Demo Abstract: SonarBeat: Sonar Phase for Breathing Beat Monitoring with Smartphones

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***Abstract*—Vital sign (e.g., breathing rate) monitoring has become increasingly more important because it offers useful clues of medical conditions such as sleep disorders or anomalies. It is necessary to provide contact-free, easy deployment, and long-term vital sign monitoring for healthcare. In this demo, we present SonarBeat to leverage a phase based active sonar to monitor breathing rates with smartphones.**

I. Introduction

Breathing signals are helpful to physical health monitoring since such vital signs can offer important information for health problems, such as sudden infant death syndrome (SIDS) and sleeping anomalies. Traditional systems require a person to wear special devices such as a pulse oximeter or a capnometer. which are inconvenient to use. It is appealing to offer contact-free, easy deployment, and long-term vital sign monitoring for healthcare [1], [2].

In this demo, we leverage smartphones to monitor breathing rates using an inaudible sound signal, which emulates an active sonar system [3]. We use the speaker to send an inaudible sound in the frequency range of 18-22 kHz as a continuous wave (CW) signal. The signal is reflected by the chest of the patient and is then received by the microphone. We can then accurately extract the phase of the received signal to estimate the breathing rate.

II. The SonarBeat System

Our goal is to achieve real-time breathing rate monitoring of a single person using an active smartphone based sonar in a realistic setting. The main challenge for breathing rate monitoring based on phase modulated data is to mitigate the static vector effect, which directly influences the sensitivity and correctness of the phase data. For example, the larger the static component of phase data, the larger the estimation error. This is because the signal-to-noise-ratio (SNR) at the receiver will become low when there is a large static component, making it hard to demodulate the phase from the dynamic breathing data. An existing method [4] uses local extreme value detection (LEVD) to remove the stationary components in the I/Q traces for hand tracking indoors. However, this method is not effective for solving our problem because the LEVD based method needs to set an empirical threshold for different environments. We propose an *adaptive median filter method* for SonarBeat to effectively remove the stationary component for different scenarios.

The second challenge is to be adaptive to body movements and environment noise. On one hand, because body movement always happens during sleep, the breathing monitoring systems need to be adaptive to such movement. An exiting work in [5] employs the FMCW technique for breathing monitoring, where the system needs to accurately estimate the distance between the smartphone and the chest before breathing rate can be detected. When the body suddenly moves (e.g., turning over), the system needs to estimate the new distance, thus leading a large time complexity. The proposed sonar phase based breathing monitoring is adaptive to body movements. On the other hand, there could be more than one persons in the indoor environment. Their activities (e.g., walking or talking) generate audio noises that interfere the transmitted inaudible signal. We incorporate I/Q demodulation to remove the environment noise from other audio sources.

We design the SonarBeat system with commodity smartphones. Specifically, SonarBeat utilizes sonar phase data to monitor the periodic signal caused by the rises and falls of the chest while the person inhales and exhales. Based on an analysis of sonar phase, SonarBeat can effectively extract the breathing signal from the sonar phase information. First, the phase information represents the periodic signal of breathing beats with a high accuracy. Moreover, the CSI phase is sensitive to, and thus effective to capture the small movements of breathing. Second, compared with other traditional methods such as Doppler shift and FMCW, the phase based breathing monitoring technique has a lower latency and lower complexity. Finally, the sonar phase data is robust to different orientations, different distances, different cloth thicknesses, and different persons. Moreover, it is robust even when the body makes a large movement. The movement only leads to a change of the stationary component of the phase data, which can be effectively removed by the proposed adaptive median filter method.

Fig. 1 presents the SonarBeat system architecture. It includes four basic modules: Signal Generation, Data Extraction, Received Signal Preprocessing, and Breathing Rate Estimation. The Signal Generation module mainly implements a Pulse-code Modulation (PCM) of the inaudible signal, where a CW inaudible signal at 18 kHz to 22 kHz is generated and modulated with the PCM technique. The Data Extraction module implements short-time Fourier transform (STFT) for audio signal detection. A threshold based method is proposed for detecting the beginning of the received inaudible signal.

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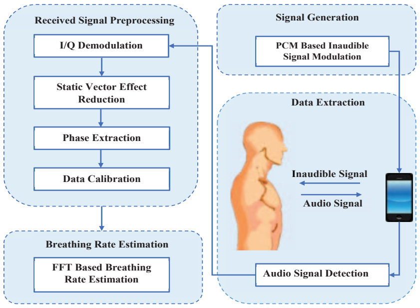

Fig. 1. SonarBeat system architecture.

