Blue Scale: Early Detection of Impending Congestive Heart Failure Events via Wireless Daily Self-Monitoring

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***Abstract*— Congestive heart failure (CHF) is a chronic medical condition, and early detection of acute cardiac events caused by CHF can lead to life saving results. In this paper, we present Blue Scale, a measuring device that allows both patients and their physicians to monitor cardiac health at home on a daily basis by providing the necessary feedback for early cardiac event detection. Blue Scale measures electrocardiography (EKG), systolic time intervals through photoplethysmography (PPG), weight, and whole body bioimpedance. Collected datasets are transmitted to a central database using a secure Wi-Fi 802.11b/g protocol for remote data analysis and disease management. Following a test deployment in different populations, we conclude that off-device signal processing is required to ensure the accuracy of derived measurements. Furthermore, our anomaly emulation experiments yield average Z-scores of below 2 for most EKG and PPG related metrics, and the resulting Z-scores also vary significantly across different patients. These observations indicate that a standard 95% confidence interval is not sufficient for attribute-by-attribute anomaly detection, and any cardiac monitoring systems need to be tailored to each individual.**

I. Introduction

Congestive heart failure (CHF), the inability of the heart to maintain its pumping capacity, is currently the leading cause of death in the United States [1]. Studies have shown that early detection can aid in preventing acute cardiac events [2] [3], but many patients are unable to monitor key heart metrics, such as an electrocardiogram, on a regular basis. In fact, patient data is primarily collected in a clinical or ambulatory setting, often only when a cardiac event occurs or during a periodic check-up. Thus, patients may have difficulty in managing their cardiac condition and in recognizing early signs of impending cardiac events.

The Blue Scale device was developed to improve home-based management of CHF by allowing daily measurements of cardiovascular parameters and by analyzing their trend over time at the individual level, thus providing valuable feedback to the individual and their caregivers. Blue Scale is a modified bathroom scale paired with a T-shaped pole structure with hand electrodes and an optical sensor embedded in the handlebars (Fig. 1). It represents the evolution of a hand-held device previously developed and tested [4], and a preliminary version of this work was previously reported [5]. Blue Scale measures electrocardiography (EKG), photoplethysmography (PPG), whole body bioimpedance, and weight.

Fig. 1. A full-device view of the Blue Scale, which is used for wireless point-of-care cardiovascular self-monitoring.

The cardiovascular measurements are then remotely transmitted and analyzed to detect feature and/or trend anomalies. In this work, we specifically tested algorithms aimed at identifying anomalous heart activities that could be early indicators of an acute event. A pilot deployment of the scales was carried out in three different locations in the Houston, TX, area: at Rice University, at *Technology for All* community center, and at a private residence. Twenty-two healthy adult volunteers took daily measurements for one to four weeks following an IRB approved protocol. The measurement analysis concluded that the waveforms obtained required further processing to remove the effects of noise, and the metrics derived from the measurements showed that norms varied considerably from person to person. Hence, they need to be tailored to each individual.

The rest of the paper is organized as follows. Section II presents how the Blue Scale works. Section III reviews the data trends across different subjects and discusses some basic anomaly experimentation with the scale. Finally, the conclusions are presented in Section IV.

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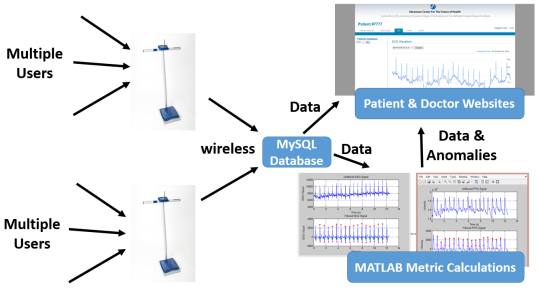

Fig. 2. Data flow model for the Blue Scale.

