Continuous, Real-Time, Tele-monitoring of Patients with Chronic Heart-Failure

Lessons Learned From a Pilot Study

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ABSTRACT

We present a smartphone-based system for remote real-time tele-monitoring of physical activity in patients with chronic heart-failure (CHF). We recently completed a pilot study with 15 subjects to evaluate the feasibility of the proposed monitoring in the real world and examine its requirements, privacy implications, usability, and other challenges encountered by the participants and healthcare providers. Our tele-monitoring system was designed to asses patient activity via minute-by-minute energy expenditure (EE) estimated from accelerometry. In addition, we tracked relative user location via global positioning system (GPS) to track outdoors activity and measure walking distance. The system also administered daily-surveys to inquire about vital signs and general cardiovascular symptoms. The collected data were securely transmitted to a central server where they were analyzed in real time and were accessible to the study medical staff to assess patients' health status and provide medical intervention if needed. Although the system was designed for tele-monitoring individuals with CHF, the challenges, privacy considerations, and lessons learned from this pilot study apply to other chronic health conditions that would benefit from continuous monitoring through mobile-health (mHealth) technologies, such as diabetes and hypertension.

1. INTRODUCTION

High re-hospitalization rates among patients with chronic heart-failure (CHF) and other chronic life-threatening conditions represent a significant cost to current health care system. It is estimated that the economic burden of CHF alone is about $30 billion [18]. Giamouzis et al. found that approximately 50% of patients with CHF are readmitted to the hospital within 6 months of discharge [10]. In another study, Jencks et al. reported that about 27% of patients with CHF in Medicare are re-hospitalized within 30 days of being discharged [13]. Reduction of re-hospitalization rates has thus been one of the main goals of Affordable Care Act (ACA) since 2010 by imposing financial penalties to medical institution with high re-admissions [17].

Recent studies suggest benefits of medical intervention based on tele-monitoring patients with CHF, including reduction in re-admissions [2, 4, 5, 11, 12, 15]. Tele-monitoring in health care can be performed using various telecommunication and information technologies. In general, the tele-monitoring systems can be categorized based on the following properties: *a*) type(s) of collected data; *b*) modality and frequency of data collection (e.g., continuous vs. periodic monitoring) *c*) means of data transmission (e.g., phone call, internet connection, etc.) *d*) type and number of devices used (e.g., a network of distributed sensors, a single device, etc.); and *e*) level of real-time operation.

The proposed workflow for tele-monitoring consists of several stages. Patient's physical activity and vital signs data are being collected via a smartphone and reported to a central server. The central server in turn analyzes the data and makes the results of the analysis available to the medical care team. The medical care team assesses the health status of the patient based on the processed data and intervenes if necessary. The overall flow is depicted in Figure 1a.

To address the need for tracking the health status of individuals with CHF, we designed a tele-monitoring system that would deliver real-time information on patient's overall activity levels via energy expenditure (EE) estimates, self-reported vital signs (heart rate, blood pressure, and weight), and relevant cardiovascular symptoms (fatigue, activity, dizziness, shortness of breath, etc.). The changes in these symptoms represent important markers that can predict early worsening of the CHF condition. As opposed to the

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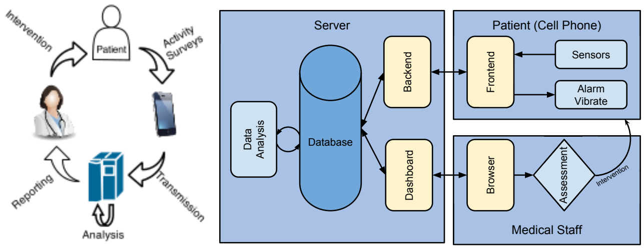
BODYNETS 2014, September 29-October 01, London, Great Britain

DOI 10.4108/icst.bodynets.2014.257036



(a) (b)

Figure 1: (a) The proposed flow of tele-monitoring and intervention; (b) The architecture of the proposed system.

traditional health care model, where such information is reported to the caring physician only intermittently, the tele-monitoring technology can support automatic analysis of the data in real-time and alert the physician when significant changes are detected. Although several tele-monitoring systems have been proposed in the past, the majority of the research systems have been deployed only in a controlled (laboratory) environment or used only by healthy individuals. When deploying such a system to actual patients in a real environment (e.g., home, work place), there are several new challenges that need to be addressed. The challenges include system reliability issues, usability of the device and software, user compliance, data security, and privacy.

