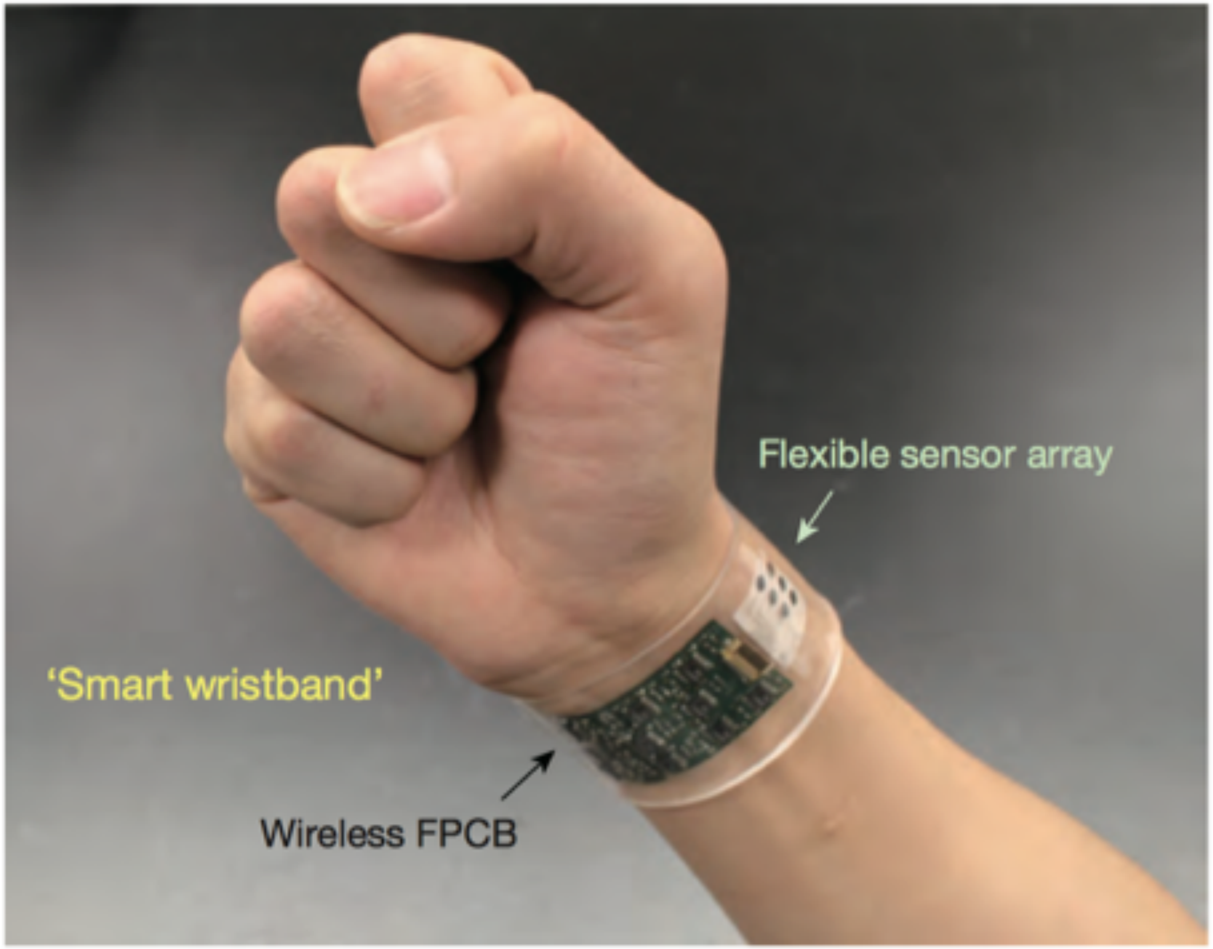

Applications: Health

EE382V Activity Sensing and Recognition

UT Austin • Dept. Electrical and Computer Engineering • Fall 2016

Today

Any questions?

