Battery Optimization in Smartphones for Remote Health Monitoring Systems to Enhance User Adherence

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ABSTRACT

Remote health monitoring (RHM) can help save the cost burden of unhealthy lifestyles. Of increased popularity is the use of smartphones to collect data, measure physical activity, and provide coaching and feedback to users. One challenge with this method is to improve adherence to prescribed medical regimens. In this paper we present a new battery optimization method that increases the battery lifetime of smartphones which monitor physical activity. We designed a system, WANDA-CVD, to test our battery optimization method. The focus of this report describes our in-lab pilot study and a study aimed at reducing cardiovascular disease (CVD) in young women, the Women's Heart Health study. Conclusively, our battery optimization technique improved battery lifetime by 300%. This method also increased participant adherence to the remote health monitoring system in the Women's Heart Health study by 53%.

Categories and Subject Descriptors

J.3 [**Health and Medical information systems**]: LIFE AND MEDICAL SCIENCE

Keywords

Remote Health Monitoring, Power Optimization, User Adherence

1. MOTIVATION AND BACKGROUND

Cardiovascular disease (CVD) remains the leading cause of death for both men and women, costing the United States $444 billion in 2010 [1], yet CVD is one of the most preventable diseases. Remote health monitoring (RHM) systems are proving to be effective in saving costs, reducing illness and prolonging life [10]. Of growing popularity is the use of smartphones as an information gateway, facilitating provider-patient communication while extracting patient context in real time. At the forefront for this technique is the observation of physical activity [12, 2].

Patient adherence is defined as adherence to defined medical prescriptions. When smartphones are utilized for RHM, patient adherence can be affected by several factors including: lack of proper education, poor mobile phone coverage (lack of Wi-Fi or cellular network), and loss of battery power [12, 11]. When systems fail even for a short time participants lose momentum as in the case with heart failure patients that resulted in poor outcomes [4, 6].

In this paper we investigate the effects of battery lifetime of smartphones on RHM system user adherence. The constant use of the phone for real time monitoring uses up battery life and requires frequent charging. By decreasing the frequency with which a user must charge the smartphone, we increased user adherence to the system. We focused on enhancing adherence through battery optimization. This battery optimization technique was tested both in-lab as well as by real participants in the Women's Heart Health study who wore smartphones for six months. The purpose of the Women's Heart Health study is to provide sustainable, preventive self-care through heart health education of lifestyle changes in young black women aged 25-45 years. The study focus is on the use of technology to monitor and coach women for behavior change to support CVD risk factor reduction over a period of 6 months.

This paper is organized as follows. Section II discusses relevant related works. In Section III, we discuss our battery optimization within WANDA-CVD, a remote health monitoring system. Section IV analyzes the experimental setups and results. Finally, we conclude in Section V.

2. RELATED WORK

Recent advances in pervasive and networking technology have enabled many RHM systems [9]. Despite the increasing research on RHM systems, it remains to be seen whether the technical feasibility and effectiveness of such systems can truly enhance patient care. Most mobile-based interventions are limited to data transfers that are not able to provide wireless coaching and feedback [8]. Roychoudhury et al. designed MediAlly [5], a prototype system that would dynamically activate the collection of data from other external sensors based on a specified context. In contrast,

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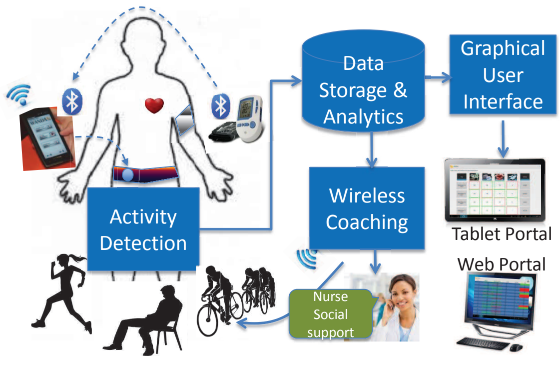

Figure 1: WANDA-CVD System Architecture

our WANDA-CVD system is designed to detect active and inactive states and adjust the sampling rate of the sensors accordingly. Our system also delays processing power until nurses need data, or until the smartphone is charged at night in order to enhance battery lifetime.