We thus focus here primarily on the outcomes of the pilot study from the system perspective. The main contributions of this paper are as follows:

1. The implementation of a tele-monitoring system based on a smartphone that *a*) collects continuous estimates of EE in real-time, daily self-reported vital signs, and cardiovascular symptoms, *b*) performs data analysis, and *c*) provides alerts to the medical staff.

2. The report on lessons learned from the deployment of the system to patients with CHF in their everyday environment.

The rest of the paper is organized as follows. Section 2 gives an overview of related works in tele-monitoring. Section 3 briefly describes the design of the proposed system and its components followed by the findings of the pilot study in Section 4. Section 5 discusses directions of future work based on the challenges and lessons learned in deploying this system in a real environment.

2. RELATED WORK

In this section we first review the literature on tele-monitoring of patients with CHF. There has been a significant increase in the number of such systems in the last decade with the aim to study its effect on the hospital re-admission rates and associated costs of care. For brevity, we summarize results from several systematic reviews while interested reader is encouraged to refer to cited papers for more information.

Tele-monitoring comes in different forms and shapes. Chaudhry et al. conducted a tele-monitoring randomized clinical trial, where tele-monitoring was accomplished by means of telephone-based interactive voice-response system that collected daily information about symptoms and weight of CHF patients (826 patients in the tele-monitoring group and 827 in the usual care group). The collected data were subsequently reviewed by patients' clinicians. The study reported no significant difference in hospital re-admissions or mortality within 180 days from the enrollment between the two groups [2].

In [4], Clark et al. reviewed 14 randomized controlled trials (4262 patients in total) of tele-monitoring and/or structured telephone support for patients with CHF. Among the reviewed trials, only one study collected some form of daily physical activity information (self-reported to a nurse via telephone). Only five of the studies collected vital signs (e.g., weight, blood pressure, heart rate and/or periodic electrocardiogram) on daily basis; four of which also collected information about related symptoms (e.g., fatigue). The authors reported average reduction of hospital re-admissions by 21% (95% confidence interval 11% – 31%) and average reduction in all-cause mortality by 20% (8% – 31%).

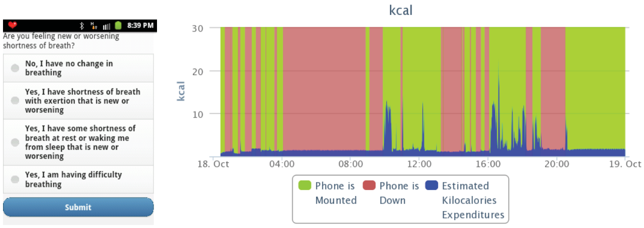
The review by Giamouzis et al. reported results of 12 studies on tele-monitoring of patients with CHF in [11], two of which were also included in [4]. Although some of the studies collected self-reported data about physical activity, none of the trials captured any quantitative information, such as EE, that could provide more objective estimate of patients' physical activity levels [11].

Inglis [12] reviewed another 30 studies on tele-monitoring and structured telephone support with medical intervention mechanisms for patients with CHF. Only one study provided subjects with activity monitors; however, the data were used for self-monitoring only and were not transmitted to the medical staff [9]. One structured telephone support study inquired daily about patients' physical activity (the study was also included in the review by Clark et al. in [4]). However, none of the reviewed studies performed continuous activity monitoring.

