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Wireless Patch Sensor for Remote Monitoring of Heart Rate, Respiration, Activity, and Falls

Alexander M. Chan, Nandakumar Selvaraj, Nima Ferdosi, and Ravi Narasimhan*

***Abstract*— Unobtrusive continuous monitoring of important vital signs and activity metrics has the potential to provide remote health monitoring, at-home screening, and rapid notification of critical events such as heart attacks, falls, or respiratory distress. This paper contains validation results of a wireless Bluetooth Low Energy (BLE) patch sensor consisting of two electrocardiography (ECG) electrodes, a microcontroller, a tri-axial accelerometer, and a BLE transceiver. The sensor measures heart rate, heart rate variability (HRV), respiratory rate, posture, steps, and falls and was evaluated on a total of 25 adult participants who performed breathing exercises, activities of daily living (ADLs), various stretches, stationary cycling, walking/running, and simulated falls. Compared to reference devices, the heart rate measurement had a mean absolute error (MAE) of less than 2 bpm, time-domain HRV measurements had an RMS error of less than 15 ms, respiratory rate had an MAE of 1.1 breaths per minute during metronome breathing, posture detection had an accuracy of over 95% in two of the three patch locations, steps were counted with an absolute error of less than 5%, and falls were detected with a sensitivity of 95.2% and specificity of 100%.**

I. INTRODUCTION

With the rising cost of healthcare and an aging worldwide population, there is an increasing need for effective methods of reducing hospital readmissions, home-based screening tests, and technologies that allow for aging-in-place. Remote monitoring technologies have the potential to provide near real-time health information and may also facilitate a means to observe important cardiopulmonary and activity information in patients and aging adults in the comfort of their own homes. The reduction in size of digital processors, accelerometers and components for electrocardiographic (ECG) monitoring has allowed such technologies to become increasingly unobtrusive. Furthermore, the widespread use of smartphones and wireless connectivity make real-time monitoring in ambulatory conditions possible.

The ability to monitor ECG and heart rate can provide important information for patients with cardiovascular diseases such as supraventricular tachycardia (SVT) or congestive heart failure (CHF). Furthermore, rapid detection of acute events like myocardial infarctions (MI) or atrial fibrillation (AF) is possible. Monitoring of breathing rate is also important for the screening of abnormal respiration that may occur in obstructive sleep apneas or CHF. Activity monitoring can be highly useful for providing a snapshot of the total daily activity in patients who require moderate exercise, for detecting and providing notifications of falls in the elderly population, or determining duration and position in bed for those in assisted living facilities.

Here, a performance validation is presented of a wireless Bluetooth Low Energy (BLE) patch sensor that remotely monitors ECG, heart rate (HR), heart rate variability (HRV), respiration rate, posture, steps, and falls. The sensor, designed by Vital Connect Inc., transmits these data to a relay (e.g., smartphone, wristwatch, pendant or wall-mounted station) that can then send the appropriate information to the cloud, healthcare providers, caregivers, or loved ones.

II. METHODS

A. Vital Connect Patch

The Vital Connect sensor device consists of two main components: a disposable adhesive patch that houses the ECG electrodes and battery, and a reusable electronics module that houses the embedded processor, tri-axial accelerometer, and BLE transceiver (Fig. 1). The patch can be worn in three possible locations: (1) in a modified lead-II configuration on the left midclavicular line over intercostal space (ICS) 2, (2) vertically over the upper sternum, or (3) horizontally on the left midclavicular line over ICS 6. The patch includes a skin adhesive on its base and is powered by a coin-cell battery. Two electrodes are positioned on the bottom of the patch (one at each end), and each electrode is covered with a disc of hydrogel. These electrodes allow for the recording of a single-lead bipolar ECG at a sampling rate of 125 Hz. The patch has a typical wear cycle of three days, and continuous monitoring is possible even if the patch is placed in a different location for each wear cycle.

Fig. 1. Disposable Vital Connect patch sensor and reusable electronics module

Authors are with Vital Connect Inc., Campbell, CA 95008, USA. (*corresponding author's e-mail: rnarasimhan@vitalconnect.com)

A tri-axial accelerometer is present within the electronics module that allows for the recording of accelerations within the range of ±4 g per axis with a resolution of 0.0078 g, where g = 9.81 m/s^2 is the gravitational acceleration. These acceleration signals are sampled at 62.5 Hz, and an automatic calibration during an initial period of standing is performed to rotate the coordinate system and obtain the true superior-inferior, anterior-posterior, and left-right acceleration axes.

