Detection of Left Ventricular Ejection Fraction Abnormality Using Fusion of Acoustic and Biopotential Characteristics of Precordium*

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***Abstract*— This study develops a wearable monitoring platform for the detection of abnormal left ventricular ejection fraction (LVEF) using a fusion of an accelerometer contact microphone (ACM) and an electrocardiogram (ECG) sensor. Two signal processing chains are designed to annotate ACM and ECG recordings. Afterwards, the pre-ejection period (PEP) and left ventricular ejection time (LVET) are estimated as the time difference between the first heart sound (S_1) and the R-peak in ECG signals, and the time difference between the first and second heart sounds (S_1 and S_2), respectively. The ratio of PEP to LVET is then utilized to differentiate between healthy and abnormal-LVEF groups. The model is evaluated on 15 subjects (8 healthy subjects and 7 subjects with LVEF abnormality) where the ground truth values are the LVEF parameter acquired by the echocardiography machine. An average (± standard deviation) accuracy of 84.47% (± 17.58%) is obtained for the detection of LVEF abnormality for a total of 5989 heartbeats. It is demonstrated that the proposed method is capable of LVEF abnormality detection with accuracies within the range of 54.35% - 100%.**

Keywords—left ventricular ejection fraction (LVEF); wearable sensors; accelerometer contact microphone; electrocardiogram; pre-ejection period; left ventricular ejection time (LVET)

I. Introduction

Heart failure (HF), defined as a condition in which the cardiac muscle fails to pump adequate blood to meet the needs of the body, affects 6.2 million in the US annually [1]. HF is primarily accompanied by gradual decreases in the volumetric fraction of the blood ejected from the left ventricle per heartbeat [2]. This fraction is referred to as left ventricular ejection fraction (LVEF) which normally falls within the range of 52%-72% [3]. Lower percentages of LVEF suggest cardiovascular abnormalities such as cardiomyopathy, heart valve problems, and chronic hypertension [4], which require timely medical intervention. As such, continuous monitoring of LVEF in patients with cardiovascular diseases is critical, contributing to timely risk management. This motivates the need for round-the-clock monitoring devices.

LVEF is predominantly monitored by echocardiogram (echo) machines in the clinic. Echo utilizes ultrasound technology to produce images of the heart, and accurately quantify the blood volume ejected from the left ventricle at each heartbeat. Nevertheless, the bulky nature of echo monitors inhibits their use as ubiquitous monitoring devices. Several studies have addressed cardiovascular monitoring using phonocardiogram recorded by a stethoscope [5]–[7]. While stethoscopes provide useful information about mechanical activities of the cardiac system, their use for real-world continuous monitoring is limited due to susceptibility to ambient noise. On the other hand as demonstrated in [8] and [9], accelerometer contact microphones are capable of monitoring the cardiopulmonary system and pulmonary disorders respectively.

The authors in [10] have demonstrated that LVEF is proportional to cardiac time intervals extracted from heart sounds. In this paper, we revisit the detection of left ventricular ejection fraction, and adapt it to wearable settings. To this end, we establish a monitoring platform based on the fusion of acoustic and biopotential characteristics of the precordium recorded by the recently-developed accelerometer contact microphone (ACM) in [9] and an electrocardiogram (ECG) sensor respectively. This framework is comprehensively discussed in the following sections.

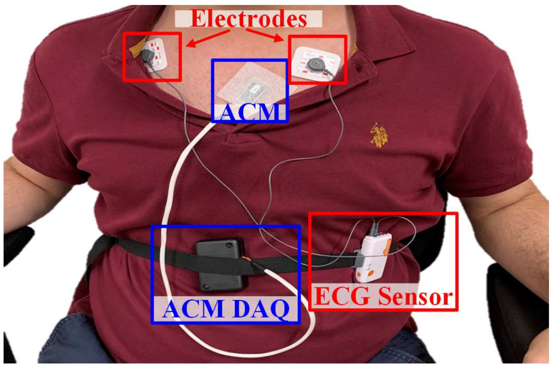

Fig. 1. The experimental setup including an accelerometer contact microphone (ACM from StethX Microsystems) on the chest connected to a data acquistion (DAQ) module, and a single lead of an electrocardiogram (ECG) sensor node (Shimmer3 ECG Development Kit) strapped around the torso.