From the above literature review it is clear that there is a need to implement continuous monitoring of chronic conditions, such as CHF, that could alert physicians when changes in physical activity or relevant vital signs occur. Although many of the previous works used telephone support to monitor patients, such process requires substantial involvement of the support staff and may as such be cost-prohibitive to track larger number of patients. In addition, self-reporting through telephone creates additional burden to patients and does not provide objective means of quantifying the activity levels and reporting vital signs to make reliable predictions which could be used in an automated alert system

Objectively measured physical activity can thus facilitate relevant information on patient's health status. In turn, this information could be used to encourage the patient to be more active through health coaching, as it has been demonstrated in various wellness applications [14]. Physical activity can be in general quantified by estimating EE. Several off-the-shelf products for EE data collection are currently available. Some examples include Nike+ FuelBand [1]; Fitbit's Activity Wristbands and Trackers [2], and others. Several research studies that examined the

[1] http://www.nike.com/us/en_us/c/nikeplus-fuelband
[2] http://www.fitbit.com/



(a) (b)

Figure 2: (a) Sample screenshot of the daily survey; (b) an example of minute-by-minute estimates of energy expenditures (kilo-calories), overlaid by the classified state of the phone ('Mounted' denotes the phone is properly mounted on subject, 'Down' denotes that the phone is not mounted);

accuracy of such monitoring showed that many of these devices are accurate in counting steps but inaccurate in EE estimation [16, 7, 1]. Many of these monitoring devices require (or benefit from) a smartphone (or other internet-connected device) and would as such require patients to carry with them an additional device at all times while having to keep track of the battery charge and connectivity. With smartphones becoming ubiquitous, we believe that the smartphone alone is currently the most convenient device for continuous EE estimation as opposed to a dedicated wristband, hip clip, heart rate monitor or other discrete tracking device. The smartphones have thus the necessary sensory (e.g., accelerometer) and computing capabilities to accomplish this task. Accelerometers have been used for activity monitoring and recognition in many previous studies (for example, [8, 19, 20, 16]). These studies have shown that accelerometers can be used reliably to estimate EE [16, 19]. Estimation of EE in our study was performed using the algorithm presented by Chen and Sun in [3]. The algorithm was validated by Donaire-Gonzalez et al. in [8].

To the best of our knowledge and review of related work, the framework proposed in this paper is the first to continuously remotely monitor the activity levels of discharged patients with CHF.

3. SYSTEM OVERVIEW

In this section, we provide details on the developed tele-monitoring framework depicted in Figure 1b. The design of the framework included the following features: *a)* collection of all pieces of data using only a smartphone; *b)* calculation and continuous reporting of EE estimates, collection of daily self-reported vital signs (heartbeat rate, blood pressure and weight) and cardiovascular symptoms (fatigue, activity, dizziness, shortness of breath, etc.); *c)* transmission of data via internet link; and *d)* real-time analysis and reporting of the data to medical staff via a web-based dashboard.

After the initial development and testing phase, we found that accelerometry and GPS alone are not sufficient to reliably determine physical activity, therefore we collected additional sensor data as shown in Table 1. More details on these challenges are presented in Section 4.

3.1 Smartphone Application Implementation Details

The smartphone application has two main responsibilities,

Table 1: Data Collected by The Application, Per Minute.

Symbol	Description
$B \in \mathbf{R}^3$	Tri-axial magnetic field, averaged over a minute period
$O^* \in \mathbf{R}^3$	Tri-axial phone orientation, averaged over a minute period
$G^* \in \mathbf{R}^3$	Gravity pointer, averaged over a minute period
$R^* \in \mathbf{R}^3$	Tri-axial phone rotation, averaged over a minute period
$L \in \mathbf{R}^2$	Latitude and shifted longitude reading from the GPS sensor
$E^* \in \mathbf{R}$	EE estimate (kilocalories), a minute aggregate
SL$\in [0,1]$	Screen light: proportion of the minute that the screen light was on
$P \in [0,1]$	Proximity: proportion of the minute that an object was close to the face of the phone
Ch$\in [0,1]$	Charging status: proportion of the minute that the phone was being charged
Call$\in [0,1]$	Call status: proportion of the minute that the phone was in a call
Batt$\in [0,1]$	Battery level