The electronics module processes incoming signals, runs algorithms, and transmits a stream of desired data via an encrypted BLE wireless link to a smartphone (e.g. iPhone), which can then display and store the data. The smartphone may then relay portions of the information to a cloud-based server that can perform additional processing, send notifications to caregivers, or monitor long-term trends.

QRS complexes are automatically detected from the ECG waveforms using a wavelet algorithm [1, 2]. The R-R intervals are computed as the time duration between successive QRS-complex peaks, and these data are output for later use in the computation of HRV. The reciprocal of the R-R intervals is computed to determine an instantaneous heart rate that is passed through a 10-beat lowpass filter to obtain a smooth heart rate profile.

Respiration rate is estimated using a combination of two ECG-derived respiratory signals (the respiratory sinus arrhythmia (RSA), and the QRS-amplitude) and the accelerometer signal. Peak-picking is performed on each of the signals, and the respiratory rate from each signal is computed independently. A quality metric, Q, is derived that estimates the regularity of the peaks in each of the signals, and these quality metrics are used to compute a weighted average of the individual respiratory rates to obtain a final breathing rate estimate. Additional details on the respiratory rate computation are provided in [3].

Fall detection is performed using the tri-axial accelerometer data. Similar to the algorithm described in [4], a fall is detected by checking several criteria: (1) impact or free-fall, (2) large differences in acceleration over a small temporal window, (3) change in thoracic posture from vertical to horizontal, and (4) low activity for a specified duration after the change in posture.

The Vital Connect patch sensor also performs posture detection to identify the subject as upright, leaning, lying, walking, or running within 5 seconds of posture change. The static postures are detected based on the thoracic angle of the individual, while walking and running are detected based on a threshold of acceleration in the vertical axis as well as the successful detection of steps. Steps are counted using peak-picking on the vertical acceleration. Only peaks that are regularly spaced in time (based on a threshold on the kurtosis of the inter-step intervals) are counted as true steps.

B. Experimental Protocol

A total of 25 subjects participated in the study, and each subject wore a total of three patches (one in each of the recommended locations) for the duration of the test to evaluate the performance at each location independently.

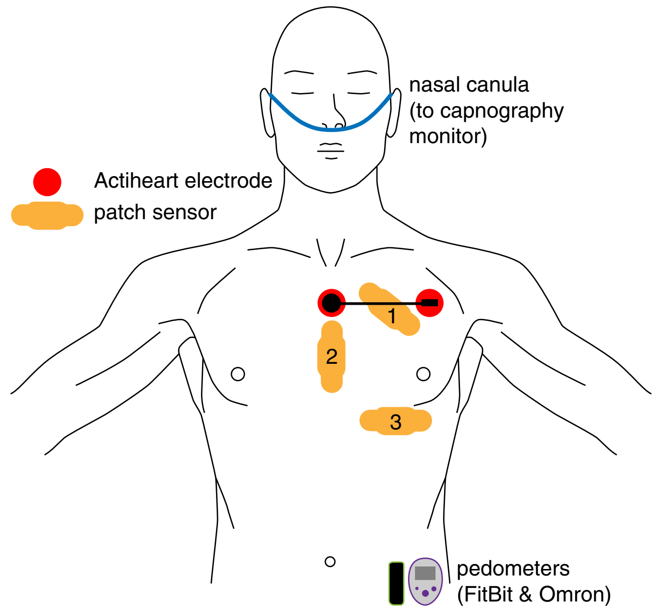

Fig. 2. Patch sensor and reference device locations

Subjects were recruited from two populations: a group of older adults for testing of heart rate, HRV, breathing rate, specificity of fall detection, and posture, and a group of younger adults for testing of the pedometer and sensitivity of fall detection. Data from each patch were streamed to an iPhone in real-time and stored for later processing.