TABLE I

KEY HEALTH METRICS OBSERVED BY BLUE SCALE

Metric Name	Description	Data Origin Type	Priority
QRS Interval	Time interval of QRS range	EKG waveform MATLAB® script	High
RR Variation	Variation of RR time interval	EKG waveform MATLAB® script	High
ST Interval	Time interval of ST range	EKG waveform MATLAB® script	High
RR Interval	Time interval of RR peak range	EKG waveform MATLAB® script	Med
PR Interval	Time interval of PQ range	EKG waveform MATLAB® script	Med
Pulse Transit Time (foot, slope, peak)	Time interval for blood to travel from heart to fingertip	PPG/EKG waveform MATLAB® script	Med
Weight	Body weight	Scale measurement	Low
Whole Body Bioimpedance	Body water measurement	Scale measurement	Low

II. MATERIALS AND METHODS

A. Design Concept

Blue Scale was designed for ease of use by an elderly population who do not normally have a strong technological background. For this reason, a large, color touchscreen display and loudspeaker were embedded to optimize device-patient communication. To take a measurement, the patient is required to step onto the scale while barefoot and enter their unique ID number on the touchscreen. The patient is then instructed to grab the EKG handle electrodes and place their right index finger into the fingerclip PPG sensor. While the patient remains as still as possible, the scale measures EKG and PPG signals for approximately 12 seconds at a sampling rate of 1 kHz. The average whole body bioimpedance is also measured during this phase. The patient is then instructed to let go of the handlebars to guarantee an accurate weight measurement. After the measurement process is complete, the scale wirelessly transmits the raw dataset to a centralized database for further processing and analysis. Immediately after data transmission, the readings and all extracted analytical features are available for display on a secure website. The general data flow model is shown in Fig. 2.

B. Health Metrics

Blue Scale is capable of acquiring 3-lead EKG derivations, i.e. left to right hand (lead I), left hand to right foot (lead II), and right hand to left foot (lead III). Lead I was typically the least noisy reading, which was chosen for further analysis and feature extraction.

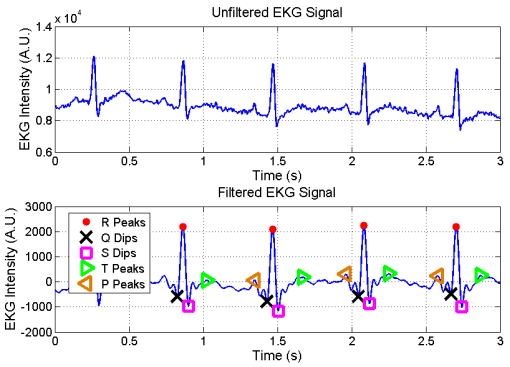

Fig. 3. Unfiltered (top) and filtered (bottom) EKG signals with P-QRS-T detections.

In this project, eight key health metrics, including the post-signal processing metrics, were computed as shown in Table I. The priority column for this table indicates the importance of a particular metric in diagnosing a significant cardiac event. These metrics can be classified into two broad categories: direct indicators of cardiac function and indirect indicators of cardiac compensation. Direct indicators of cardiac function are metrics derived directly from EKG or PPG signals and are reliable early indicators of a cardiac event [6]. On the other hand, indirect indicators of compensation, such as weight and bioimpedance, are deemed to be lagging indicators of a cardiac event [7]. Hence, since compensation indicators occur later than cardiac output indicators, an ideal algorithm of cardiac anomaly detection would be primarily focused on cardiac output indicators so that anomalies may be detected early on. The priorities indicated in Table I are the results of this classification.

C. Data Processing

The EKG and PPG datasets collected by the scale carried a substantial amount of noise, which typically impeded calculation of the metrics directly from these waveforms. Therefore, in order to minimize processing time on the device and to allow advanced noise filtering, signal processing was executed on a remote server after the physiological measurements were transmitted to the database (Fig. 2).

In order to filter out low-frequency baseline drifts and other sources of noise, low pass and high pass Butterworth filters were employed on both waveforms in MATLAB® [8]. The resulting passbands were 1-20 Hz and 0.5-20 Hz for the EKG and PPG signals, respectively. The cutoff frequencies were determined experimentally using datasets from multiple patients. As shown in Fig. 3, the application of these filters substantially reduced noise levels, thus allowing for easier metric calculations.

D. Key Metric Detection

Most of the top-priority metrics were obtained from the EKG waveform, the features of which are directly related to events of a cardiac cycle. The QRS complex is produced by ventricular depolarization (i.e., contraction) in which the

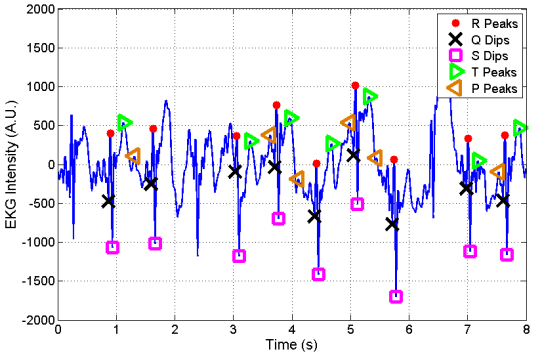

Fig. 4. EKG QRS missed detections for a volunteer with high T peaks and deep S dips. Missed detections are at approximately 2.4 and 6.4 s.