* Data calculated from other raw sensory data.

acquisition of sensory data and collection of self-reported information through daily surveys. The application collects the sensory pieces of data as listed in Table 1. For each one-minute long interval it calculates energy expenditure estimate using the data from the tri-axial accelerometer based on the algorithm presented by Chen and Sun in [3]. To obtain information on geographical distribution of activity, the application also collects readings from the phone GPS output. The longitude of the GPS data are shifted by a random quantity which is assigned within the application and is not externally accessible. The process of shifting is done in order to protect the privacy of patients in a manner that would still allow the system to calculate useful measures from the data, such as the traveled distance (therefore, latitude is not shifted).

The second responsibility of the application is to provide an interface for the patients to answer daily surveys about their potential cardiovascular symptoms (fatigue, activity, dizziness, shortness of breath, etc.) and vital signs (heart-beat rate, blood pressure and weight). Figure 2a shows a sample from the survey screen. The application is designed to give a daily reminder to patients to fill in the survey by generating an alert at specified time. When the patient opens the daily survey, the questions are fetched from the server. This approach provide more flexibility and control for the medical staff to potentially tailor questions to individual patients.

When the application is running in the background, it continues to respond to the requests sent by the server. The server requests include the following: *a)* application update requests (see Subsection 4.2 for details); *b)* a poke request that reminds the patient of the daily survey in addition to the scheduled reminder (This poke message can also be used by the medical staff to manually remind patients to answer the survey.); and *c)* a request to change the schedule of the daily survey reminder.

The client application was designed to support any Android-based smartphone with API level 9 and above (equivalent to Android 2.3 GINGERBREAD and above) [3].

3.2 Server Implementation Details

The server in our tele-monitoring framework performs several tasks, which include communication with the client applications to receive data, data storage, data analysis for determination of risk scores, access to the data via web-based dashboard, and delivery of daily surveys. The server has the following four key components:

3.2.1 The backend

The backend is responsible for providing a server-side interface to the cellphone application. The backend both collects data from the monitoring component and provides server requests back to the application when needed.

3.2.2 The database

MySQL-based database system responsible for data storage and management.

3.2.3 The data analysis component

This component performs basic data analysis in the background in order to support visual review of patient's data by the medical staff. For example, this component calculates the risk scores based on the survey replies which in result help the medical staff assess the symptoms related to CHF. The risk score calculation formula was designed by the cardiologists involved in this project and is computed as follows. A score is first assigned for each symptom related question and answer. A score is also assigned for each vital sign entry as reported by the patient: *a*) for blood pressure and heartbeat rate: based on their absolute value; and *b*) for weight: based on the relative value to the previous weight. Finally, all the individual scores are linearly added. Depending on the range of the final score, patients receive a predefined message at the end of the survey. The feedback messages range from encouraging the patient if the risk score is below a certain threshold to checking in with their clinic or advising the patient to call the emergency number (911) if the patient's risk score is too high. In addition to the feedback, this component will flag the patient and notify the medical staff if the score is higher than a preset threshold.

Additionally, this component performs classification of the phone state based on the data received. More information about the classification is provided in Subsection 4.2. The existence of a data analysis component in every tele-monitoring system is in our opinion vital in enabling the deployment of the system to a large number of users.

3.2.4 The dashboard

The dashboard is a web-based user interface that allows the medical staff to monitor the status of the enrolled patients. A screenshot of the main page of the dashboard is depicted in Figure 3a. The medical staff can access patients activity and related geographical information (obscured for privacy by shifting GPS data as described previously) by clicking on the "View" link under "Data" for the corresponding subject. Examples of the possible plots that can be viewed using this link are shown in Figures 2b and 3b.

