HEART-TREND: AN AFFORDABLE HEART CONDITION MONITORING SYSTEM EXPLOITING MORPHOLOGICAL PATTERN

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ABSTRACT

In this paper we leverage the power of smartphone to enable proactive in-house heart condition monitoring. We introduce Heart-Trend, a nonparametric model to analyze and detect heart abnormality conditions like arrhythmia from photoplethysmogram (PPG) signal. It does on-demand heart status monitoring using smartphones (can also be implemented in PC/ICU monitors) and facilitates timely detection of heart condition deterioration to permit early diagnosis and prevention of fatal heart diseases. Proposed robust anomaly analytics engine accurately detects the morphological trend to find abnormal heart condition in real time through machine learning based trend prediction. PPG signal is frequently corrupted by ambient noise, and motion artifacts, which lead to high amount of false alarms. We introduce precise denoising technique that identifies and eliminates the corrupted segments of clinical signal to minimize its impact on the decision process and analytics. We demonstrate that Heart-Trend ensures high detection capability with lower false alarm rates.

Index Terms**—** Cardio-vascular disease, PPG, denoising, signal processing, statistics, anomaly, analytics.

1. INTRODUCTION

Cardiac related loss of human life is rising in every decade. According to World Health Organization (WHO), around 17 million people die every year due to cardiac problems. It is perceived that Internet of Things (IoT) has the potential to prevent such huge human life loss through affordable and effective preventive cardiology-care. In this paper we demonstrate that our proposed scheme Heart-Trend can effectively detect cardiovascular conditions like extreme bradycardia and tachycardia that implicate urgent medical attention. For example, bradycardia can turn into lethal ventricular arrhythmias [20]. Heart-Trend generates alerts by indicating the heart condition and the need of immediate medical supervision. However, the incidents of high amount of false alarms render most of the evidence based hard-decision algorithms impractical. Heart condition alarms are often desensitized by both the patient (smartphone user) and the doctor [1]. Another intriguing problem is the frequent presence of corruption in PPG signal from multiple noise sources like motion artifacts, ambient noise. Data preprocessing through denoising results in improved interpretation of the cardiovascular systems and removal of false alarms. In fact, the occurrence of high false alarms (precisely false positives due to the presence of noise) leads to '*alarm fatigue*'. In contrary, high false negatives would be fatal to the patients. The novelty of our proposed scheme is minimization of false negatives ($\approx$ least number of undetected conditions) and physiological signal morphology related trend analysis. It detects arrhythmia and classifies normal, tachycardia and bradycardia conditions from smartphone-extracted PPG signal with higher accuracy. Heart-Trend can be used in-house, in ambulances or in ICU. Typically $\approx 43\%$ critical arrhythmia alarms were found to be false in ICU [2]. Our goal is to develop precise computational, rather than human-in-loop expert-based solutions to detect heart-related ailments with real-time alerts and advice.

The paper is organized as follows. In Section 2, we present the novelty of our contribution. We briefly describe Herat-Trend architecture in Section 3. In Section 4, we discuss Heart-Trend algorithm. Description of datasets and results are depicted in Section 5. Future roadmap is depicted in section 6. Finally we conclude in section 7.

2. OUR CONTRIBUTION

PPG signal is acquired from video sequence of user's index fingertip and is captured through inbuilt smartphone camera [3] and we do not have the luxury to analyze other cardio-signals like electrocardiogram (ECG) [13] in smartphone setup. PPG is the only cardio-signal directly captured using smartphone without additional hardware in non-invasive manner. Our main novelty is that we analyze only PPG signal to interpret the heart condition unlike most of the state-of-the arts that considers ECG or arterial blood pressure signals as well [16, 7-9]. Another novelty is that proposed denoising is mono-signal based, whereas current literature tends to remove noise through time-aligned multi-signal based joint analysis [10, 14]. PPG signal denoising and quality assessment presented in [11] is not suitable to deliver real-time performance. We claim to the best of our knowledge that Heart-Trend is the first method using single pulsating signal (PPG) to 1. Enhance cardiac arrhythmia detection rate 2. Improve denoising of PPG signal and 3. Analyze the trend of a person being into cardiac arrhythmia. Heart-Trend significantly reduces the eternal crying wolf menace [12].

3. ARCHITECTURE

Heart-Trend has three blocks. 1. Preprocessing – PPG signal denoising, 2. Parameter extraction – valid Heart Rate (HR) estimation, and 3. Anomaly analytics – nonparametric analysis and heart condition detection. We depict our proposed Heart-trend architecture in figure 1.

