

NOISE DETECTION IN SMARTPHONE PHONOCARDIOGRAM

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ABSTRACT

This paper presents a demo proposal of a standalone smartphone application that can automatically analyse the signal quality of PCG, as it is recorded on a low-cost smartphone-based digital stethoscope. Features, related to the inherent pattern of the autocorrelated signal envelope, have been used for classifying and discarding the noisy portions from a continuous PCG. Our application has been successfully deployed on Nexus 5 and tested on several clean and noisy PCG signals with sensitivity 78.91% and specificity 70.83%

Index Terms— Diagnosable quality, Phonocardiogram, Noise, Classification, Feature Selection

1. INTRODUCTION

PCG analysis is the most fundamental method of diagnosing various cardiovascular disorders. TCS has developed a smartphone-based low-cost e-Stethoscope [1] to record heart auscultation sounds, also known as Phonocardiogram (PCG). This PCG can be of varying quality, as it is susceptible to motion artefact, instrumentation error arising due to very low-cost equipment, background noise etc. Also the PCG is collected by untrained personnel like the users themselves or medically untrained volunteers.

This data quality, in terms of intensity and periodicity, may not be suitable for analyses and inferences by machine learning algorithms. In spite of several works [2] [3], accurate preprocessing of PCG is still an open research area. Here, we have proposed a robust, sensor-agnostic system for detecting noisy PCG.

2. PROPOSED METHODOLOGY

We designed a binary classifier for classifying a windowed PCG segment as clean or noisy. Fig. 1 shows the basic architecture of this application. Acquisition of PCG, temporary buffering and final display of the processed signal, indicating the noisy portions, are performed in the *Input/Output layer*.

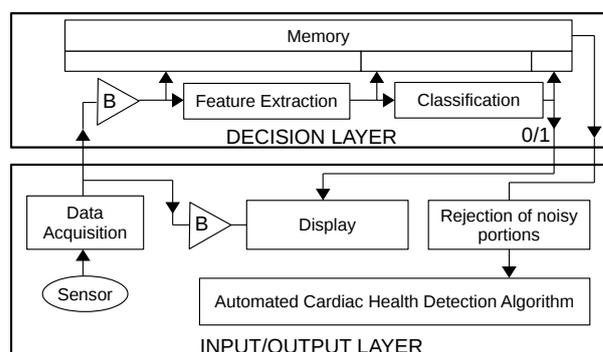


Fig. 1. Proposed System Architecture

Feature extraction and classification are performed in the *Decision layer*. As detailed in [1], our in-house digital stethoscope front-end is attached to a smartphone for collection of PCG at 8 KHz sampling frequency. The temporary buffer can store 5 seconds of digitized data, which is then processed by the decision layer.

At the decision layer, a filtered version of the autocorrelated waveform of the signal envelope is obtained [2], as shown in Fig. 2. A clean PCG has three dominant peaks at (a) *systolic*, (b) *diastolic* and (c) *cardiac cycle* durations, whereas this distinct pattern is absent for a noisy PCG. Along with features taken from [2], novel features introduced here include spectral flux, correlation coefficients of the *autocorrelation waveform* and the *sum of 1, 2 or 3 fitted, rectified sinusoids* and similarly with *decaying sinusoids*.