There have been many studies that perform detailed analysis of energy consumption in smartphones; Carroll et al. [3] and [7] showed how usage patterns affect overall energy consumption and battery life. In this paper, we focus on battery longevity in a real world scenario under the continuous monitoring of physical activity. According to Desai et al. [6], a major challenge of remote monitoring systems is to design systems that improve patient's adherence and self-care. Ensuring that participants minimize the need to charge the smartphone throughout the day increases their potential to use the device. WANDA-CVD attempts to tackle a more preventive approach by reducing risk factors in accordance with the Institute of Medicine Report and the goals of Healthy People 2020 for chronic disease prevention.

3. BATTERY OPTIMIZATION IN WANDA-CVD

In order to reduce risk factors for patients, we designed and developed our own remote health monitoring system called WANDA-CVD. Several parts of the WANDA-CVD system are illustrated in Figure 1. The first component is the smartphone hub which involves a smartphone application measuring, communicating and collecting data from sensors. It stores data locally as well as transmits this data through a network for data storage and processing, where the raw data collected from multiple smartphone gateways is collected, and data analytics and wireless coaching is performed. The data analytics determine what messages to transmit to the participants and nurse practitioners. In this paper we focus primarily on the smartphone gateway as a means to optimize battery consumption for enhanced adherence.

A key component for maximizing adherence is that the smartphone be able to last a full day of regular use. The majority of battery life is spent processing accelerometer data and transmitting data to the servers. Initially we designed the system to consistently process data and upload it to the servers at a fixed time interval for it to be viewed by the nurse. Realizing that individuals spend much of their day inactive, the smartphone could enter sleep mode to decrease the sampling rate of the accelerometer when the user is not in motion. We developed a battery optimization technique so that when the phone is connected to a charger, it enters an initial state, where the accelerometer can be turned off. Once the phone is disconnected, it enters an active state, where the accelerometer is turned on and the sampling rate is set at 10Hz. If the user becomes stationary, where they are sitting on a couch or at the dinner table, little physical activity is captured and the smartphone enters an inactive state, where the sampling rate decreases to 1Hz.

To determine the participants' physical activity level, we used the algorithm proposed by Panasonic [13], which has been shown to have high correlation ($R^2 = 0.86$) with Doubly Labeled Water, which is one of the most accurate methods for evaluating total energy expenditure under free living conditions. K_m values, shown in Equation 1, are calculated for a given time window and are mapped to activity levels. In our application we achieved optimal results using a 10Hz sampling rate and a time window of 5 seconds; as such, the number of samples n in 5 seconds is 50.

$$\begin{aligned} K_m &= \sqrt{\frac{1}{n-1}[Q - \frac{1}{n}(P)]}\ , \quad where \\ Q &= \sum_{i=0}^{n} x_i^2 + \sum_{i=0}^{n} y_i^2 + \sum_{i=0}^{n} z_i^2\ , \ and \\ P &= (\sum_{i=0}^{n} x_i)^2 + (\sum_{i=0}^{n} y_i)^2 + (\sum_{i=0}^{n} z_i)^2. \end{aligned} \tag{1}$$

In order to quantify the feasibility of our system, we defined a metric of adherence in coordination with our nurses and medical experts. We provide an overall adherence rate, as well as a per category adherence rate. There are currently four categories each requiring feedback from the participant: daily questionnaire (DQ), weekly questionnaire (WQ), blood pressure monitor (BP), and physical activity (Activity). We determine adherence on a weekly basis for each category c. Adherence in DQ means participants completed at-least 3 out of the 6 daily questions each week. Adherence in WQ means participants completed the questionnaire once a week. BP adherence requires participants to measure their blood pressure at least once a week. Activity adherence is defined as participants exerted at least 20 minutes of low intensity activity per day. We calculate the total adherence TC_c for a specific category c, for all subjects s (total of m subjects), over n weeks by:

$$Com(i)_s^c = \begin{cases} 1 & \text{if } S \text{ compliant in week } i \text{ in category } c \\ 0, & \text{otherwise} \end{cases}$$

$$\begin{aligned} Com_s^c &= \frac{\sum_{i=1}^{n} Com(i)_s^c}{n}, \\ TC_c &= \frac{\sum_{j=1}^{m} Com_s^c}{m}. \end{aligned} \tag{2}$$

An overall adherence rate is calculated which gives credit to the participant if they complied with at-least one of the four categories.

