found to be highly sensitive and specific for several important diagnosis tasks ranging from heart valve dysfunction [4][5] to systolic cardiac function [6][3].

Unfortunately, cardiac auscultation - the interpretation of heart sounds - requires highly proficient physicians. Several studies (e.g. [7]) have shown that the ability of physicians to perform cardiac auscultation is reduced and significantly impaired as time progresses. Hence, the existence of signal analysis algorithms for HS to deploy decision support systems, both for the physicians in their clinical practice as well as to deploy pHealth systems, are one possible solution to fully explore this highly informative, low cost and non-invasive information source on cardiac state.

There are few known integrated frameworks for heart sound acquisition and processing. Rajan *et al.* [8] introduce an integrated framework for HS processing based on Morlet wavelet bank of correlators. Their framework tackles the problems of noise detection, S1 and S2 segmentation and murmur/click/snap classification. Javed *et al.* [9], describe a signal processing module that includes a signal acquisition functionality. Time-frequency processing is wavelet-based and is limited to HS segmentation and murmur detection. More recently, Syed *et al.* [10] introduced a framework with similar functionalities as the one described in [8]. It is observed that none of the sited frameworks include modules for systolic time interval measurement, i.e., the pre-ejection period (PEP) and the left ventricle ejection time (LVET), which is related directly to the left ventricle function.

In this paper we introduce a Matlab framework for the acquisition and processing of cardiac auscultation. The paper is organized as follows: Section 2 outlines the algorithms that have been developed by the team and are integrated into the heart sound processing toolbox. In section 3 we present and discuss results of the main modules that comprise the toolbox. Finally, in section 4 some main conclusions are drawn and the main directions for future work are outlined.

II. ALGORITHMS

A. Noise Detection

The proposed approach for noise handling is to identify and to exclude signal portions with noise contaminations. The foundations for this approach are twofold: (i) noise contamination of HS is typically non-linear, time-variant and complex, and (ii) it usually suffices to detect contamination in order to generate an alert to the user to eliminate/avoid the contamination source and to discard the contaminated data. Noise interference in HS might come from internal (e.g. physiological noises) as well as external (e.g. noises by bystander) sources. These noise sources exhibit a very broad range of spectral bands, loudness and durations. Noise detection is tackled in the toolbox by observing that HS are quasi-periodic signals. This characteristic manifests itself both in the time domain as well as in the time-frequency domain for different frequency bands. A detailed description of the strategy proposed [11] is depicted in the flowchart in Fig. 1: in phase I a non-contaminated HS clip of one complete heart cycle is selected. This HS will serve as a reference template for further processing; since this selection operation is always performed at the start of the signal acquisition process, it ensures that the method exhibits resilience towards auscultation site, posture changes and changing physiological characteristics. In order to grant that this reference template does not exhibit noise contamination, the template is selected from candidates that exhibit the aforementioned quasi-periodicity characteristics. In the second phase this template is applied to each signal window using temporal energy and spectral similarity criteria to check for noise contamination.

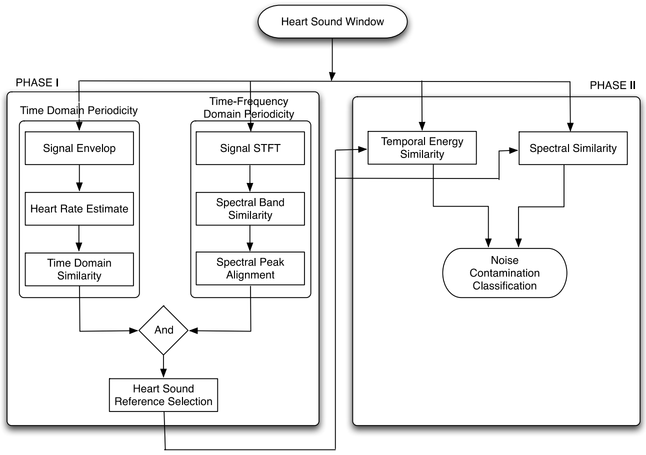

Fig. 1: Noise detection algorithm.