The 15 older subjects (7 male, 8 female) were between the ages of 63 and 79 (70±5 years), with body mass between 44.7 kg and 99.2 kg (69.4±14.8 kg) and height between 147 cm and 185 cm (167±11 cm). These subjects performed metronome breathing and a set of activities of daily living (ADLs). The breathing exercises included 4 minutes of spontaneous breathing, followed by metronome breathing at 12, 15, 18, 21, and 24 breaths per minute (BrPM) for 3 minutes each with a one-minute break between each block. ADLs included sitting and standing from various chairs, reclining and rocking in a chair, lying on a bed, bending, walking, and climbing stairs.

During the test, the older subjects also wore a number of reference devices to allow for comparison of measurements (Fig. 2). An Actiheart reference device for recording heart rate and inter-beat intervals was worn horizontally at left ICS 2. To monitor breathing rate, subjects wore a nasal cannula that was attached to an Oridion Capnostream bedside capnography monitor. Two pedometers for measuring steps (manufactured by Omron and FitBit) were worn at the waist.

The 10 younger subjects (5 male, 5 female) were between the ages of 18 and 29 (25±3.6 years), with body mass between 52 kg and 79 kg (66.4±10.1 kg) and height between 157 cm and 183 m (170±8.5 cm). These subjects performed a series of stretches, stationary cycling, walking, running, and simulated falls. During the pedometer portion of the test, the subject as well as the experimenter used a manual handheld counter to count the total number of steps taken. The manual

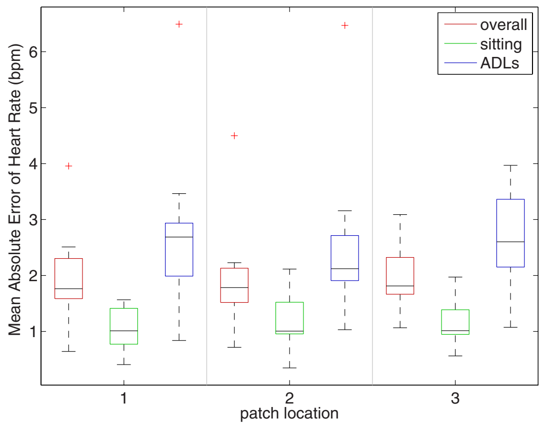

Fig. 3. Boxplots of mean absolute error of heart rate measurements with respect to patch location and activity. The black horizontal line indicates the median, the box indicates the 25^{th} and 75^{th} percentiles (interquartile range), and the whiskers indicate the extreme values not considered outliers. Outliers are shown by red crosses determined as points that lie beyond 1.5 times the interquartile range above the 75^{th} or below the 25^{th} percentiles.

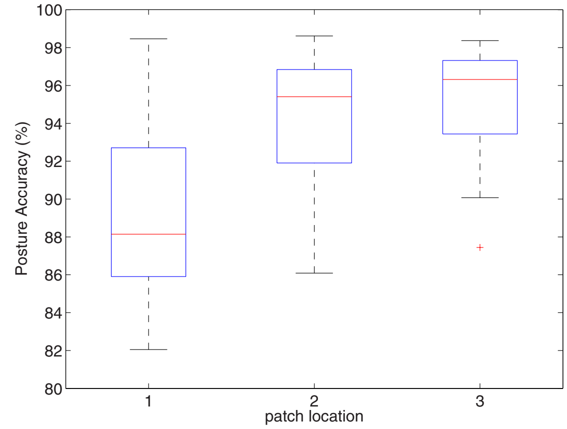

Fig. 4. Boxplots of posture detection accuracies.

step counts, as well as all pedometer and patch step counts, were recorded before and after each activity. The participants also performed a total of 11 types of simulated falls onto crash mats, with each fall type performed three times. Falls included falling forward, backward, to the left, and to the right with knees straight or bent, attempting to sit on but missing a chair, tripping over an object, and falling out of bed.

For all subsequent analysis, patches that had mean contact impedance greater than 5 MΩ were excluded because of poor contact with the skin. In most cases, this poor skin contact occurred in male participants with an abundance of chest hair. The impedance threshold resulted in excluding 5 out of 75 total patches.