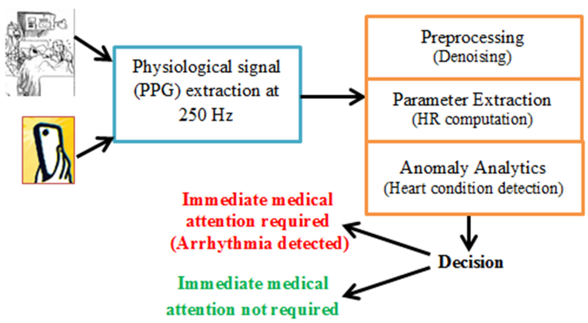


Figure 1. Heart-Trend architecture

4. HEART-TREND SCHEME

We face three challenges. 1. Precise detection of physiological parameters like cardiac pulse duration from PPG signal [4], 2. Valid HR extraction at each cardiac cycle, and 3. Accurate detection of the morphological trend in the heart rate that is indicative of heart condition.

4.1. Preprocessing and Precise Detection of Physiological Parameters (Valid Heart Rate Detection)

Representative expected PPG signal is shown in figure 2 (a) and commonly extracted noisy PPG signal is shown in figure 2 (b). When we correctly discover the cardiac cycle onset times, peak-to-peak interval is proportional to the instantaneous HR at that cardiac cycle.

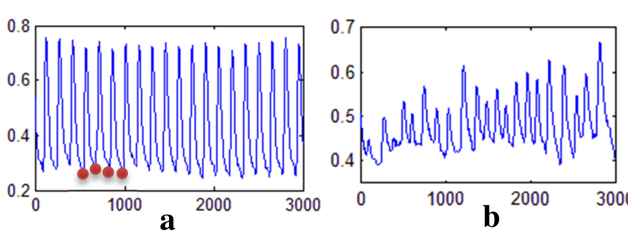


Figure 2. (a) Expected PPG signal, (b) captured PPG signal, exemplary onset times are shown as red dots (●).

Heart rate detection. For heart rate detection, we closely follow the method described in [4, 18, 10]. The scheme is shown in figure 3, where PPG signal $\mathrm{P} = \{\mathrm{p_n}\}$ is the PPG signal. The raw PPG signal is first filtered with a low pass filter (LPF) with transfer function: $\mathrm{H(z)} = \frac{(1-\mathrm{z}^{-5})^2}{(1-\mathrm{z}^{-2})^2}$. The filtered PPG $P_{\mathcal{F}}$ is slope-adjusted and realigned through weighted slope sum function (SSF).

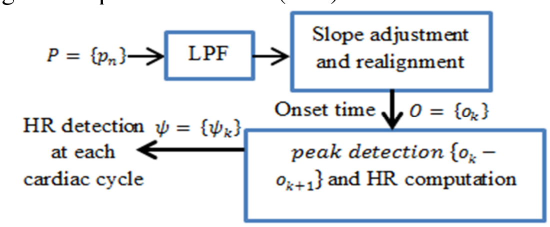


Figure 3. HR detection process from preprocessed PPG

Clinical utility enhancement. It is intuitively obvious that higher false alarm rates would result when preprocessed PPG signal is directly analyzed as depicted in figure 4. We propose cleaning the PPG signal at each cardiac cycle, i.e. for each $\Omega = \{\mathrm{o_{k-1}}: \mathrm{o_k}\}$ by detecting the most probable misalignment of each cardiac cycle of PPG with personalized segment template, where $\mathrm{O} = \{\mathrm{o_k}\}$ is the train of onset times depicting each of the cardiac cycle. It has two components:

1. Finding the most probable segment length that corresponds to the individual's cardiac characteristics
2. Detection of misalignment and reconstruction.

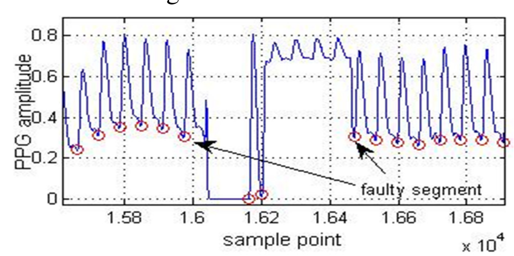


Figure 4. Practical PPG signal contains faulty/ corrupted segments, which may lead to incorrect diagnosis. As depicted above for patient #v848s from [5], faulty segment may force to conclude the patient is bradycardia, which is incorrect.