Regarding phase I, first each individual heart beat is identified in the HS signal. If an ECG is available, this can be obtained using the R-peaks. Otherwise, the heart cycle limits can be estimated from the prominent peaks (which correspond to S1 and S2) of the signal's envelop and the heart rate assessed from the singular value decomposition (SVD) of the envelop of the signal. Let $y(t)$ be the envelop of the HS obtained using the Hilbert transform. Let $k(wT) = [y(wT), \ldots, y((w+1)T)]$ and $S(T) = [k^T(T), \ldots, k^T(nT)]^T$, nT is limited by the available duration of $y(t)$. The cardiac beat period T can be obtained from $T = argmax_{\gamma\in\Omega}(\alpha_2/\alpha_1)^2$, where α_1 and α_2 are the singular values of $S(\gamma)$ and the search interval Ω is defined using physiological limits of admissible heart rates. Once each heart cycle section of the signal's envelop has been identified, time domain similarity is checked using the inner product. Only those cycles which exhibit a similarity towards its neighbor greater than 0.8 (obtained empirically) are retained for further processing. The second test performed during this phase is performed in the time-frequency bands. First the spectrogram (0-600Hz) is split into 15 contiguous, non-overlapping frequency bands. Since the main energy sources in HS are due to the S1 and S2 components, it is observed that the envelops in each time-frequency band tend to exhibit linear dependent auto-correlation functions (with decreasing linear dependency for natural and bioprosthetic valves and with increasing linear dependency for mechanical valves) with aligned peaks. The linear dependency is assessed using the SVD of the matrix Λ, whose rows are the autocorrelation functions of the time-frequency bands. Namely, it is observed that it has to verify $\rho_1 \geq \rho_2 \geq \rho_3$ or $\rho_1 \leq \rho_2 \leq \rho_3$, where $\rho_k=(\alpha_{k+1}/\alpha_k)^2$ and α_k represents the kth singular value of Λ. The heart cycle with the highest average similarity (radial distance) with respect to all available heart cycle template candidates is selected as the template.

Once the reference heart sound has been defined, phase II is initiated where a template matching approach is applied to each HS signal window using the following spectral and temporal features: first the correlation between spectral power of the template and the signal under analysis is assessed. If it is greater than 0.98, then the signal is subject to a temporal energy test (required to capture very short duration contaminations). In this test, the energy of each 50ms signal window is checked against the energy of the template.

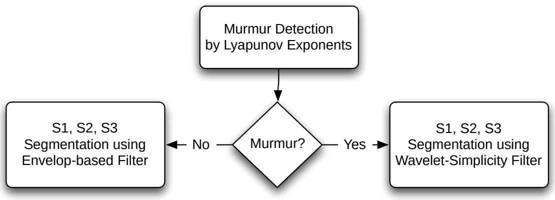

Fig. 2: HS segmentation method.

B. *Segmentation*

HS segmentation into its main constituent parts is approached using two distinct methods: one is based on the signal's envelogram, the other is based on a wavelet-simplicity filter. The former algorithm is very efficient computationally. However, its performance degrades rapidly for HS with murmur. To automatically select between both methods, a selection stage has been incorporated into the segmentation module (see Fig. 2).

Heart sounds, particularly those with murmur, contain nonlinear and non-Gaussian information whose dynamic behavior, such as chaos and complexity, can be assessed using the embedding theory. In the proposed method, the degree of chaos is measured via the Lyapunov exponents estimation. Suppose the heart is considered as a nonlinear dynamical system $X(t+1) = F[X(t)]$ that generates the heart sound time series $x(t)$, $t = 1....N$. Signal $x(t)$ can be treated as a one dimensional projection of the unknown multidimensional dynamic variable $X(t)$. Phase space transformation of the one dimensional observation $x(t)$ is performed using the embedding theorem, which states that, using some suitable assumptions, a phase space can be formed that is topologically equivalent to an original system [12]. The method of delay is applied to reconstruct the attractor in the multidimensional space or embedding space P, i.e., $y_i(t) = [x(t), x(t-\tau), \ldots\ldots, x(t-(m-1)\tau)] \in IR^m$, where $i = 1, 2, 3, \ldots, P$ and $y_i(t)$ are row vectors of the embedding matrix $Y(t)$. To determine the exponents from the embedded matrix $Y(t)$, the nearest neighbor points are located to measure their distance from the initial points as given in equation.