4. PILOT STUDY FINDINGS

In this section, we present some of the findings from the pilot study and discuss the related challenges and lessons learned based on the system performance evaluation and the feedback from the medical staff and study participants. All 15 patients received a study phone (Samsung Galaxy Young, Samsung Electronics Co.) with a prepaid plan for about 3 months of tele-monitoring (phone and plan were paid for by the research grant). The pilot study ran from July 2013 through May 2014.

4.1 Challenges and Lessons Learned

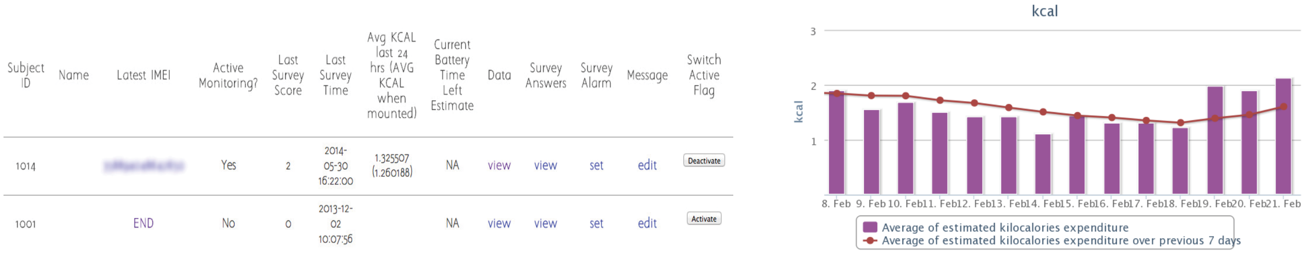
First, many of the tele-monitoring technologies in general, and the CHF related tele-monitoring specifically, are meant to take place in real-world conditions that include patients home, workplace, commute, etc. Many of the design assumptions developed during the laboratory testing may therefore change. For example, in our study, the algorithm designed to estimate EE from tri-axial accelerometer data assumes that the sensor is worn on the right hip at the waistline level [3, 8]. For instance, if the phone is in a purse, on the table or in the car on the tableau, this assumption is violated and the EE calculation cannot be trusted. Such assumptions need to be identified and verified in order to ensure the validity of the data. This may be less important in fitness application but is crucial when such data are used to assess person's health status. In addition, a more systematic approach and mechanisms are needed to validate the *proper authorship* of data, i.e. to ensure that the data were indeed created by the patient under assumed study design requirements, and to detect when any of the above assumptions is violated.

Another challenge in our study was *compliance*. Patients' willingness to use the pilot technology tends to wear off over time (we call this *usage fatigue*). Patients tend to fill less daily surveys and are less committed to ensure proper mounting of the phones on their hip. Based on the initial feedback from the study participants, there is an indication that the technology is too passive and does not sufficiently interact with them. We found that a better understanding of *user-feedback*, *user-interface*, and *incentives* is needed to achieve higher compliance since the value of such technologies lies in continuous monitoring over longer time periods.

The objectiveness of data can also be an issue. For example, self-reported survey answers may suffer from bias, subjectiveness and other effects that may cause the health-related risk assessment to become unreliable. Sensory data may also suffer from inaccuracies due to specifications, environmental factors or calibration. Data *reliability and objectiveness models* are required especially when the number of monitored patients grows as the potential harm of unreliable data grows accordingly.

Once data are collected, in order to assess the necessity of medical-intervention, *physio-behavioral models* need to be designed and employed. These models can be used to automate the decision process for providing the intervention, especially in larger groups of patients. The design of such models is not trivial and poses a challenge in current tele-monitoring systems. Many tele-monitoring systems solely collect data and therefore have to employ human-based (manual) assessment for the intervention decision-making process. The manual intervention assessment is not practical if a system is to be used by a higher number of patients.