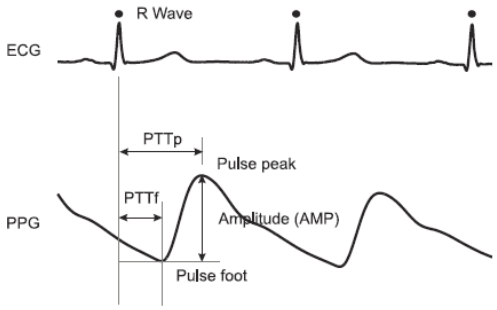

Fig. 5. Visualization of pulse transit time foot and peak [9].

R-wave is the main peak, while the Q-wave and S-wave are the smaller dips occurring immediately before and after the R-wave peak, respectively. To the left and right of each QRS complex, two smaller peaks can be detected: the P-wave associated with atrial depolarization and the T-wave associated with ventricular repolarizarion, respectively.

Unlike conventional interval definitions which are defined from baseline to baseline, the EKG wave time intervals measured by the Blue Scale are defined as Q min to S min (QRS interval), S min to T max (ST interval), and P max to Q min (PR interval). These are clear points that can be used to standardize the EKG and PPG metrics that are less sensitive to any remaining noise following filtering. Finally, the RR interval (or heart period) refers to the time interval between successive R-wave peaks (or heart beats), and RR variation refers to the standard deviation of such time interval.

The QRS detection algorithm works by stepping through the entire waveform in short non-overlapping windows (0.15 seconds) to find the absolute maximum point in each window. If the maximum within a window is a local maximum (i.e., its neighboring points smaller), then such point is considered as a candidate peak for an R-wave. Similarly, the algorithm finds the local minima on each side of the R-wave as the Q (left) and S (right) dips of the QRS complex.

The true QRS complexes are distinguished from the false positives by looking at the QR and RS amplitudes and slopes. If the complex amplitude is within two standard deviations of the mean, and if the absolute slopes are greater than the mean, the QRS complex is accepted as valid. This approach worked well since the QR and RS slopes are the sharpest slopes after noise filtering, and it helped minimize false positives from any remaining noise after filtering.

After finding the true QRS complexes, the interval from one complex's S-wave to the next's Q-wave is partitioned in half. The maximum of the left partition is used to approximate the first complex's trailing T-wave, while the maximum of the right partition is used to approximate the second complex's leading P-wave. As seen in Fig. 3, this is generally a good approximation, but it can occasionally identify the wrong point and skew the ST and PR intervals.

Occasionally, the QRS detection algorithm failed to detect a QRS complex, as seen in the EKG waveform in Fig. 4. The QRS detection algorithm minimizes the effect of these missed QRS complexes. If an RR interval is larger than 1.5 seconds (normal RR interval ranges from 0.6-1 seconds [10]), then that interval is not considered in the calculation of the average RR interval. Losing an entire QRS complex also minimally affects the measured QRS time.

Pulse transit times (PTTs) are defined as the time interval between the EKG R-wave and PTT foot, PTT maximum rising slope, and PTT peak, respectively (Fig. 5, [9]), which describes (in various ways) the time interval it takes blood to reach the fingertip from the heart. For the pulse transit times, no single QRS complex can be used more than once when calculating the PTT. This means that the effect of a missed QRS complex will only factor into the mean PTT once, which minimizes the effect on the calculated average.

The weight and whole body bioimpedence, obtained directly from the scale, did not need further calibration.

III. Results

Because all the volunteers for this project are healthy adults, we expected each volunteer's EKG waveforms to follow the commonly observed patterns. Although most volunteers did follow this trend, a few did not. One volunteer's EKG readings were noticeably different (Fig. 4).

This volunteer's EKG regularly featured deep S-waves and irregularly tall T-waves. Although the QRS detection algorithm was able to account for most variations in the EKG contour, the detection of the QRS complex failed occasionally, affecting the derived metric accuracy. Although the script accounted for missed QRS complexes fairly well (noticeably, no P-waves and T-waves were identified whenever a QRS complex was not detected), individual patients may need specially tuned filtering to optimize measurement accuracy. This emphasizes the importance of establishing a patient-by-patient baseline.