$$l = \frac{1}{t_M - t_0} \sum_{k=1}^{M} \log_2 \frac{L'(t_k)}{L'(t_{k-1})}$$

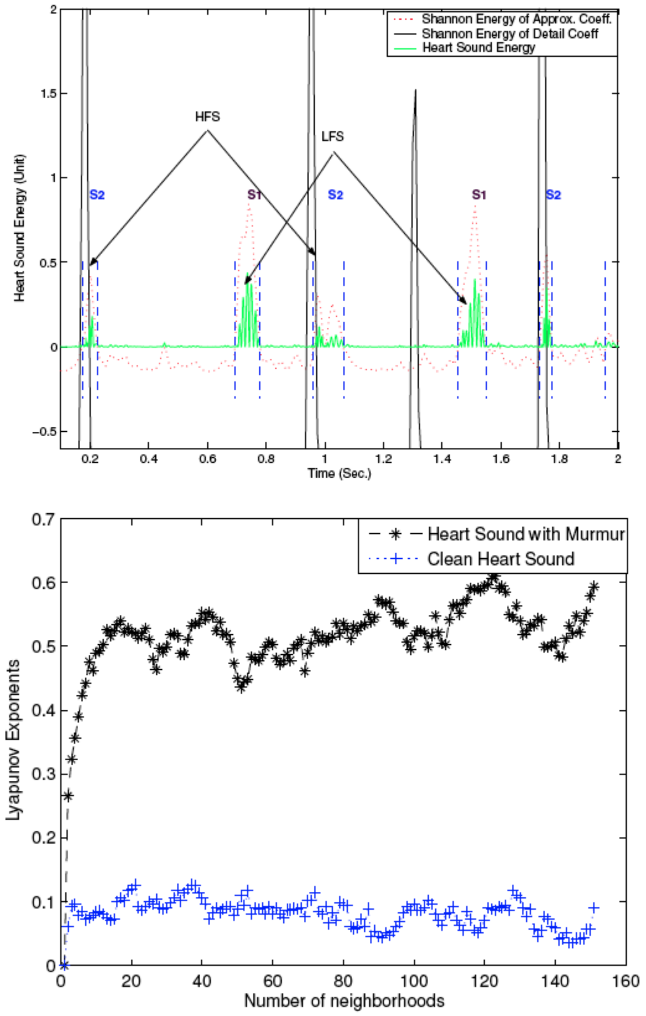

Fig. 3: (top) High frequency signature applied to detect the S2 sounds; HFS and LFS stand for high and low frequency segment, respectively. (bottom) Lyapunov exponents for sound heart sounds with and without murmur.

where M is the number of repetitions the trajectory takes in traversing the entire data and denotes the Lyapunov exponents. Fig. 3 depicts the average of 150 exponents obtained from 35 HS clips (20 clips without murmur and 15 clips with murmur). As can be observed, HS without murmur are significantly less chaotic. The decision stage in is implemented using a simple threshold decision rule.

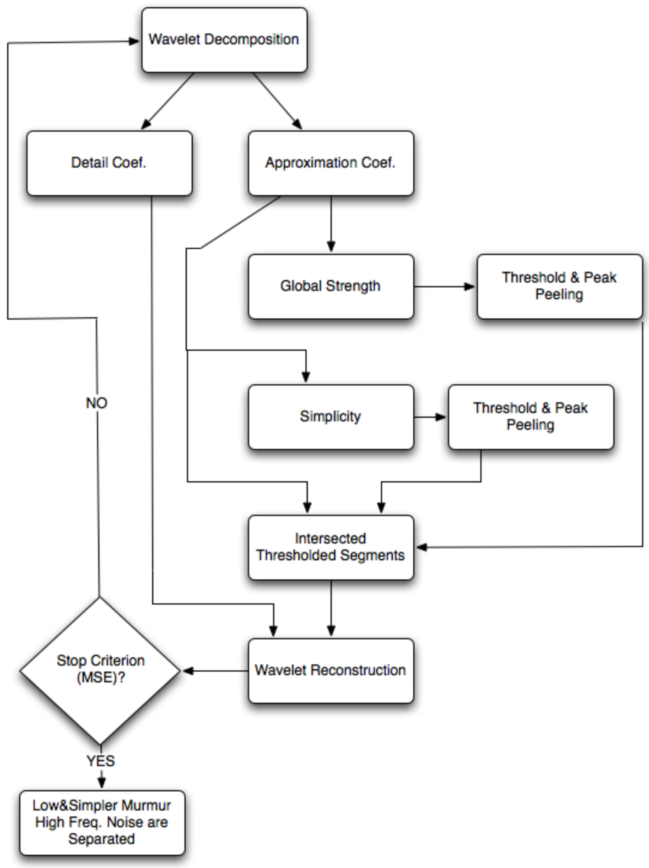

Fig. 4: Wavelet-Simplicity Filter segmentation algorithm.