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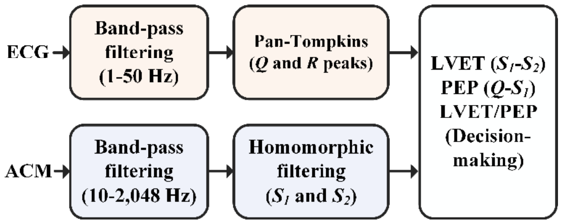

Fig. 2. The signal processing chain including pre-filtering, signal annotation, and decision-making stages for noise cancellation, time intervals estimation, and LVEF abnormality detection, respectively.

II. Experimental Setup & Methodology

A. Data Collection

This study includes seven cardiovascular patients (5 males and 2 females) with average (± standard deviation) LVEF of 27.85% (± 12.86%). The average (± standard deviation) age, height, and weight of the patients are 72 (± 13.97) years, 170.18 (± 12.44) cm, and 73.03 (± 20.79) kg, respectively. Additionally, eight subjects (3 males and 5 females) with average (± standard deviation) LVEF of 58.75% (± 2.31%) constitute the healthy cohort whose average (± standard deviation) age, height, and weight are 60 (± 18.05) years, 169.22 (± 11.83) cm, and 85.21 (± 18.02) kg, respectively. All subjects are studied at the cardiac care unit of Sorin Medical P.C. under measurement protocols approved by the Institutional Review Board (IRB) of Stevens Institute of Technology with protocol number 2022-044 (N).

Fig. 1 describes the experimental setup designed for LVEF abnormality detection. A ± 4 g sensitive accelerometer contact microphone (ACM) with micro-g resolution and a small form-factor of 27 mm × 15 mm × 2.5 mm from StethX Microsystems is attached to the pulmonary region of the subjects using medical-grade adhesive tape. This device is a low-noise accelerometer with a wide operational bandwidth of 0-10 kHz, allowing for recording heartbeat-induced sounds and vibrations on the chest wall. The ACM is not sensitive to airborne emission sounds, making it a robust phonocardiogram sensor against acoustic ambient noise. The subjects were seated at rest on a chair for a period of five minutes, followed by five minutes of ACM measurements at a sampling rate of 22.33 kHz, still at a seated position. Simultaneously, the left arm-right arm (LA-RA) lead of a four-lead ECG sensor (Shimmer3 ECG Development Kit; Shimmer, Dublin, Ireland) was used to record the electrical activities of the cardiac system at a sampling rate of 512 Hz. The patients' LVEF values were also measured by an ultrasound echocardiography machine as the reference modality. The collected data were transferred to a computer and processed in a Python framework.

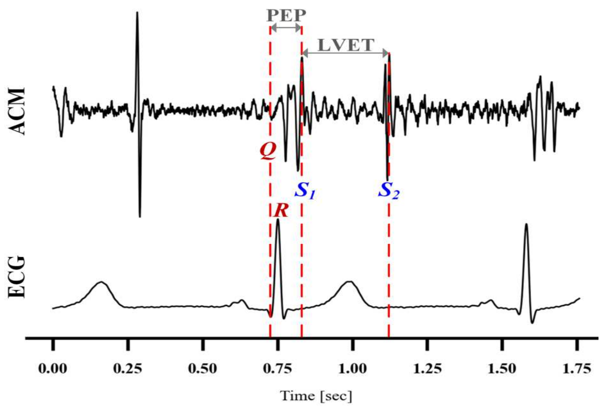

Fig. 3. ACM (top) and ECG (bottom) annotations and time intervals, including pre-ejection period (PEP) and left ventricular ejection time (LVET) corresponding to time difference of Q-S_1 and S_1-S_2, respectively.