Because our study looks at physical activity trends over time, we chose to accept an increase in latency when receiving data to significantly increase battery life and thus achieve higher adherence. By delaying until an external power source is connected, the processing and uploading of accelerometer values into meaningful data can be done without impacting battery life or generating excess heat that

Procedure 1: Battery Management

We set a fixed window size W (5 seconds), a buffer rate B (seconds), and a K_m threshold value T. We calculate the current state $State_C \in \{Charge, Active, Inactive\}$, while adjusting accelerometer sampling rate f. Experimentally: $W = 5, B = 60$.

for $i = 1$ **to** $i = B$ **do**
  Calculate K_m from i to $i + W$
  $i = i + W$.
end for
$K_m^A = mean(K_m)$
if $K_m^A < T$ **then**
  $State_C = Inactive$;
  $f = 1$;
else if $K_m^A >= T$ **then**
  $State_C = Active$;
  $f = 10$;
end if
if $Phone = Charging$ **then**
  $State_C = Charge$;
  Upload K_m values for previous day
  $f = 0$; Turn off accelerometer
end if

could be bothersome to participants. The battery optimization technique is presented in *Procedure 1*. Recorded data is queued for upload in a SQLite database which is used to maintain a synchronized state with WANDA-CVD servers. Upon connecting the device to a charger, data values are processed and uploaded. The process is completely invisible to the end user and requires no intervention on their part. In the case of network connectivity concerns, an attempt at synchronization of all queued data will automatically occur the next time the phone is charged.

4. EXPERIMENT SETUP AND RESULTS

4.1 Experiment Setup

In preparation for the Women's Heart Health study, we performed an in-lab pilot study with 5 participants to test the smartphone application with and without battery optimization. To test effects of battery lifetime on adherence in real-life, we selected 7 participants from the Women's Heart Health clinical trial to test the system without battery optimization for two months and with battery optimization for the remaining four months. The system transmits participant-measured data using Wi-Fi and 3G/4G technology. The participants were taught how to wear and manage a smartphone (Motorola Droid Razr Maxx with 3300 mAh Li Ion battery) in their pocket or around their waist throughout the day. We also recorded and transmitted battery usage events, when the phone was connected, disconnected, ran out of battery and powered up.

We tested the WANDA-CVD smartphone application under four configurations: 1) Airplane mode, 2) Wi-Fi only, 3) NG only, and 4) Wi-Fi and NG both enabled. NG represents the cellular network coverage which can range based on local coverage from 2G or 3G to 4G/LTE networks.

In the in-lab setting participants wore the smartphone in a pouch all day, performing typical day-to-day activities, and as a result were subject to intermittent Wi-Fi and NG com-

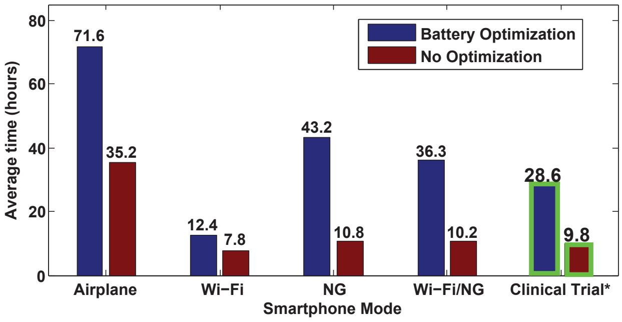

Figure 2: We notice substantial improvement in battery lifetime with battery optimization in all smartphone settings: Airplane mode, Wi-Fi-only mode, NG-only mode, and Wi-Fi/NG mode. Results from the Women's Heart Health clinical trial* are provided that show substantial improvement in battery lifetime by approximately 300% in a real world setting.

munication. Participants in the in-lab setting did not use features such as talk-time, camera, browsing and gaming. We acknowledge that in a real setting such limitations do not exist, so for this reason we also tested our system in a real world setting via the Women's Heart Health study.