The segmentation method based on the signal's envelop is basically formed by two simple steps [13]: (i) first the S1 and S2 candidates are identified using the zero-crossings of the envelop of the approximation coefficients of the 5th level wavelet decomposition. The envelop is computed with a running average of the Shannon energy. The identification of the S1 and S2 components is based on the observation that pressure gradients are usually higher across the aortic valve compared to the mitral valve. Hence, the S2 heart sound should exhibit more pronounced high frequency components compared to S1. In order to capture this, a new high frequency feature was introduced. This new feature is composed by the Shannon energy of the detail coefficients of the wavelet transform. As can be seen in Fig. 3 (top), this signature coupled to some simple physiological motivated rules enable the discrimination between the different components of the heart sound.

Regarding the wavelet-simplicity filter algorithm, it follows the same steps of the algorithm we developed using the Wavelet-Simplicity transform [14]. Therefore, only fundamental changes in the steps of the basic algorithm are described herein. Murmurs occur between S1 and S2 or S2 and S1 sounds. Therefore, the first task consists of the identification of the boundaries of the S1 and S2 sounds. The main steps for achieving S1, S2 and murmur separation using the strength and simplicity features are (see Fig. 4):

Step 1: Heart sound is decomposed using the wavelet *db6*. The approximation coefficients are used in further processing.
Step 2: Simplicity (S^l) and global strength (GS^l), where l is the depth of wavelet decomposition, of the decomposed signal is computed.
Step 3: The S1 and S2 components of a heart sound exhibit high strength and simplicity, hence clear peaks can be observed in these curves. In severe heart murmurs, murmurs overlap S1 or S2 sounds. Other unknown sounds may occur due to physiological events (e.g. S3) that exhibit similar characteristics of S1 and S2 components. Usually, S1 and S2 sounds exhibit relatively high simplicity as well as strength, whereas other artifacts exhibit high simplicity but on the contrary low strength. Therefore, the width (or duration) of S1 and S2 sounds are separately segmented using both feature curves. For this task, the peak peeling algorithm (PPA) [15] based upon an iterative thresholding process is applied. PPA is applied first to the *GS* curve and then to the *S* curve successively. Subsequently, start and stop times of S1 and S2 sounds are achieved and can be gated. The segmented time gates using both feature curves are shown in Fig. 5.
Step 4: It is observed from Fig. 5 that correct start and stop times of S1 and S2 sounds can be achieved by common segmented time gates in both thresholded feature curves.
Step 5: The suitable decomposition depth is found by applying the mean square error criterion on gated decomposed heart sound signal.

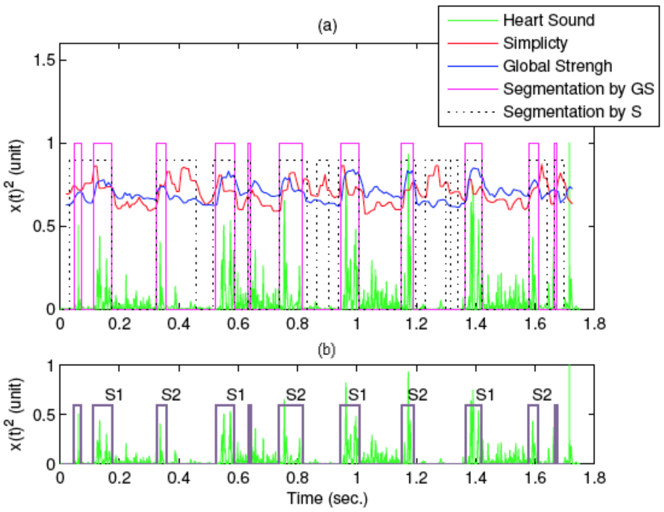

Fig. 5: Segmentation results in severe (grade V) mitral regurgitation murmur.