In addition to the contour of the EKG and PPG, each volunteer showed noticeably different ranges for some attributes and similar ranges for others, as seen in Table II. In particular, the QRS, ST, PR, and PTT intervals were fairly consistent, with only slight variations across the selected subjects. RR interval and variation both showed a relatively larger magnitude of variation. Some similarity is expected

TABLE II

MEAN AND STANDARD DEVIATION OF A SUBSET OF THE KEY HEALTH METRICS FOR FOUR DIFFERENT VOLUNTEERS.

Volunteer	QRS Time (s)	RR Interval (s)	RR Variation (s)	PTT Peak (s)	PR Interval (s)	ST Interval (s)
1	0.076 +/- 0.001	0.696 +/- 0.136	0.007 +/- 0.024	0.314 +/- 0.038	0.102 +/- 0.021	0.173 +/-0.020
2	0.075 +/- 0.002	0.547 +/- 0.034	0.004 +/- 0.010	0.315 +/- 0.035	0.122 +/- 0.025	0.149 +/- 0.016
3	0.076 +/- 0.001	0.693 +/- 0.155	0.049 +/- 0.174	0.275 +/- 0.008	0.099 +/- 0.014	0.143 +/- 0.012
4	0.067 +/- 0.001	0.705 +/- 0.103	0.030 +/- 0.035	0.335 +/- 0.039	0.112 +/- 0.023	0.187 +/- 0.027

TABLE III

SELECT Z-SCORE OBSERVATIONS FROM THE ANOMALY EXPERIMENTS.

Scenario	Metric	Average Z-Score
Weight Up	Weight	6.22 +/- 3.85
Weight Down	Weight	-44.89 +/- 34.34
Exercise	RR Average	-1.34 +/- 0.53
Exercise	QRS Average	-1.38 +/- 0.92
Exercise	PTT Peak Average	-2.56 +/- 2.45
Nap/Relax	RR Average	0.22 +/- 0.43
Nap/Relax	QRS Average	0.44 +/- 0. 03
Nap/Relax	PTT Peak Average	-0.12 +/- 1.10

given all the volunteers in this subset are between 18 to 25 years old, but the variation present is difficult to predict. Hence, initializing a unique baseline for each patient is key before attempting any anomaly detection.

To emulate an anomaly for a healthy patient, four of the volunteers were asked to take four special measurements after completing a four week calibration period. The goal of this experiment was to find potential anomaly detection thresholds for each metric. Each volunteer added weight, reduced weight, exercised before a measurement, and slept for a short time before a measurement. Afterwards, a Z-score was calculated for all metrics for each scenario. The Z-score is defined as (metric - mean)/(standard deviation).

Table III shows the results. As expected, the weight Z-score is noticeably large and above 5. However, the nap/relax scenarios have non-noticeable effects. This makes sense because volunteers normally take measurements at their resting heart rate, meaning relaxing and napping can only affect a person's heart rate and metrics slightly.

On the other hand, exercising does have a noticeable effect, but the average deviation is below or around 2 Z-scores. This means that a typical 95% confidence interval is not sufficient for detecting changes in EKG and PPG attributes, and tighter thresholds are needed. Furthermore, the large standard deviations in Z-score for most of these observations re-emphasizes that no single anomaly threshold is sufficient for all people. Anomaly detection thresholds should depend on both the attribute and the person.

IV. CONCLUSION

The Blue Scale paradigm of daily self-measurements is a promising way to give patients and doctors regular feedback on a patient's cardiovascular health. We developed an off-device MATLAB® script that reliably derives several key health metrics for most patients available wirelessly for physicians to monitor their patients' daily health. However, our test deployment emphasizes the importance of tuning any scripts and anomaly thresholds to the patient because an anomalous looking EKG or PPG waveform or metric for one patient could actually be his or her healthy norm. Following individual calibration, the models can then be extended to an online setting.

In the future, we hope to test the Blue Scale system on a wider scale, with volunteers who have cardiovascular disease. These volunteers can then be clustered to see if certain demographics reliably follow the same patterns. Future deployments will also let us conduct an in-depth performance evaluation of the system. We also hope to provide patients with easy-to-access feedback, potentially on a patient-oriented web page or even on the scale's display monitor immediately following a measurement. We will also implement an algorithm that combines the measured attributes to compute each patient's norm for complete anomaly detection instead of just attribute-by-attribute detection.

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