HEARTMATE: AUTOMATED INTEGRATED ANOMALY ANALYSIS FOR EFFECTIVE REMOTE CARDIAC HEALTH MANAGEMENT

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ABSTRACT

Remote cardiac health management is an important healthcare application. We have developed Heartmate that enables basic screening of cardiac health using low cost sensors or smartphone-inbuilt sensors without manual intervention. It consists of robust denoising algorithm along with effective anomaly analytics for physiological signals. Heartmate identifies and eliminates signal corruption as well as detects cardiac anomaly condition from physiological cardiac signals like heart sound or phonocardiogram (PCG) and photoplethysmogram (PPG).

1. INTRODUCTION

Heartmate users get necessary alerts when unusual cardiac events are detected from the sensor-extracted cardiac marker signals like PPG or PCG. When PCG signal is captured cardiac abnormality is detected and when PPG is captured additionally cardiac arrhythmia condition is detected. The main challenge is to guarantee low false alarms as both PCG and PPG signals are often highly corrupted with ambient noise and motion artifacts [1]. Heartmate identifies the noisy physiological signals (PPG or PCG) and consequently removes the noisy portions or discards them. Further, it detects cardiac condition (normal or abnormal) by effectively analyzing the clean signal. Additionally, we have also considered Arterial Blood Pressure (ABP) signal to consolidate our claim of consistent performance guarantee. Functional flow of Heartmate is shown in figure 1.

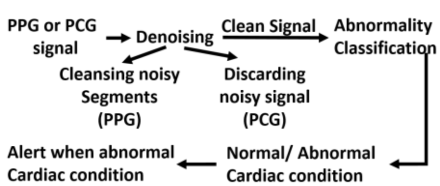

Figure 1. Heartmate Functional Flow

2. SYSTEM OVERVIEW

We depict the overall architecture of Heartmate in figure 2. The alert (when cardiac anomaly is detected) is locally generated for the patient/ user and sent online to concerned hospital and doctor.

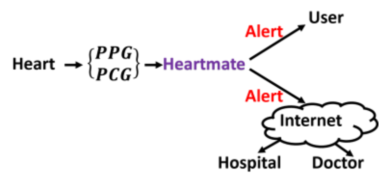

Figure 2. Heartmate Architecture

3. HEARTMATE SCHEME DESCRIPTION

Heartmate consists of two main components: 1. Denoising, 2. Anomaly analytics.

We propose semi-supervised learning based denoising method, where an ideal template of PCG or PPG signal is selected, as both PPG and PCG signals are quasi-periodic and periodicity $\approx$ heart rate. PCG signal $\mathcal{P}$ being highly oversampled to maximize human auditory sensitiveness, we first band-limit the PCG signal by band-pass filter with cutoff frequencies of [0.7, 5 Hz]. ***Segmentation:*** First, the physiological signal is segmented and each segment corresponds to one complete cardiac cycle. We use weighted slope sum function to segment PPG [2] and Springer method to segment PCG [3]. ***Pattern Recognition by template matching****:* Let, $\mathbb{T}_{\mathrm{PPG,PCG}} = \{\tau_1, \tau_2, \ldots, \tau_{\mathcal{H}}\}$ be the template (template for PPG and PCG are different, but template duration is same = $\mathcal{H}$ = ideal human heart rate = 72 beats per minute = 0.833 Second = 1.2 Hz) and $\mathcal{S}_{\mathrm{PPG,PCG}} = \{\omega_1, \omega_2, \ldots, \omega_{\mathbb{M}}\}$ be the segment of the captured PPG or PCG signal ($\mathbb{M}$ may fluctuate at each segment, $\mathbb{M}$ corresponds to the instantaneous heart rate). If the whole signal length is $\mathbb{L}$, then there are $\vartheta = \left\lfloor \frac{\mathbb{L}}{|S_{\mathrm{avg}}|} \right\rfloor$ number of complete segments present. Clean and noisy segments are segregated by their dynamic time warping (DTW) distance feature. ***Dissimilarity Measure by DTW****:* We compute DTW distance for each of the components $\mathcal{S}$ with respect to $\mathbb{T}$, $\delta_i = \mathrm{DTW}(\mathbb{T}, \mathcal{S})$, $i = 1,2,\ldots,\vartheta$. ***Noise Identification****:* When it is found the segment pattern is far from ideal pattern, i.e. δ_i is significantly high, the segments (PPG)/ signal (PCG) are declared noisy.

Cardiac feature detection from PPG [7] and PCG as well as anomaly detection are different methods, because

PPG is an optical domain signal, whereas PCG is an acoustic signal.