B. Signal Processing for PEP/LVET Estimation

Fig. 2 represents the signal processing chain for LVEF abnormality detection. A zero-phase, 3rd-order Butterworth filter over the frequency range of 10 Hz - 2 kHz is initially applied to ACM recordings to mitigate noise, respiration artifacts, and baseline wander. The filtered signals are then downsampled to a sampling rate of 4 kHz to accelerate the processing steps. In order to determine the first and second heart sounds (S_1 and S_2 respectively), the envelope of the signal is calculated using a homomorphic filter [11]. This results in the appearance of peaks corresponding to the main heart sounds (S_1 and S_2) as well as murmurs and the remnant noise in the envelope. To extract S_1 and S_2 from ACM recordings, a peak detector algorithm is employed to filter out the peaks corresponding to noise and heart murmurs. This algorithm considers a peak as a heart sound only if its amplitude is greater than 0.2 times the maximum value of the envelope, and its distance from the previous heart sound is at least 100 ms. Finally, the detected peaks are labeled as S_1 and S_2. This is performed by comparing the time differences of a peak with its preceding and following peaks. If the time difference of a peak with its following peak exceeds the time difference of that peak with its preceding peak, the peak is labeled as S_2; otherwise, it is considered S_1.

As shown in Fig. 2, the simultaneously-recorded ECG signal is band-pass filtered retaining the frequency components within the range of 1-50 Hz. Furthermore, to attenuate the power-line interference, a second-order infinite impulse response (IIR) notch filter centered at 60 Hz with a quality factor of 25 is applied to the filtered ECG signal in forward and backward directions. The R-peaks in the ECG signal are detected by the Pan-Tompkin algorithm [12]. The Q-peaks are then annotated by finding the minimum value of the signal within 50 ms backward of the corresponding R-peaks.

After annotation of ACM and ECG signals, the left ventricular ejection time (LVET), which is defined as the time interval between aortic valve opening (S_1 in ACM signals) and its closure (S_2 in ACM signals), is estimated per heartbeat as shown in Fig. 3. Additionally, the pre-ejection period (PEP), which signifies the time elapsed between the electrical depolarization of the left ventricle (Q peak in ECG) and the beginning of the ventricular ejection (S_1 in ACM), is estimated. It has been demonstrated that LVEF is inversely proportional to PEP/LVET [10]. In this study, we leverage a fusion of ACM and ECG sensory data to detect LVEF abnormality. The use of ACM in this study is significant. The aortic closure point in accelerometric data is often contaminated by noise, hindering the accurate estimation of LVET.

TABLE I. PERFORMANCE EVALUATION OF ABNORMALITY DETECTION (0.3 < PEP/LVET < 0.4)

Subject	#Beats	#True beats	#False beats	Accuracy (%)
1 (H)	467	467	0	100
2 (H)	531	426	105	80.22
3 (H)	510	496	14	97.25
4 (H)	317	181	136	57.09
5 (H)	473	449	24	94.92
6 (H)	335	329	6	98.21
7 (H)	553	406	147	73.41
8 (H)	557	398	159	71.45
9 (P)	424	422	2	99.52
10 (P)	364	364	0	100
11 (P)	425	231	194	54.35
12 (P)	371	371	0	100
13 (P)	328	271	57	82.62
14 (P)	334	334	0	100
15 (P)	409	237	172	57.94
Average (± std.)	**426.53 (± 84.79)**	**358.8 (± 93.77)**	**67.73 (± 75.05)**	**84.47 (± 17.58)**

Owing to its state-of-the-art sensitivity and low noise, the ACM on the other hand provides S_2 sounds which correspond to the aortic closure, but with more evident patterns in the signal. This helps estimate LVET periods with much higher confidence. As shown in Fig. 3, heart sounds are represented by evident peaks resulting from the absolute robustness of the ACM against the ambient noise. *This allows for wearable monitoring of LVEF, which traditionally was not feasible with hand-held stethoscopes due to their susceptibility to background noise and low signal-to-noise ratios (SNRs).*