[3] https://developer.android.com/guide/topics/manifest/uses-sdk-element.html



Subject ID	Name	Latest IMEI	Active Monitoring?	Last Survey Score	Last Survey Time	Avg KCAL last 24 hrs (AVG KCAL when mounted)	Current Battery Time Left Estimate	Data	Survey Answers	Survey Alarm	Message	Switch Active Flag
1014			Yes	2	2014-05-30 16:22:00	1.325507 (1.260188)	NA	view	view	set	edit	Deactivate
1001		END	No	0	2013-12-02 10:07:56		NA	view	view	set	edit	Activate

(a) (b)

Figure 3: (a) A screenshot of the dashboard.; (b) An example of a daily average energy expenditure estimate, bars depict averages over a day and the line depicts averages over the previous 7 days from the day in question (including the day itself)

In mHealth tele-monitoring, as in many other technologies, understanding the *privacy* preferences of patients is key to wider adoption. These technologies need be minimally intrusive to the privacy of individuals using the technology (i.e., patients) and the individuals the users interact with (e.g., family members, co-workers). For instance, such tele-monitoring architecture should allow patients to view the data collected about them, provide them with controls to change what data are being collected and when. For example, patients may not want their location to be tracked if they are doing something private, but are open to be tracked at other times.

4.2 Addressing the Challenges

The *proper authorship* challenge has serious implications on the medical intervention decision-making process. One would expect the medical intervention, or the lack thereof, not to be based on the data that are deceptive because they suffer from great deal of inaccuracy due to system-specific, subject-influenced or environmental factors. In order to deal with this problem, we designed a classifier and integrated it in the *data analysis component* of the server (see 3.2.3). This classifier uses all collected data to predict the state of the phone for each data-point between the following two states: phone mounted and phone down. A support vector machine (SVM) [6] with Gaussian kernel was trained with the following features (symbols taken from Table 1): $\sigma^2(B_{-15})$, $\sigma^2(O_{-15})$, $\sigma^2(G_{-15})$, $\sigma^2(R_{-15})$, $\sigma^2(\mathrm{SL}_{-15})$, $\sigma^2(P_{-15})$, $\sigma^2(\mathrm{Ch}_{-15})$, $\sigma^2(\mathrm{Call}_{-15})$, $\sigma^2(\mathrm{Batt}_{-15})$, SL, P, Ch and Call. The notation $\sigma^2(\cdot)$ denotes the variance and X_{-15} denotes the past 15 minutes worth of data X (relative to the data-point in question). Considering the 'Mounted' class as the positive (P) class, the SVM obtains accuracy, defined as $\frac{TP+TN}{P+N}$, of 97.94% (number of training data points = 1491, number of test data points = 2285). The classifier output is demonstrated in Figure 2b, where the green background denotes that the phone is classified as "properly mounted" and the red background denotes otherwise.

Since this was a pilot study that targeted patients with CHF, in addition to the logistics of recruiting and consenting patients to the study, the smartphone application was not added to the Google Play store [4]. This means that the system cannot benefit from the update mechanism provided by Google Play, therefore a customized updating system had to be implemented. When a new update of the application is available, under the assumption that it does not require new consent from the user (e.g., in case of collecting new pieces of data), the server sends a request to the application to update itself. The application in return, updates the application by downloading the update from the server and restarts it to stage the updates.

[4]https://play.google.com/store

Privacy is a big part of health care. Understanding the privacy preferences of patients and their acceptability of the technology is a key point in its success and adoption. In our pilot study we therefore performed a pre- and post-surveys on privacy and acceptability of the system. Pending the post-surveys of some of the subjects, the results of these surveys are not available for dissemination in this paper. We plan to analyze and report the findings of the privacy study in the future. We believe the answers to these surveys, and the differences in the answers to the pre-study and the post-study surveys, will provide valuable insights into privacy consideration of individual patients that will guide future implementation of such tele-monitoring systems.

