OLAM: A Wearable, Non-Contact Sensor for Continuous Heart-Rate and Activity Monitoring

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***Abstract*—A wearable, multi-modal sensor is presented that can non-invasively monitor a patient's activity level and heart function concurrently for more than a week. The $4in^2$ sensor incorporates both a non-contact heartrate sensor and a 5-axis inertial measurement unit (IMU), allowing simultaneous heart, respiration, and movement monitoring without requiring physical contact with the skin [1]. Hence, this Oregon State University Life and Activity Monitor (OLAM) provides the unique opportunity to combine motion data with heart-rate information, enabling assessment of actual physical activity beyond conventional movement sensors. OLAM also provides a unique platform for non-contact sensing, enabling the filtering of movement artifacts generated by the non-contact capacitive interface, using the IMU data as a movement noise channel. Intended to be used in clinical trials for weeks at a time with no physician intervention, the OLAM allows continuous non-invasive monitoring of patients, providing the opportunity for long-term observation into a patient's physical activity and subtle longitudinal changes.**

I. INTRODUCTION

Continuous monitoring of patients is becoming increasingly important in personalized healthcare. Conventional data obtained from a medical clinic – such as blood tests, saliva swabs, and vital sign measurements (blood pressure, pulse rate, respiration) – are typically coarsely captured at infrequent doctor's visits, thereby offering a limited glimpse into the condition of a patient's health. This paper presents the Oregon State University Life and Activity Monitor (OLAM), a low-cost, robust, non-invasive device designed for monitoring the activity of patients continuously for weeks at a time. The OLAM is composed of a contactless heart-rate sensor similar to [2] coupled with a five-axis inertial measurement unit (IMU). This combination of movement fused with heart-rate data provides a more accurate measurement of activity over these extended periods compared with sensors that capture either of these senses individually.

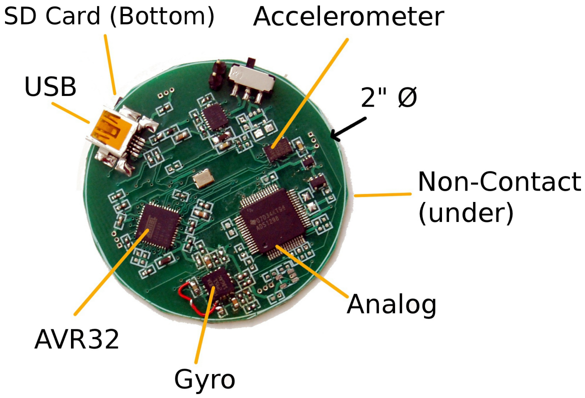

Figure 1. OLAM top view without battery.

Continuous patient monitoring can exhibit numerous benefits, including a reduction in the number of in-person clinical visits, which can result in both reduced healthcare costs and minimized patient's inconvenience. Furthermore, the impact of a clinical visit on measurement error can be quite large [3], such that continuous monitoring in a patient's home setting can improve the prescribed treatment. For example, sleep diagnosis from a sleep clinic can be expensive, inconvenient, and inaccurate [4] due to the requirement for the patient to be evaluated only within the hospital setting.

The OLAM presented here is specifically designed with non-invasiveness in mind.Other devices exhibit similar functionality but are less optimal due to large size, uncomfortable attachment at the interface with the body, poor sensor resolution and accuracy, or limited capabilities of the sensor measurements [5], [6], [7]. OLAM is unique because it is small, comfortable, and can sense both movement activity as well as ECG/heart rate. This is critical because it allows for correlation of movement artifacts with non-contact heart-rate data, and minimization of large movement noises seen in non-contact interfaces [2]. The non-contact sensor pad [2], capable of sensing through a T-Shirt, is adopted and shown in Fig. 1 and Fig. 2 on the next page.

II. DEVICE SPECIFICATIONS

The OLAM was optimized to meet several main design goals: Minimal intrusion into a patient's daily life, long battery life, ease of use, and high accuracy. Each of these main design goals were addressed throughout the design process. The top level design is similar to [8], and is broken

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Figure 2. OLAM bottom view of sensor pad (Left). OLAM top view with battery (Right).