4.1.1. Finding most probable cardiac pulse duration

Following algorithm describes how to find the most probable cardiac pulse duration from a given PPG signal.

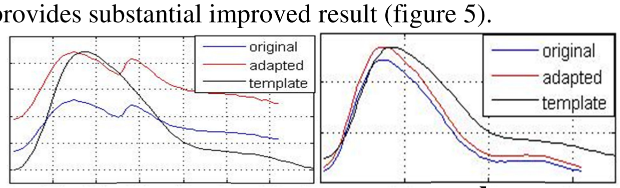
1. We employ DBSCAN algorithm [15] to identify the most probable segment length. Let, $\Omega\,(= \{\mathrm{o_{k-1}}: \mathrm{o_k}\}$, $k = 1,2,\ldots.K)$ be the set of segment lengths. In DBSCAN algorithm, two parameters ϖ, η are to be tuned, where ϖ, η are the distance and density parameters respectively. Let $\Omega^1, \ldots, \Omega^M$ be the M clusters following ϖ, η. Anomalous segment lengths Ω' are the subset in Ω that are not part of any Ω^m, *m= 1,2, …. M* and Ω^N (normal segment length) = $\Omega - \Omega'$.

2. l_p (most probable segment length) = median (Ω^N).

4.1.2. Misaligned segment detection and fault removal

PPG signal being physiological in nature, it has deterministic pattern as depicted in figure 2(a) and valid PPG signal follows a well-defined pattern, which we term as 'Morphologically Valid PPG Template' (MVPT). We apply Dynamic Time Warping (DTW) technique [11, 19] to compute the optimal alignment or similarity between the PPG segment and MVPT for cardiac cycle. When for a particular segment the dissimilarity is higher than certain threshold, that segment is considered to be machine-generated faulty segment and replaced with valid segment.

Let $P^{\lambda} \coloneqq \{p_1,\ p_2, \dots ,\ p_L\}$ be the PPG signal of length $L \in \mathbb{N}$ for segment λ corresponds to certain onset cycle and $\mathbb{T} \coloneqq \{\mathrm{t}_1,\ \mathrm{t}_2, \dots, \mathrm{t}_M\}$ be the template MVPT of length $M \in \mathbb{N}$. Heart rate varies intra-person and inter-person due to dynamicity of cardiac output that results in non-stationarity and nonlinearity in each of the pulse duration or segment. We segments due to present Window-Adaptive DTW (WADTW) to compensate this effect in the following statistical computing. the Instead of computing on the entire length of each segment at cardiac cycle $\{\mathrm{o}_{\mathrm{k}-1}\!:\mathrm{o}_{\mathrm{k}}\}$ (which is variable in length due to change of heart rate), we eliminate the temporal-length mismatch bias by fixing the analysis segment length to its most probable segment length, i.e. $L = l_p$. We also amplitude-normalize each segment as: $P^{\lambda} \times \frac{max(\mathbb{T})}{max(P^{\lambda})}$ that minimizes the effect of nonlinear changes in the amplitude of each segment due to changes in cardiac output without distorting any pattern information. Our proposed template adaptive corrupt segment identification provides substantial improved result (figure 5).



a b

Figure 5. Adaptation to the template, MVPT (a) corrupt signal segment, (b) non-corrupt signal segment.

For comparing $P^{\lambda}, \mathbb{T}$; we need to find a local cost measure, which is a distance function. Here, Euclidean distance $\varphi_{i,j} = \|P^{\lambda}{}_i - \mathbb{T}_j\|, i \in l_p, j \in M,$ is considered as the local cost measure to construct the pairwise local distance matrix. $\mathcal{D} = \varphi_{i,j}, \forall l_p, \forall M.$

$$\mathcal{D} = \begin{bmatrix} \varphi_{1,1} & \cdots & \varphi_{1,l_p} \\ \vdots & \ddots & \vdots \\ \varphi_{M,1} & \cdots & \varphi_{M,l_p} \end{bmatrix}$$