III. RESULTS

A. Heart Rate and Heart Rate Variability

The heart rate obtained from the Vital Connect Patch was compared to that obtained from the Actiheart device. Periods where the Actiheart device reported no heart rate were excluded. For each patch, the mean absolute error (MAE) and the root-mean-square error (RMSE) of the instantaneous heart rate as compared to the Actiheart reference device were computed. This analysis was done separately for the 25-minute period of sitting during the breathing exercises, and the 30-minute period of ADLs. The median MAE was less than 2 bpm in all three locations for the sitting period as well as overall, and was less than 3 bpm during the ADLs (Fig. 3 and Table I).

Measures of heart rate variability (HRV) were computed offline using non-overlapping 5-minute epochs of R-R interval series obtained from the patch sensor and Actiheart device during the first 25 minutes of the ADL protocol. The HRV measures include mean of normal R-R intervals (meanNN), standard deviation of normal R-R intervals (SDNN), root-mean-square of the difference of successive R-R intervals (RMSSD), and triangular index (Triang8) calculated as the ratio of total number of R-R intervals to the height of the histogram with bin width of 8 ms. The MAE and RMSE calculated with reference to HRV measures based on Actiheart are given in Table I.

B. Respiratory Rate

To assess the accuracy of the respiratory rate measurement, the final minute of each metronome breathing block was extracted, and the MAE was computed between the patch-derived respiratory rate and the capnography-derived respiratory rate. The resulting MAE was 1.0±0.1 breaths per minute (BrPM), 1.1±0.1 BrPM and 1.0±0.1 BrPM from locations 1, 2 and 3, respectively. Further details regarding the respiratory rate performance results can be found in [3].

C. Posture and Steps

Posture accuracy was computed using the data from the elderly participants performing ADLs. The accuracy was computed as the percent agreement between the estimated posture from the patch and periods of known posture. The periods of known posture included a 4-minute block of sitting and standing, a 2-minute block of standing and lying supine, a 3-minute block of lying in different positions (supine, prone, left lateral, and right lateral), and a 2-minute block of walking. The median accuracies were highest for location 3 at 96.3%, slightly lower for location 2 at 95.4%, and lowest for location 1 at 88.1% (Fig. 4).

The pedometer functionality of the patch sensor was tested using the data from the younger participants. To measure the sensitivity of the step counting algorithm, the absolute percent error of step counts was computed with respect to a manual step count (performed by the experimenter) during blocks of walking, running, and stair climbing. The specificity of the algorithm was measured during the stretching, cycling, and rocking chair blocks, and the ratio of false steps to all possible step-like movements was computed. The mean absolute percent error was 3.6%, 2.9%, and 4.0% for locations 1, 2, and 3 respectively. The mean ratio of false steps to all possible step-like movements was 11.7%, 6.9%, and 11.9% for the three locations respectively (Fig. 5).

TABLE I

HEART RATE AND HEART RATE VARIABILITY ERRORS GIVEN AS MEAN ± STANDARD ERROR

	HR - sitting (bpm)		HR - ADLs (bpm)		MeanNN (ms)		SDNN (ms)		RMSSD (ms)		Triang8	
loc.	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE
1	1.1±0.1	1.7±0.2	2.7±0.3	4.3±0.6	6.8±1.6	7.5±1.7	9.1±2.4	11.5±3.2	12.1±3.0	14.6±3.6	1.0±0.2	1.2±0.3
2	1.2±0.1	1.9±0.2	2.6±0.4	3.8±0.6	7.5±1.6	8.3±1.8	8.7±2.5	11.4±3.6	11.7±2.9	13.8±3.4	0.9±0.2	1.0±0.2
3	1.1±0.1	1.8±0.2	2.7±0.2	4.2±0.5	5.5±1.3	6.2±1.6	8.8±2.9	10.8±3.6	11.3±2.7	13.5±3.3	1.0±0.2	1.2±0.3

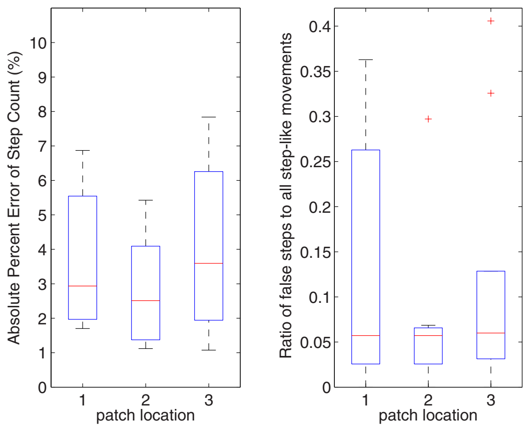

Fig. 5. Boxplots of step counting accuracy with respect to manual count. (left) Absolute percent error of step counts during walking/running. (right) Ratio of false steps to all step-like movements during stretching and cycling.