Random forest is used for classification and the estimated

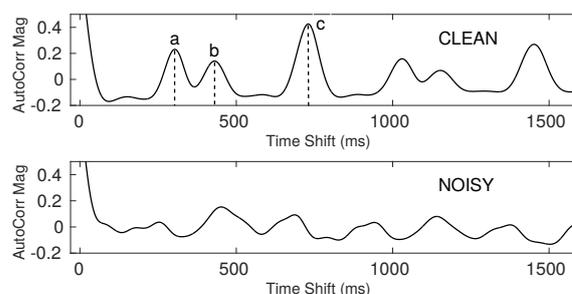


Fig. 2. Autocorrelation of PCG Envelope

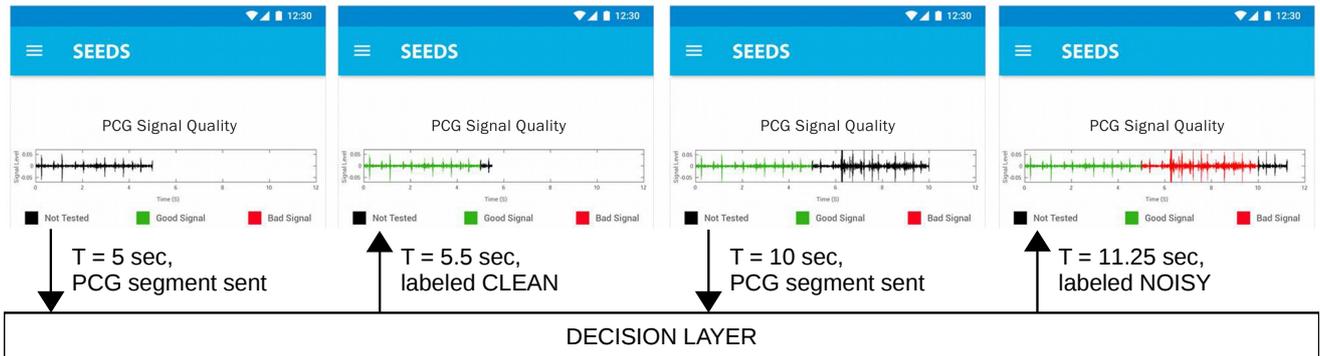


Fig. 3. GUI of Smartphone App showing Clean (green), Noisy (red) and Unlabeled (black) portions of PCG

label is sent back to the I/O layer subsequently. A colour-coded PCG is displayed on the screen and the clean portions of the signal is ready to be analysed by an automated cardiac health detection algorithm.

3. DATASET & RESULTS

For designing a robust sensor-agnostic system we used 2 datasets for training and testing. They are completely different in terms of sensor quality, patient demography and signal quality. The PCG dataset, made available in [3] (3154 recordings using medical-grade off-the-shelf digital stethoscopes) was used for training. Apart from normalcy labels, each recording was also marked as clean or noisy by expert annotators. Our test dataset was collected from an urban hospital in Kolkata, India, from different cardiac and non-cardiac patients, using our in-house digital stethoscope along with a Nexus 5. The quality of these PCG signals was manually annotated by practicing clinicians. A total of 20 PCG segments, including 12 noisy and 8 clean ones (each from a unique patient), were collected.

Performance evaluation was done in terms of Se (Sensitivity: rate of acceptance of clean signals) and Sp (Specificity: rate of rejection of noisy signals), while the accuracy was measured as $Acc = (Se+Sp)/2$. Due to highly unbalanced ratio of clean and noisy data (16:1) in the training set, we created 16 training sets each with all noisy data and equal number of randomly selected non-overlapping clean data. Each such set generated a unique predictor. Average Se , Sp and Acc across all 16 training models were 78.91%, 70.83% and 74.87% respectively. Fig. 4 presents the variation of performance scores for all training models. The results imply that though Se and Sp are low in some cases, since those do not occur simulta-

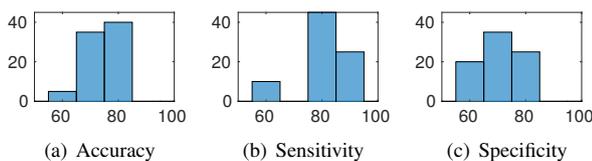


Fig. 4. Performance of all training models on hidden test set

neously, overall Acc is pretty high. For example, Fig. 4(a) shows that 40% of the test cases exhibit 75-85% Acc .

4. DEMO SET-UP

In our prototype demo system, the application runs on a Nexus 5. The user sits in an armchair and breathes normally (rest condition) during collection of data. Heart sound is captured from third intercostal space. Since essential information lies below 1 KHz, raw PCG is down-sampled to 2 KHz before processing. Fig. 3 represents communications, over time, occurring between the *User Interface* and the *Decision layer*. Processing of 5 seconds of PCG segment typically takes 0.3 second. During the live demonstration, a state-of-the-art heart rate estimation algorithm shall be deployed as standalone and also in conjunction with the proposed system. It is expected that users will see a performance improvement in the latter case.

5. REFERENCES

- [1] Arijit Sinharay et al., "Smartphone based digital stethoscope for connected health—a direct acoustic coupling technique," in *Connected Health: Applications, Systems and Engineering Technologies (CHASE), 2016 IEEE First International Conference on*. IEEE, 2016, pp. 193–198.
- [2] David B Springer et al., "Signal quality classification of mobile phone-recorded phonocardiogram signals," in *2014 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 2014, pp. 1335–1339.
- [3] Chengyu Liu et al., "An open access database for the evaluation of heart sound algorithms," *Physiological Measurement*, vol. 37, no. 9, 2016.