III. EXPERIMENTAL RESULTS AND DISCUSSION

A. LVEF Abnormality Detection Performance

Table I summarizes the performance of the proposed method for LVEF abnormality detection for 8 healthy subjects and 7 abnormal LVEF patients who are labeled by H and P respectively. Per subject, the estimated PEP/LVET value for each beat is compared with the standard range (i.e. 0.3-0.4 as defined by [13]) for healthy subjects to separate healthy and abnormal subjects. If the estimated PEP/LVET value falls within 0.3-0.4, it is concluded that the subject is healthy; otherwise, the subject is classified with abnormal LVEF. If the label of the subject is consistent with the predicted class, the beat is called a true beat; otherwise, it is called a false beat. As such, the number of true and false beats in Table I respectively represent truly and falsely classified heartbeats with respect to the ground-truth labels (H or P). An average (± standard deviation) accuracy of 84.47% (± 17.58%) is achieved for 5,989 heartbeats corresponding to all subjects together, suggesting the accurate performance of the proposed method. An average (± standard deviation) accuracy of 84.06% (± 15.86%) is obtained for healthy subjects where the highest and lowest classification accuracies among healthy subjects are reported for subject 1 with 100% and subject 4 with 57.09%, respectively. It seems that the ACM recording associated with subject 4 is distorted in a considerable number of segments due to subject movements, resulting in a low SNR and 136 false beats. On the other hand, no distortion or motion artifacts are observed in the ACM recordings of subject 1, leading all 467 beats to be correctly classified.

As reported for subjects with abnormal LVEF values (subjects 9-15 in Table I), accuracies of 100% are achieved for subjects 10, 12, and 14, whereas the largest classification error is reported for subject 11 with accuracy and falsely classified number of beats of 54.35% and 194 respectively. An average (± standard deviation) accuracy of 84.91% (± 20.66%) signifies the classification performance for subjects with abnormal LVEF. Comparing the average accuracies obtained for the healthy cohort and abnormal subjects (84.06% vs. 84.91%), no statistically significant difference is observed between the two groups ($p < 0.05$), implying a robust performance for a variety of LVEF values.

B. Limitations

Although the proposed method is capable of an adequate level abnormal LVEF detection (84.47%), it still misses almost 15% of abnormalities. This limitation can be addressed by extracting additional time intervals rather than relying merely on LVET and PEP, similar to our previous studies on valvular heart diseases (VHDs) [14], [15]. In this study, a decision-making algorithm based on the normal range of PEP/LVET is used. However, LVEF abnormality detection can benefit from machine learning techniques encouraging data-driven modeling for abnormality identification.

Another limitation of this work is the small number of subjects participating in the study. The larger the number of subjects, the more the number of left ventricular ejection fraction values, resulting in more generalizable models. Furthermore, the average age of the subject population is around 65 years which is not representative of LVEF abnormalities at younger ages. As such, extensive data collection could benefit our modeling.

IV. CONCLUSION AND FUTURE WORKS

This paper reports on the design of a novel method for the detection of left ventricular abnormalities. A recently designed accelerometer contact microphone (ACM) is fused with a single-lead electrocardiogram (ECG) sensor to estimate the pre-ejection period (PEP) as well as the left ventricular ejection time (LVET). Following previous studies, PEP/LVET is used to classify between healthy subjects and patients diagnosed with LVEF abnormalities. The proposed method is evaluated on 8 healthy subjects and 7 cardiovascular (CVD) patients with abnormal LVEF values. It is demonstrated that the model can detect LVEF abnormalities with an accuracy of 84.47%, a highly promising value for wearable settings. In our future studies, we will investigate additional time intervals and their relationships with abnormal LVEF values. Furthermore, we will take advantage of machine learning techniques which are capable of extracting the signal patterns existent in the ACM recordings. These models can be used for more robust decision-making systems for the identification of LVEF abnormalities and their respective severity levels.

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