Activity Sensing and Recognition in Health

Class Discussion about the Papers

- Self-organize in ~5 groups
- Discuss the paper amongst yourselves (10 mins)
- Identify 3 aspects of the work you like or dislike
- Identify 2-3 questions you have about the paper

Using Passively Collected Sedentary Behavior to Predict Hospital Readmission

Sangwon Bae
Carnegie Mellon University
Pittsburgh, PA
gracebae@andrew.cmu.edu

Anind K. Dey
Carnegie Mellon University
Pittsburgh, PA
anind@cs.cmu.edu

Carissa A. Low
University of Pittsburgh
Pittsburgh, PA
lowca@upmc.edu

ABSTRACT
Hospital readmissions are a major problem facing health care systems today, costing Medicare alone US$26 billion each year. Being readmitted is associated with significantly shorter survival, and is often preventable. Predictors of readmission are still not well understood, particularly those under the patient's control: behavioral risk factors. Our work evaluates the ability of behavioral risk factors, specifically Fitbit-assessed behavior, to predict readmission for 25 postsurgical cancer inpatients. Our results show that sum of steps, maximum sedentary bouts, frequency, and low breaks in sedentary times during waking hours are strong predictors of readmission. We built two models for predicting readmissions: Steps-only and Behavioral model that adds information about sedentary behaviors. The Behavioral model (88.3%) outperforms the Steps-only model (67.1%), illustrating the value of passively collected information about sedentary behaviors. Indeed, passive monitoring of behavior data, i.e., mobility, after major surgery creates an opportunity for early risk assessment and timely interventions.

Author Keywords
Colorectal cancer surgery; wearable tracker; sedentary behavior; physical activity; healthcare outcomes

ACM Classification Keywords
H.5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous.

INTRODUCTION
Hospital readmissions are a significant problem facing health care systems. 1 in 7 surgery patients are readmitted within 30 days of discharge [20], and many of these are preventable [15]. Readmissions cost Medicare alone US$26 billion dollars annually, of which US$17 billion is considered to be preventable. Preventable readmissions are associated with increased health care costs, significantly shorter survival, and patient and family stress and suffering. Previous research has identified medical predictors of readmission [2][6], but behavioral factors including inadequate levels of activity in the hospital may also play an important and relatively unexplored role [11]. In this paper, we identify some behavioral factors that can both serve as predictors of readmission and targets for patient and provider interventions to improve hospital discharge decisions and postoperative recovery.

In particular, we analyzed the physical activity data from a Fitbit Flex wearable tracker worn by 25 post-surgical cancer patients during their in-hospital recovery. We then built a behavior-based machine-learning model that can identify with an 88.3% accuracy which patients were readmitted to the hospital within 30 days of discharge. The contribution of our paper is a demonstration of the value of passively sensed behavioral data in predicting readmissions, and a discussion of how our predictive model highlights opportunities for patient interventions during postoperative recovery.

In the next section, we describe previous work predicting hospital readmissions and highlight the need to focus on behavioral factors, and sedentary behavior in particular, as predictors. We describe our data collection and data analysis approach for predicting readmissions. We identify which behavioral factors strongly differentiate the readmitted from non-readmitted patients and then describe our machine-learning model that can predict these two classes. We end with a discussion of the limitations of our model, how the model could be used to support patient interventions, and finally identify opportunities for future work on how our model could be extended to other clinical populations. In the future, such models can be used to identify readmission risk behaviors in real time and to provide just-in-time intervention with patients to encourage a change in physical activity patterns.

RISK BEHAVIOR FOR HOSPITAL READMISSION
Post-hospital syndrome, a generalized physiological vulnerability caused by prolonged hospitalization, has been identified as a contributing factor to 30-day readmissions [11]. During hospitalization and recovery from surgery, patients commonly experience sleep disruption and deprivation and become physically weak and deconditioned by long periods of sedentary behavior and inadequate physical activity. Off-the-shelf Fitbits and similar wearable

UbiComp '16, September 12-16, 2016, Heidelberg, Germany
© 2016 ACM. ISBN 978-1-4503-4461-6/16/09…$15.00
DOI: http://dx.doi.org/10.1145/2971648.2971750