Table I
SYSTEM SPECIFICATIONS

Specification	Value
Size	2”x2”x1/2”
Battery	2200mAh
Power Consumption (avg)	20mW
Expected Battery Life (min)	15 Days
Sample Rate	100 Hz
Unit Cost (1k Quantity)	$65
Heart Rate Detection	30-250bpm
Acceleration Detection	$\pm 8g$
Rotation Detection	±1200°/s

into three basic blocks: data acquisition, data processing, and data storage. System specifications can be seen in Table I.

Data Acquisition, Processing and Storage

The vital-sign data acquired by OLAM is limited by the sensors that are attached, but can be expanded to other sensing modalities (i.e. respiration, EMG) with little design overhead. In the current setup, the sensors are worn by elderly patients involved in a 6-week, double-blind clinical trial, in order to determine the effects of Lipoic Acid (LA) supplementation, recording any subtle changes in heart health as well as patient general activity level before/after LA ingestion.

Given the projected patient outcomes as a result of Lipoic Acid supplementation [9], the required sensing capabilities of this wearable system are limited to: heart rate (single channel ECG), and movement activity (three-axis accelerometer and two-axis gyroscope).

The sample rate was determined by balancing the acquisition of accurate data with the minimization of power consumed. The most critical concern was the sample rate and the duty cycle required for the system, affecting both the wakeup/sleep times of the sensors and microcontroller. The timing of both wakeups and sleeps can be seen in Fig. 3. A power cycling of five-second long sampling intervals every minute was chosen to provide a reasonable resolution without loss of information. A sample rate of 100Hz was therefore chosen to resolve any quick movements observed during the sensing periods.

Commercially available, off-the-shelf components were chosen in the design of OLAM. A custom application-specific integrated circuit (ASIC) is planned for future revisions [10] that will result in lower power operation and smaller size, but for this particular design, “off the shelf” devices enabled quick design iteration. For data acquisition, the following devices were used: Texas Instruments (TI) ADS1294 - A full ECG analog front-end, Analog Devices ADXL345 - Three-axis digital accelerometer, and a STMicroelectronics LPR530AL - Two-axis gyroscope.

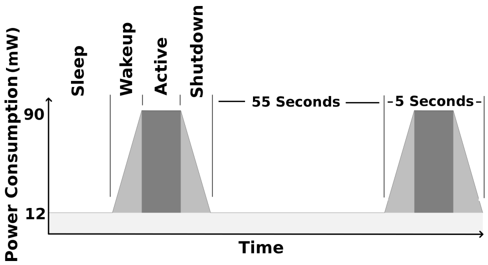

Figure 3. System Power States

These three devices provide a flexible input system that can cover a wide variety of sensor interfaces. Another important consideration was the addition of an isolation buffer placed on the input for the capacitive non-contact input. The contactless ECG input requires a very high input impedance to appropriately couple the signal into the sensor. Therefore, a simple opamp voltage buffer, as previously used in [11], was utilized to provide the required input impedence. Due to the use of this high input impedance, however, coupling noise from 60Hz power lines can be substantial. Hence, a single-pole passive low-pass filter was implemented to mitigate this 60Hz signal (a DC-blocking filter is already available due to the capacitive input).

A data-capturing window of 5 seconds ensures that even with relatively large wakeup times, the system can fully wakeup and shutdown without taking too long. This is very important for maintaining a low power consumption, as it leads to a power savings of nearly 80%.

Data storage on the OLAM is handled with an onboard 2GB micro-SD card, capable of storing over a month of data and allows straightforward data transfer.

Human Interface

The interface to the patient is accomplished with a custom-designed elastic band. The device’s heartrate sensor allows the OLAM to be completely enclosed in fabric without impacting sensing performance. The device is attached to the user by a thin band of 87% Nylon 13% Spandex material, much like that used in swimwear, giving it a smooth connection to the body as well as the ability to stretch and form to the user’s movements. The OLAM on a patient can be seen in Fig. 4 on the following page.