Abnormality Detection from PPG Signal: From PPG signal, we detect the presence of cardiac arrhythmias like extreme bradycardia, extreme tachycardia. It is a three step process and follows our earlier proposed Heart-Trend algorithm [4]. *Feature Derivation:* First mean heart rate feature is extracted from the captured PPG signal**.** ***Closeness*** *Prediction:* The closeness condition of the heart rate to the arrhythmia or normal cardiac state is predicted through *k*-means algorithm. *Classification:* We use *k*-nearest neighbor (*k*NN) method for three class classification: normal, bradycardia and tachycardia. The denoising and abnormality detection methods for ABP are same as followed in PPG.

Abnormality Detection from PCG Signal: For PCG signals, supervised learning method is used, where 628 number of normal and 628 number of abnormal PCG signals are used to ensure balanced training. *Feature Selection:* We first select total 54 features from temporal, spectral and wavelet domains. In order to achieve optimal classifier performance, we choose top m features from minimum Redundancy Maximum Relevance (mRMR) feature selection criteria [5] such that $Per(F_{mRMR|m=1}) < \cdots < Per(F_{mRMR|m=5}) \geq Per(F_{mRMR|m=6}) \geq \cdots Perf(F_{mRMR|m=54})$, $Per \rightarrow$ Performance for identifying target class. Let the complete feature set be $F = [F_1, F_2, \ldots, F_{54}]$, $F_{mRMR}|_{rank} \subseteq F$, $F_{selected} = \{F_{mRMR}|_{m=5}\}$. *Training:* Support Vector Machine (SVM) classifier with non-linear radial basis function kernel [8] is trained with $F_{selected}$ features, i.e. top 5 mRMR features. The trained model is used for validation to classify the PCG signal as normal and abnormal. It is to be noted the abnormality detection is strictly performed on the clean physiological signal.

4. DEMO DESCRIPTION AND RESULTS

- *Demo Requirement and Description:* Demo would be presented in MATLAB environment as shown in figure 3. No special hardware is required. First, the cardiac signals, PCG, PPG or ABP are to be selected. Then denoising algorithm works on it. We demonstrate by showcasing the raw signal, the corresponding template, and the denoised signal. After denoising, the clean signal is analyzed for cardiac abnormality detection. When cardiac abnormality is detected, alert is generated. We establish our claim of performance efficacy of inferring cardiac anomaly condition from PPG and PCG signals in figure 4 and 5.
- *Results on PPG datasets:* We have taken 750 patients' PPG and/or ABP signals, sampled at 250 Hz. These signals were captured from various US and Europe hospitals [6] with expert arrhythmia annotations. We have tested our PPG anomaly analytics on these signals. We have achieved close to 100% sensitivity and more than 80% accuracy of cardiac arrhythmia detection. It is to be noted good amount of signals are noisy in nature.
- Results on PCG datasets: In order to show the efficacy of Heartmate for detecting the cardiac abnormality condition (≈ cardiac conditions that need medical attention) from PCG signals. Total 665 number of abnormal and 2488 number of normal subjects' PCG signals are captured and out of which 279 are noisy [1]. It is depicted in figure 5 that we have achieved more than 85% accuracy in detecting cardiac abnormality condition. It is to be observed that we have attained approximately 10% higher accuracy when denoising is performed than when denoising is avoided.

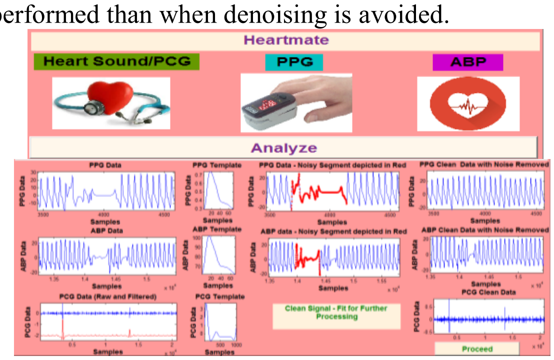

Figure 3. Heartmate Demo

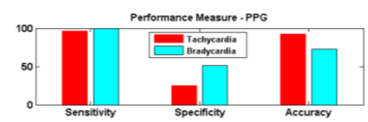

Figure 4. Cardiac Arrhythmia Detection from PPG signal

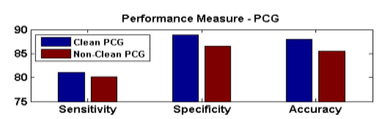

Figure 5. Cardiac Anomaly Detection from PCG signal

5. REFERENCES

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