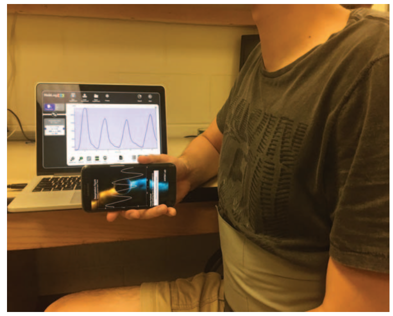

Fig. 2. Experiment setup.

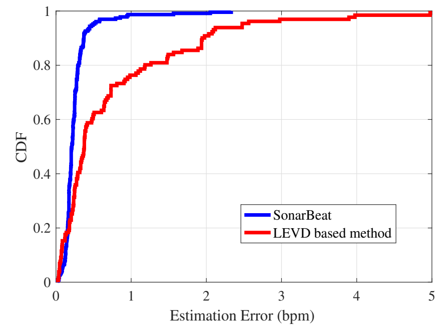

Fig. 3. CDFs of estimation error.

The Received Signal Preprocessing module consists of I/Q demodulation, static vector effect reduction, phase extraction, and data calibration. The I/Q demodulation component first reduces the sampling rate from 48 kHz to 480 Hz, for the sake of a lower processing delay for realtime monitoring. Then, a coherent detector structure is used to down-convert the received sound signal to the baseband signal, and a low-pass filter is used to remove the high-frequency components and environment noises to obtain the I-phase and Quadrature signals. For static vector effect reduction, we implement an adaptive median filter method to remove the static vector in the In-phase and Quadrature signals, which is suitable for online processing. For phase extraction, we derive the sonar phase information, which only includes the breathing signal. Moreover, we need to unwrap the phase data to obtain the calibrated breathing phase. For data calibration, we implement a median filter as a simple Low Pass FIR to remove the noises. The Breathing Rate Estimation module employs an FFT based method to estimate the breathing rate.

III. Prototyping and Experimental Study

We develop a prototype of the SonarBeat system using Android based platforms, e.g., a Samsung Galaxy S6 or a Samsung Galaxy S7 Edge. We implement all the signal processing algorithms using Java with the Android SDK. Both smartphones can achieve very good performance on processing audio data for realtime breathing rate estimation and display. The first edition of SonarBeat is implemented with the minimum version of Android 5.1.1 OS (API 21). So it works with all the more recent Andriod systems such as Android 6.0 and Android 7.0. For breathing monitoring, we only incorporate one speaker and one microphone to transmit and receive the inaudible audio data, where the microphone and speaker positions are at the bottom on the smartphone. Furthermore, we use the AudioTrack class to play inaudible sound and the AudioRecord class to record sound. The buffer of the recording thread is set to 1920 points with a sampling rate of 48 kHz. Therefore, we set the realtime signal processing unit to 1920 points, which is about 40ms. The experiment setting is shown in Fig. 2, where the SonarBeat result matches the ground truth provided by the NEULOG Respiration Monitor Belt Logger Sensor wrapped on the body.

Fig. 3 presents the cumulative distribution functions (CDF) of estimation error in breathing rate estimation with SonarBeat. For comparison purpose, we also developed an LEVD based system [4], where the LEVD method is used for estimating the static vector and all other signal processing methods are the same as in SonarBeat. The LEVD based system is used as a benchmark in the experiment. We find that SonarBeat and the LEVD based method achieve a median error of 0.2 bpm and 0.3 bpm, respectively. This illustrates that both systems can effectively estimate breathing rates. However, it is worth noting that for SonarBeat, 95% of the test results have an estimated error under 0.5 bpm, while only 60% of the test results with the LEVD based method have an estimated error under 0.5 bpm. Moreover, the maximum estimation error for SonarBeat and the LEVD based method are 2.4 bpm and 5 bpm, respectively. This is because the LEVD based method requires setting the empirical threshold based on the standard deviation of the baseband signal in a static environment. It is not robust in varying environments where the same threshold will not work. However, SonarBeat leverages the adaptive median filter method, and is thus more robust to changes in the environment. Therefore, the SonarBeat system can achieve a higher and more stable breathing rate estimation accuracy than the LEVD based method.

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