III. USAGE

The OLAM was designed to require very little interaction from the patient. Currently the device is switched on when

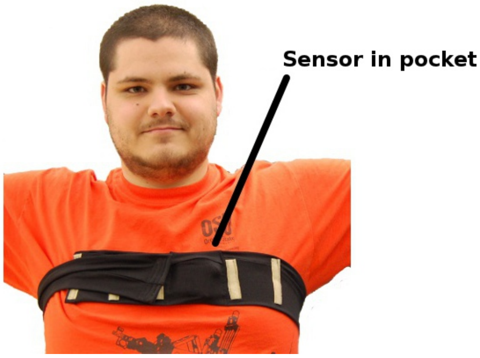

Figure 4. OLAM Human Interface

given to a patient, and never turned off until they return it up to two weeks later. When returned, the device is charged over USB.

Collecting data requires only removal of the SD card. The data is formatted as a comma separated value (CSV) file. Alternative formatting and encryption could be added if required. In our clinical application, IRB approval (institutional review board) ensures that the patients' private health data is only available to IRB-cleared individuals administering the clinical study.

IV. RESULTS AND DISCUSSION

Testing of the OLAM reveals that the largest problem with non-contact capacitive sensors is noise. This noise can obscure the heart-rate measurement, and is a function of how well the device is physically compressed against the body. This means that during any patient movement, the accuracy of the captured data can be difficult to assess. These noise artifacts come from two main sources: decrease of the coupling capacitance associated with the increased distance between body and sensor, and static charge build-up due to the movement. The static charge buildup is difficult to predict because it depends on the location of multiple external materials such as clothing. The first problem, however, is highly correlated with movement. Because the OLAM monitors motion activity and heart-rate data simultaneously, there is the potential for data sensor fusion to filter the motion artifacts [12].

While the OLAM prototype is effective in measuring the required sensor inputs, the size, weight, and cost of the many components could be potentially eliminated by designing a complete ASIC system-on-a-chip (SoC). As can be seen in Table I on the previous page, major problems of size, weight, and cost are apparant. For example, the ADC, MCU, and several other IC's (amplifiers, filters) could be incorporated into an ASIC. Power consumption would also be lowered using a SoC design, reducing the battery requirements leading to decreased system size, weight, and cost.

Table II
SIZE, WEIGHT AND COST

Major Component	Size	Weight	Cost
Battery	50mm x 50mm x 9.2mm	42g	\$16.00
ADC	16mm x 16mm x 1mm	< 2g	\$11.95
MCU	12mm x 12mm x 1mm	< 2g	\$5.60
Sensors	~	< 2g	\$8.07
Passive Components	~	< 2g	\$7.95
Other IC	~	< 2g	\$13.11

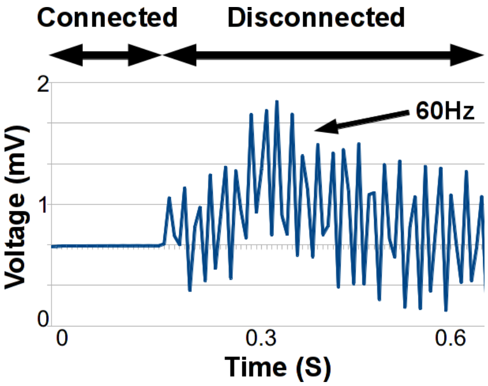

Figure 5. Increase in 60Hz noise due to disconnect from the body

Heart Rate and Movement Data

Consider the waveform captured by the contactless sensor shown in Fig. 5. We observe a large increase in power line noise when the sensor is separated far from the body surface. When the non-contact sensor is securely compressed against the body, multiple heartbeats are observed in a single sample window, as in Fig. 7 on the next page, allowing for accurate estimation of the heartrate. In Fig. 6, we show a large correlation between the heart-rate and accelerometer signals during times of large physical movement.