Finally, there is a huge benefit from assessing the *reliability and objectiveness* of the self reported symptoms by patients. This can provide the medical staff with an instrument to better assess the health status of patients. We are currently studying ways to provide better assessment of objectiveness for the self-reported symptoms. However, no such models are currently incorporated in the deployed system.

4.3 Evaluation

4.3.1 Data Plan Consumption

The use of cellular data plans to transmit data can become a financial bottleneck in a smartphone application deployment if data consumption is too high. To assess the data consumption of the smartphone application, we conducted a lab test to calculate statistics about packet sizes and data consumption. The setting for the lab test was as follows. The smartphone application was used to transmit the sensory data (Table 1) and as a result, packet sizes were calculated from the server side. Each packet embeds 30 data points (worth of 30 minutes of data), and the results were as follows. The packet size distribution had mean of 19.15KB and standard deviation of 1.6KB. The monthly data consumption is a random variable that is the sum of all packet sizes in a month. Precisely, there are 1440 minutes a day. Equivalently, there are at most 48 packets a day (assuming monitoring is active all day), since each packet encodes 30 minutes worth of data. This means that there is at most 1488 packets a month. Assuming all packet sizes

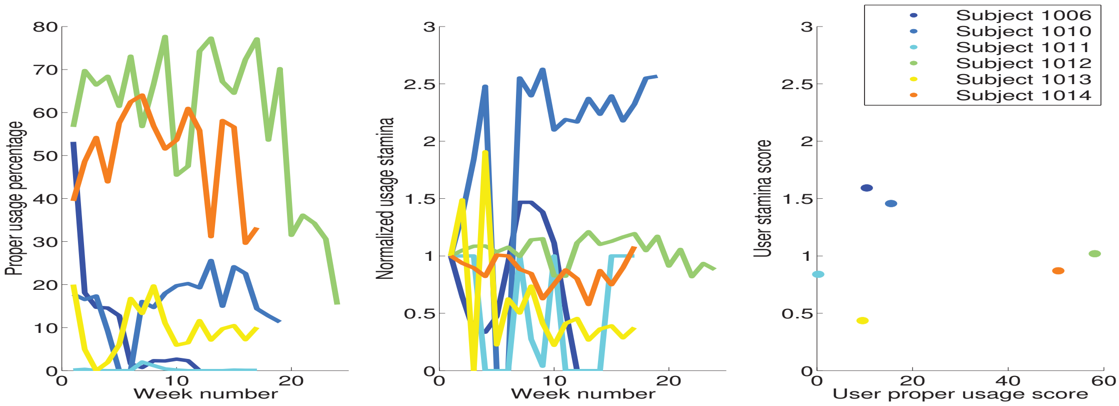


Figure 4: Usage stamina and proper usage percentage per user (for all quantities, the higher the better). Left to right: the proper usage percentage vs. time (weeks since the beginning of the study) per user; normalized usage stamina vs. time per user; and users in the stamina and proper usage scores domain.

are independent, the monthly data consumption (excluding surveys) is normally distributed with mean 27.82MB and standard deviation 2.33MB. We conclude that the monthly data consumption is at most 33.24MB with 99% confidence.

4.3.2 Battery Consumption

During the system design process, lab tests were performed to assess the burden of our smartphone application on the battery consumption. It was found that the phone battery, while running the tele-moniroting application, can consistently last more than 20 hours in a standby state (i.e., CHF tele-monitoring application is running but other features, such as calling, texting and/or web surfing are not being utilized). However, some of the study subjects reported that the phone required recharging every few hours while other patients reported normal battery operations with the phone having to be recharged only once per day or less. We believe the main reasons for the excessive battery consumption experienced by some of the users were *a*) extensive use of the smartphone for other functions (e.g., texting, web surfing, music, calling, etc.) and/or *b*) poor cellular coverage.