TABLE II

FALL DETECTION SENSITIVITY (%)

	Location			
Fall Type	1	2	3	avg
Forward (legs straight)	100	96.7	100	98.9
Backwards (legs straight)	100	100	100	100
Left (legs straight)	90.0	100	93.3	94.3
Right (legs straight)	100	100	100	100
Forward (knees bent)	90.0	86.7	93.3	90.0
Backwards (knees bent)	100	100	100	100
Left (knees bent)	100	100	96.6	98.9
Right (knees bent)	100	100	92.3	97.6
Tripping	96.7	100	89.7	95.5
Rolling out of bed	96.2	91.3	100	96.2
Missing a chair	80.0	73.3	76.7	76.7
avg	95.7	95.3	94.7	95.2

D. Fall Detection

To estimate the sensitivity of the fall detection algorithm, the simulated falls performed by the young subjects were used. In total, 330 physical falls were performed among the 10 subjects, resulting in 990 captured fall data (each fall captured by three patches). Data from 23 falls were excluded from analysis due to loss of data from the patch during the fall. The overall sensitivity of the detection algorithm was 95.2%. A detailed breakdown of sensitivities between patch locations and fall types is shown in Table II.

Specificity was estimated using the ADLs from the elderly subjects. Each ADL that could possibly result in a fall (e.g. sitting in a chair, lying on a bed, reclining) was counted as one possible false fall event. A total of 27 ADLs that could be construed as a fall were present for each elderly subject, resulting in a total of 405 events that could have triggered a false fall detection. There were no false detections in any of the elderly subjects, resulting in a specificity of 100%.

IV. CONCLUSIONS

In this study, we have demonstrated that a small wireless patch sensor allows for robust acquisition, recording, and transmission of a number of important vital sign and activity measurements. These measurements are of comparable accuracy to those made by traditional, larger medical devices. All three tested locations demonstrated accurate measurement of many physiological and activity parameters. The unobtrusive form-factor enables continuous monitoring of heart rate and HRV, while the accelerometer facilitates detection of posture, steps, and falls. Fusion of both ECG-derived features and accelerometry provides an accurate measurement of respiratory rate. It may be possible to apply this type of sensor fusion to the measurement of other types of health and activity information such as energy expenditure, psychological stress, and sleep-related information.

The advancing age of the world population makes remote monitoring an important technology for preventive care and rapid response to critical events. The minimalist form-factor of the patch design enables long-term, unobtrusive wear of such a sensor, and the rapid expansion of wireless connectivity over the last several years makes possible the continuous, real-time streaming of important health information to caregivers or healthcare professionals. Finally, while a wireless patch device like the one described here facilitates long-term remote monitoring of important vital signs and activity metrics, it is important to note that such a device must be easy to use if it is to be widely adopted and useful.

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REFERENCES

[1] C. Li, C. Zheng, and C. Tai, "Detection of ecg characteristic points using wavelet transforms," *Biomed. Eng., IEEE Trans. on*, vol. 42, no. 1, pp. 21–28, 1995.

[2] J. P. Martinez, R. Almeida, S. Olmos, A. P. Rocha, and P. Laguna, "A wavelet-based ecg delineator: evaluation on standard databases," *Biomed. Eng., IEEE Trans. on*, vol. 51, no. 4, pp. 570–581, 2004.

[3] A. M. Chan, N. Ferdosi, and R. Narasimhan, "Ambulatory respiratory rate detection using ecg and a tri-axial accelerometer," in *Eng. in Med. and Biol. Society, Conf. of the IEEE*, 2013.

[4] R. Narasimhan, "Skin-contact sensor for automatic fall detection," in *Eng. in Med. and Biol. Society, Conf. of the IEEE*, 2012, pp. 4038–4041.