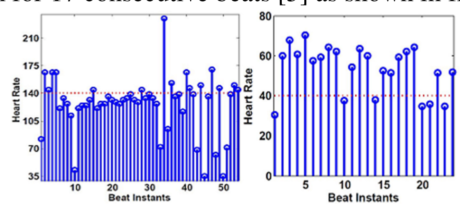
The optimal alignment is the warping path between $P^{\lambda}, \mathbb{T}$ that indicates minimum distortion; $\mathcal{D}_{opt} = argmin \sum \mathcal{D}(i,j)$, which forms a grid from P^{λ} to $\mathbb{T}$ and the dissimilarity factor or DTW distance $\mathcal{D}_{P^{\lambda},\mathbb{T}} = min\left(\mathcal{D}_{opt}(P^{\lambda}, \mathbb{T})\right)$. We expectedly observe that warping path and DTW distance or dissimilarity factor computation and confirms that DTW distance is significantly higher for corrupted segments compared to non-corrupted/ valid signal segments.

- **Decision:** Dynamic threshold-based corrupt segment identification decision is taken, where the threshold $\Gamma = const \times min\left(mode\left(\mathcal{D}_{P^{\lambda},\mathbb{T}}\right)\right), \forall\lambda, const = 3.$
$$\begin{cases} \mathcal{D}_{P^{\lambda},\mathbb{T}} \geq \Gamma, & \text{segment } \lambda \text{ } is\ corrupt \\ \mathcal{D}_{P^{\lambda},\mathbb{T}} < \Gamma, & \text{segment } \lambda \text{ } is\ non-corrupt \end{cases}$$
- **Reconstruction:** Corrupted segment P^{λ} is replaced as: $P^{\lambda}\big|_{\boldsymbol{corrupt \rightarrow reconstructed}} = w_i \times P^{\lambda - i}$. For simplicity, we consider $w_i = 1$.
- **Valid Heart Rate (HR) detection:** Valid HR detection is done as: $\psi = \{\psi_{\mathrm{k}}\} = \frac{1}{(max(\mathrm{o}_{\mathrm{k}-1}: \mathrm{o}_{\mathrm{k}}) - max(\mathrm{o}_{\mathrm{k}}: \mathrm{o}_{\mathrm{k}+1}))}$, is the train of HR at each cardiac cycle (k).

4.2. Anomaly Analytics: Morphological Trend Determination and Heart Condition Detection

Life threatening arrhythmias like extreme bradycardia, extreme tachycardia can be clinically determined when HR is less than 40 bpm for 5 consecutive beats and more than 140 bpm for 17 consecutive beats [5] as shown in figure 6:

a



b

Figure 6. HR detected from ICU patients (patient id# t150s, b124s [4]), (a) tachycardia case, (b) bradycardia case.

Algo-1: Knowledge-based supervised detection algorithm:

If $(\{\exists\psi\ = \{\psi_i, \dots,\ \psi_{i+5}\} < 40\ \subseteq\ \psi\})$
Alert = **Bradycardia**
If $(\{\exists\psi\ = \{\psi_i, \dots,\ \psi_{i+17}\} > 140\ \subseteq\ \psi\})$
Alert = **Tachycardia**
Else Alert = **Normal**

Arrhythmia conditions may not always be directly satisfied from extracted HR data while the patients report arrhythmia with prominent symptoms or vice versa. Such observations make hard-decision bound analysis like Algo-1 error prone. Our main challenge to perform accurate detection is discovering the closeness function which is indicative of the conditions. Instead of directly mapping the alert strictly to the definition, we propose morphological trend investigation using statistical analysis with the intention of detecting closest concentration of the condition.

Heart-Trend algorithm*:*

1. *Feature selection:* Compute feature $\mathcal{F}$ from large sample HR $\tau = \{\tau|_{brady}, \tau|_{normal}, \tau|_{tachy,}\}$ from random positive bradycardia, normal and tachycardia patients respectively. Let the feature be $\mathcal{F} = \{\mathcal{F}|_{brady}, \mathcal{F}|_{normal}, \mathcal{F}|_{tachy}\}$, which can be $E[\tau]$ or other central tendency measure.