C. Murmur Characterization

This module of the toolbox performs murmur classification using features extracted from the systolic, i.e., S1-S2, or the diastolic intervals, i.e., S2-S1. The classifier (implemented using a SVM) considers seven distinct classes of murmur: 1) Aortic Regurgitation (AR), 2) Aortic Stenosis (AS), 3) Mitral Regurgitation (MR), 4) Pulmonary Regurgitation (PR), 5) Pulmonary Stenosis (PS), 6) Subaortic Stenosis+Ventricular Septal Defect (SAS+VSD), 7) Systolic Ejection (SE). It should be noted that murmur presence detection is based on Lyapunov exponents described earlier.

Murmur classification is a challenging task, whose success is mainly conditioned by the quality of the features. The features implemented in this toolbox have been obtained using a feature selection approach from a pool of 256 features. These features have been collected using a two-fold approach: features have been collected from two well-known methods described in literature and a set of new features has been introduced [16]. Regarding the feature sets taken from the literature, the sets introduced by Alhstrom *et al.* [17] and by Olmez and Dokur [18] have been considered. The most discriminative features have been selected using Pudil's sequential floating point forward selection method. The module uses 10 features listed in table I. The transition rate is defined by *transition rate* = T_{asc}/T_{desc}, where T_{asc} is the transition time taken from the first minimum of the energy curve to the maximum energy, and T_{dsc} is the time interval from the energy maximum to the last subsequent minimum energy. The remaining features are well-known in signal processing.

TABLE I: FEATURE SET FOR MURMUR CLASSIFICATION.

Loudness	*Zero crossing rate*
Transition Ratio	*Skewness (time domain)*
Fundamental frequency	*Spectral Shape*
Spectral power (100-200Hz)	*Spectral Flux*
Spectral power (200-300Hz)	*Max. Lyapunov Exponent*

D. Cardiac Function Assessment

The assessment of the left ventricle cardiac function is based on the extraction of the left ventricle systolic time intervals (STI), i.e., the pre-ejection period (PEP) and the left ventricle ejection time (LVET). STI are defined by the events of the aortic valve. Namely, PEP is defined by the time interval between R-peak of the ECG and the opening of the aortic valve, while LVET corresponds to time span between the closing and the opening events of this valve. We have shown [19] that S1 and S2 can be applied to extract the aortic valve events from S1 and S2 using synchronized echocardiography and HS under resting conditions.

The details regarding the algorithm for the detection of the aortic events using HS were presented in [6]. The method is based on a Bayesian approach using instantaneous amplitude. Once the beat-by-beat STI have been extracted, the toolbox enables the calculation of the following cardiac function measures:

Corrected STI with respect to heart rate and classification: The implemented correction algorithms are those described in [20] and [21]. For STI correction under exercise, the correction steps described by Mertens *et al.* [22] have been considered in the toolbox. The toolbox presents diagnosis information regarding if the STI are pathological or not.

Contractility index and classification: The contractility index PEP/LVET is computed average runs of 5 beats. Heart Failure diagnosis is automatically provided based on clinically validated threshold.

Stroke Volume and Cardiac Output: The beat-to-beat as well as the average stroke volume and the cardiac output are calculated using the model described in [23].

III. RESULTS AND DISCUSSION

Table II presents the sensitivity and specificity results of the algorithms implemented in the heart sound toolbox of the framework. The STI estimation entries, i.e., PEP, LVET and RS2 entries, refer to the absolute estimation error with respect to echocardiography (the clinical gold standard). These results were obtained using heart sounds acquired at several hospitals from typical target populations, i.e., patients suffering from several types of cardio-vascular diseases such as atrial fibrillation, tachycardia, premature ventricular contractions, several types of valve problems with regurgitation and stenosis, patients with artificial valve implants, as well as several degrees of heart failure. Regarding the data acquisition for noise detection, the protocol followed included contaminations by several distinct internal and external noise sources at different intensity levels. All databases have been collected and annotated under medical supervision. Table III summarizes the population characteristics and the amount of data collected for each validation database.