Data capture during movement is very noisy, but also presents an opportunity for filtering. As seen in Fig. 6, there exists a large artifact correlated with the movement, with a cross correlation calculated as in Equation 1 below:

$$(f \star g)[n] = \sum_{m=-\infty}^{\infty} f[m]\, g[m+n] \tag{1}$$

Movement detection is further aided by the two-axes gyroscope. These two-axes are used to detect rotation, which can be helpful in the classification of different activity types [13]. The gyroscope data from a walking trial can be seen together with the accelerometer data in Fig. 7.

V. FUTURE WORK

Some of the biggest problems with OLAM are related to the use of off-the-shelf components. The power consumption, size, and cost can be significantly reduced by using a custom-designed ASIC. The other critical problem is that

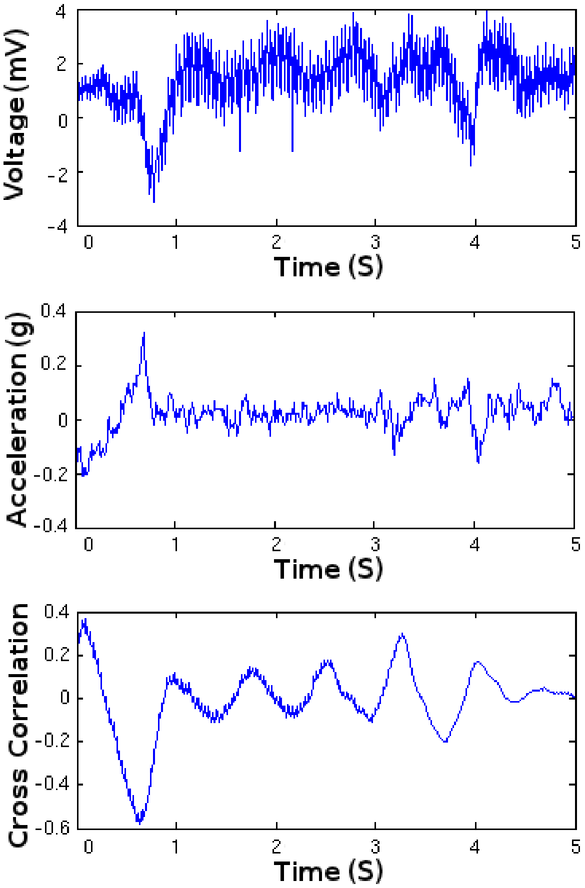

Figure 6. Cross Correlation between X-Axis of accelerometer and heartrate sensor.

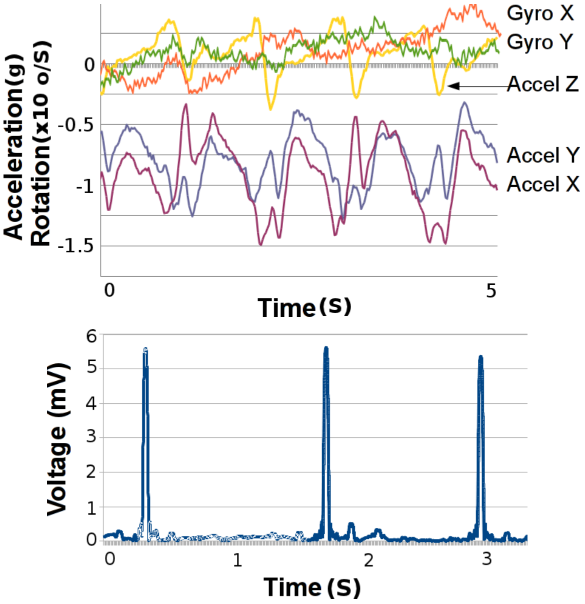

Figure 7. Movement data captured while subject was walking (Top). Multiple captured heartbeats (bottom).

data processing is currently performed manually. Heartrate data can be automatically processed from the resulting data, using data fusion that can automatically detect if the patient is wearing the monitor or not. Other activities such as sleeping can be detected similar to [14]. The final improvement on OLAM would be in the design of bandaid/patch that attaches the device to the patient, improving patient comfort and minimizing motion artifact noise.

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