2. *Prediction:* Predict the outcome set σ from the HR series ψ, which is closest to the feature τ for each case of bradycardia, normal and tachycardia. It is done by *k-nn* classifier:
    a. Compute Euclidean distance $\delta(\psi,\ \mathcal{F})$.
    b. k closest distances of each cases are chosen, $\kappa = ceil\left(\frac{|\psi|}{2}\right)$ is selected to intentionally bias towards minimizing false negative effect, $\sigma = \{\sigma_{\{brady,normal,tachy\}}\}$ set is generated that are k-closest distances with respect to bradycardia, normal and tachycardia feature.
3. *Classification:* Classify the patient to one of the three classes. We use k-means clustering technique with k=2 for binary portioning on σ for each of the three conditions (brady, normal, tachy):
    a. Set initial centroid $c = \{c_1, c_2\} \in \mathbb{R}^d$
    b. Repeat until converge:
        i. $\chi^i := argmin_j \| \sigma_i - c_i \|^2, \forall\ i$
        ii. $c_j := \frac{\sum_{i=1}^{N} 1\{\chi^i = j\}\, \sigma_i}{\sum_{i=1}^{N} 1\{\chi^i = j\}}, \forall\ j$
    c. 2 centroids of each class is generated as $\mathcal{C} = \mathcal{C}_{i,\{brady,normal,tachy\}}\ \ {}_{i=1,2}$
    d. Find the detected class $\omega = argmin(\mathcal{C})$.

4.3. Example

We consider records of patient (# b124s) [5]. For simplicity eight consecutive HR samples are taken, which means k=4 for *k-nn* from $\kappa = ceil\left(\frac{|\psi|}{2}\right), \psi = 8,$ each classification set (σ) consists four distance vectors. *K*-means (k=2) on the classification set is performed and we get the centroid set ($\mathcal{C}$) as depicted in table 1. It is found that detected class $\omega = \mathcal{C}_{\text{brady}} = \text{argmin}(\mathcal{C})$ and the patient is correctly declared as bradycardia patient, and corresponding alert is generated.

Table 1. Heart-Trend computation example

Classification set (σ)		Centroid set ($\mathcal{C}$)	
σ_{brady}	$\{2.12, 3.12, 4.29, 5.3\}$	$\mathcal{C}_{\text{brady}}$	$\{4.78, 2.62\}$
σ_{normal}	$\{25.89, 28, 30, 30.94\}$	$\mathcal{C}_{\text{normal}}$	$\{26.95, 30.47\}$
σ_{tachy}	$\{75.89, 78.01, 80, 80.9\}$	$\mathcal{C}_{\text{tachy}}$	$\{80.47, 76.95\}$

5. RESULTS AND ANALAYSIS

We have experimented with expert-annotated publicly available MIT-MIMIC datasets [5]. Heart parameters, waveforms are recorded and annotated by experts as true or false case of arrhythmia condition. It is publicly available MIT-BIH arrhythmia Physionet CinC Challenge 2015 datasets [5]. Sample framework as per [4] is initially considered, upon which we built our own scheme. We can observe in figure 7 that Heart-Trend improves the true detection by > 15% and for bradycardia case there is no false negative alarm. Such improvement of detection capability can play substantial role to bring better prognosis and early detection. In fact, supervised Algo-1 scheme does not perform patient-specific analysis and oblivion to the soft-bound detection.

Our main motivation is to reduce the false negative alarms and it can be observed from the results (figure 7), we have achieved that goal with considerable success, particularly the detection of bradycardia is achieved by Heart-trend with no false negative alarm.

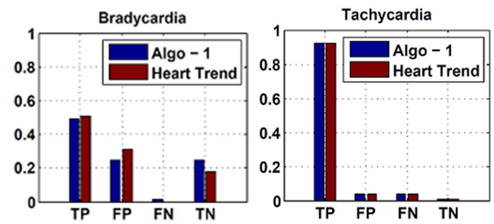


Figure 7. True and false alarms in bradycardia and tachycardia cases over the entire dataset of Algo-1 and Heart-Trend, TP= True Positive, FP= False Positive, TN = True Negative, FN= False Negative.

6. FUTURE ROADMAP

We like to extend this work using pattern discovery [6], personalized health care analysis through our ongoing research on information-aware anomaly detection [17, 21].

7. CONCLUSION

In this paper, we have described that analyzing physiological signals through intelligent blend of statistical methods and signal processing techniques would yield better outcome and superior quality of physiological condition detection. Our proposed Heart-Trend scheme significantly reduces the heart condition detection false alarm rate. Heart-Trend is universally implementable; from smartphone for in-house checking to ICU monitors. Our approach of investigating the statistical trend of heart condition has the potential of timely revealing the tendency of the heart to act abnormally, which empowers proactive cardiac diagnosis and treatment. Heart-Trend is easy-to-use and affordable and can provide effective cardiac management specifically towards preventive health care systems.

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