TABLE II – SUMMARY OF RESULTS.

Function	*SE/Abs. Error*	*SP/Corr.*
Noise detection	95.88%	97.56%
Segmentation (without murmur)	97.95%	98.20%
Segmentation (grade I-IV murmur)	91.09%	95.25%
Murmur classification (set of 10 features)	95.74%	95.01%
PEP	11.9±8.8*ms*	0.70
LVET	18.0±17.4*ms*	0.83

As can be observed from the results in table II and III, most of the algorithms developed by the team and integrated into the toolbox have been evaluated thoroughly. Furthermore, these methods exhibit very high sensitivity and specificity values.

TABLE III – VALIDATION CONDITIONS.

Function	*N*	*BMI*	*Age*
Noise detection	71	25.1±7.8kg/m^2	35.3±12.0*y*
Segmentation (without mur.)	55	24.4±1.5kg/m^2	32.6±9.7*y*
Segmentation (grade I-IV mur.)	21	24.9±2.3kg/m^2	54.73±6.0*y*
Murmur classif.	51	25.4±2.2kg/m^2	64.65±8.6*y*
STI	11	25.9±3.2kg/m^2	53.8±18.1*y*

Given the achieved maturity level of the toolbox, it is being used to deploy clinical applications. Currently, the team is developing an intelligent stethoscope using the framework. As can be observed in Fig. 6, the application fully annotates each HS component per heart cycle, i.e., it segments the main HS components, measures the STIs and the stroke volume and classifies existing murmur.

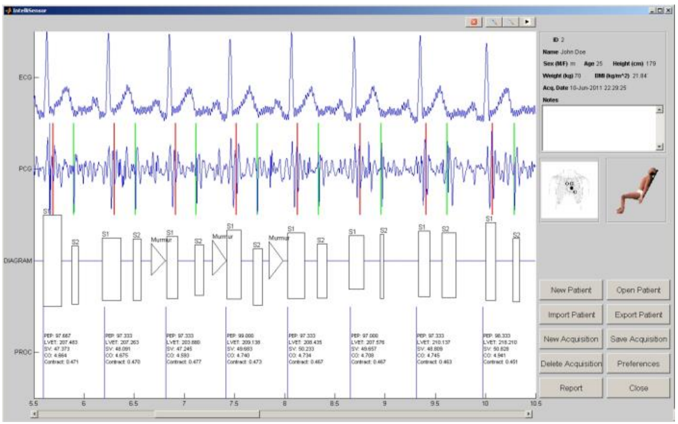

Fig. 6: Visualization of the Intelligent Stethoscope application interface with automatically annotated HS.

Fig. 7: Acquisition setup with synchronized echocardiography using the multi-channel setup.

IV. CONCLUSIONS AND FUTURE WORK

In this paper we introduce a Matlab toolbox for acoustic cardiac signal processing. The main algorithms developed specifically for the heart sound toolbox are outlined. These include solutions for the main challenges that are encountered in real life applications based on heart sounds. In comparison to other existing heart sound processing frameworks, the proposed toolbox includes methods for the processing functionalities that are commonly handled, i.e., noise contamination detection, heart sound segmentation and murmur classification, but also tackles problems that most known frameworks do not contemplate. More specifically, methods for cardiac function assessment are part of the proposed toolbox. To the best of the authors' knowledge, the proposed toolbox is the first one that enables STI measurement using heart sounds. This opens new application areas to heart sounds such as heart failure management.

The proposed framework exhibits a significant maturity level. Most of the integrated algorithms have been tested using heart sound clips obtained under medical supervision and using typical CVD populations under real-life conditions. The achieved results are comparable and in most cases exceed the state of the art in competing methods.

Currently, the described algorithms are being extended for multi-channel acquisition settings in order to increase their performance. This task is being tackled at several levels: (i) in order to enable a more robust setup to collect clean HS for processing, blind source separation algorithms are being developed using this multi-source setup, (ii) a multi-source extension to the Bayes-based algorithm is being developed in order to improve the reported performance, namely in what concerns correlation as well as the absolute error, (iii) detection of S3 components and (iv) to develop a robust S2 split detection and analysis algorithm. In our current setup (see Fig. 7), the acquisition system is being implemented using a PowerLab® system from AdInstruments.

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