4.3.3 Adoption and Usage Fatigue

We use the term "usage fatigue" to describe the decrease in subjects' willingness to use the pilot technology over time. More precisely, we define usage fatigue as the drop in proper usage of the technology over time. We consider proper usage of the tele-monitoring system as the instances where the the smartphone application was running while the phone was properly mounted on the subject's hip (proper authorship) determined by our classifier presented in Subsection 4.2. If we denote the total number of minutes of proper usage during week i (since the beginning of the study) as P_i and the number of minutes when the phone was running with the application (but not necessarily properly mounted) during week i as T_i, then for each subject we can calculate the following quantities for each week i: *a*) the percentage of proper usage out of the total week i: $100 \cdot \frac{P_i}{24 \cdot 60 \cdot 7}$ (*proper usage percentage*); and *b*) the percentage of proper usage P_i out of the total time the smartphone application was running T_i, precisely $100 \cdot \frac{P_i}{T_i}$ (*usage stamina*). We use the term *normalized usage stamina* for the usage stamina normalized by the value of the first week's usage stamina of the same user. Using these quantities, for each user, we can calculate the *user proper usage score* as the average proper usage percentage over the whole study period for that subject. By dividing the study period of each user to two halves, we can also calculate the *user stamina score* as the average stamina of the user during the second half of the study period divided by the average stamina of the user during the first half of the study period.

These quantities are presented in Figure 4 for 6 subjects[5]. Ideally, the higher these quantities, the better. Note that in some cases, patients were rehospitalized during the course of the study and their usage dropped to zero, these weeks were not extracted out from the calculation.

5. CONCLUSIONS AND FUTURE WORK

With the increasing prevalence of tele-monitoring, there is an emerging need to automate the data analysis and provide effective feedback to patients. This can be achieved by modeling behavior in order to continuously assess rehospitalization risk levels based on the underlying analysis. Such models are in particular necessary when the number of monitored patients becomes large, since manual data analytics becomes impractical or even unfeasible. Furthermore, since tele-monitoring can involve self-reported data, estimating the level of objectiveness and including the corresponding confidence levels into the models are important points to consider. For example, telephone-based monitoring involves people answering questions about their symptoms, weight and fatigue which may be biased or incorrectly reported.

In this paper, we focused on identifying system and usability challenges related to tele-monitoring of patients with CHF. Based on the review of prior work, this study was first of its kind and thus the findings are relevant to future studies aimed at remotely monitoring chronic health conditions via smartphone technology. One of the biggest challenges in smartphone-based usage and monitoring remains the battery life. In our study, we were collecting data from several sensors and performed some of the computation on the phone, which additionally decreased the battery life and consequently affected the usability factor. In our

[5]The phone state classifier was developed in the middle of the pilot study. Therefore, the usage fatigue quantities are calculated only for the 6 subjects were recruited after deploying the classifier.

next version, this issue will be addressed by collecting only the data that are required for reliable classification of the phone status and estimation of patient's activity levels, while delegating most of the computation to the server, specifically to the analysis component that performs computation on behalf of the smartphone. As a result, we can limit computation on the smartphone only to the low-frequency and low-intensity tasks. Other remaining challenges such as privacy; improving patient compliance through feedback intervention; and the study of physio-behavioral models need to be examined further and addressed in the future iterations of the tele-monitoring framework.

Based on the initial findings from our pilot study and similar findings by other researchers, we believe that a more systematic approach is needed to address the challenges outlined in this paper in order to deploy continuous tele-monitoring in large number of patients in the real world conditions that would be beneficial to both patients and health care providers.

Acknowledgment

We would like to thank Ariane Garret, Mita Goel, MD/MPH, Robert A. Gordon, MD, Daniel Schimmel, MD and Edmund Seto for the fruitful discussions, continued feedback and support; and suggestions. This publication was made possible by Grant Number HHS 90TR0003/01. The views expressed in this paper are those of the authors and do not necessarily represent the official views of the HHS.

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