4.2 Results

4.2.1 Battery Lifetime

The in-lab setting with battery optimization results show strong improvement in battery lifetime . Figure 2 compares results with/without battery optimization for both the pilot study and the Women's Heart Health clinical trial.

In Airplane mode, with no battery optimization, our system lasted on average 35.2 hours, whereas with the optimization it would last 71.6 hours, doubling the lifetime of the battery. It can be seen from Figure 2 that the results do not exceed 11 hours of battery lifetime in any non-Airplane mode. This is disconcerting as it implies that real-world participants would need to charge the phone before the end of the night. From Figure 2, with battery optimization, we see that we are able to achieve improvements of 160%, 400%, and 355% in Wi-Fi, NG and Wi-Fi/NG modes, respectively.

In a more realistic clinical trial setting, the Women's Heart Health study, we observed that on average the participants were able to achieve a battery lifetime of 28.6 hours compared to 9.8 hours without battery optimization. The battery lifetime results in the clinical trial were less than our in-lab setting for Wi-Fi/NG mode, due to the fact that some participants have Wi-Fi turned on, but also because we do not control their phone usage in terms of web browsing, camera time, downloading applications, and playing games. Participants have shown to be quite happy with battery longevity, with some realizing that if they forgot to charge their phone at night, their phone battery does not go down. By increasing expected battery life to 28.6 hours, we ensured that most participants were able to complete a full day with the ease of charging the phone at night.

4.2.2 User Adherence Results

Participant adherence to the study protocol is a very critical matter in order to ensure that a remote health monitoring system can be successfully deployed in a real world

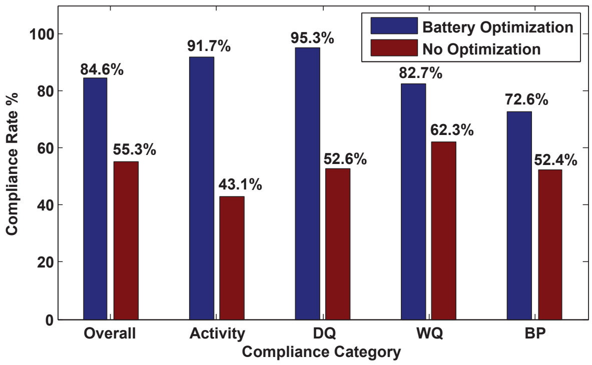

Figure 3: Comparing adherence rates with and without battery optimization based for each category.

environment. Figure 3 shows our battery optimization technique resulting in a 53% increase in overall adherence from 55.3% to 84.6%.

The effects are even more evident in Activity adherence, where adherence increased from 43.1% to 91.7%. This result is expected due to the fact that battery lifetime was not lasting the entire day, and many of the participants were complaining that they would have to charge the device midday. Many of the participants found the battery life without the battery optimization to be a main concern, and also found that the phone would overheat from the continuous processing and transmission of data. The participant's response rate to the daily questionnaire showed significant improvement from 52.6% to 95.3%. Participant response to the weekly questionnaire also increased from 62.3% to 82.7%. It is interesting to note that adherence of blood pressure measurements is significantly lower than the other categories, despite increasing from 52.4% to 72.6%. Further investigation is required to see whether the blood pressure monitor was difficult to use, or whether participants had difficulty finding the time and a quiet place to take and transmit the blood pressure reading using both the phone and the device.

5. CONCLUSION

In this paper we show the high correlation between battery lifetime and participant adherence in a remote health monitoring system that uses a smartphone as an information gateway. The WANDA-CVD system has shown success in battery optimization in both in-lab and real-world settings. Such a system could be of great use to the healthcare industry. We have shown an ability to drastically enhance adherence by optimizing the battery lifetime of the smartphone application gateway by delaying processing and communication until the phone is charged, resulting in a 300% increase in battery lifetime, yielding on average a 28.6 hour battery lifetime in the Women's Heart Health study. The simplicity and ease-of-use of our WANDA-CVD system yielded 85% overall adherence by participants, and a 95% adherence rate in physical activity. Our battery optimization improved adherence by 53%.

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