Source	Features
Fitbit Steps Only	{Sum, Min., Med., Max. Avg., Std., 1Q, 3Q} of step counts, number of minutes that steps were taken, distances, daily sum of steps
Fitbit Behavioral	Low, medium and high level of {Length, Count (sedentary breaks & bouts), Min., Med., Max. Avg., Std., 1Q, 3Q} minutes of sedentary time, sedentary breaks, sedentary bouts, daily sedentary time, step counts, number of minutes that steps were taken, distances
Medical records	Days after surgery, length of stay

Table 1: Features used in characterizing patients' behaviors for readmissions

Passive and In-situ Assessment of Mental and Physical Well-being using Mobile Sensors

Mashfiqui Rabbi*
Dept. of Information Science
Cornell University
ms2749@cornell.edu

Shahid Ali
Community and Family Medicine
Dartmouth Medical School
shahid.a.ali@dartmouth.edu

Tanzeem Choudhury*
Dept. of Information Science
Cornell University
tanzeem.choudhury@cornell.edu

Ethan Berke
Community and Family Medicine
Dartmouth Medical School
ethan.berke@tdi.dartmouth.edu

ABSTRACT
The idea of continuously monitoring well-being using mobile-sensing systems is gaining popularity. In-situ measurement of human behavior has the potential to overcome the short comings of gold-standard surveys that have been used for decades by the medical community. However, current sensing systems have mainly focused on tracking physical health; some have approximated aspects of mental health based on proximity measurements but have not been compared against medically accepted screening instruments. In this paper, we show the feasibility of a multi-modal mobile sensing system to simultaneously assess mental and physical health. By continuously capturing fine-grained motion and privacy-sensitive audio data, we are able to derive different metrics that reflect the results of commonly used surveys for assessing well-being by the medical community. In addition, we present a case study that highlights how errors in assessment due to the subjective nature of the responses could potentially be avoided by continuous mobile sensing.

Author Keywords
mental health, physical health, activity inference, mobile sensing, machine learning.

ACM Classification Keywords
H.1.2 User/Machine Systems; I.5 Pattern Recognition; J.3 Life and Medical Sciences.

General Terms
Algorithms, Experimentation.

INTRODUCTION
One of the pillars of population health is to improve overall quality of life by promoting cognitive, physical and mental well-being [1, 2]. Everyday behaviors are often reflective of physical and mental health and can be predictive of future health problems. The standard practice for collecting behavioral data in the health sciences relies on observational data collected in laboratory settings or through periodic recall surveys or self-reports. These proxy measures have several limitations: (i) the time and resource requirements are too high to simultaneously gather data from a large number of individuals; (ii) the measurements are prone to considerable bias and the manual and sporadic recording of information often fails to capture the finer details of behavior that may be important; and (iii) the end user effort is too high to be suitable for continuous long-term monitoring.

With continued rises in medical costs, the need for a model that screens and facilitates early diagnosis, as well as increased efforts in prevention, is an essential concern for healthcare providers and administrators. Consequently, a growing number of studies are demonstrating potential of behavior monitoring devices to assist in one or more of the three clinical applications mentioned above [3, 4, 5]. The ultimate vision is to develop a mobile sensing system that can contribute significantly to cognitive, physical and mental well-being while maintaining easy and universal applicability, security and patient privacy protection, and low cost.

BACKGROUND
Monitoring physical activity and mental health has been extensively investigated in the past via a variety of traditional recall surveys or Ecological Momentary Assessments (EMA) [6]. Paper-based surveys like Yale Physical Activity Survey (YPAS) [7], SF-36 [8], and Center for Epidemiological Studies - Depression (CES-D) [9] are examples of commonly accepted surveys and are some of the primary metrics for assessing physical and mental well-being in medicine. These paper-based surveys utilize recall techniques to capture daily, weekly, and seasonal patterns of behavior, but may require in-person administration and are limited by recall bias, memory dependence, current mood, and their obtrusive nature [10, 11]. Furthermore, answers to the paper-based survey questions are subjective, with risk of social de-

* The work presented here was done while both the authors were in the Computer Science department at Dartmouth College.

SpiroSmart: Using a Microphone to Measure Lung Function on a Mobile Phone

Eric C. Larson[1*], Mayank Goel[2*], Gaetano Boriello[2], Sonya Heltshe[3], Margaret Rosenfeld[3], Shwetak N. Patel[1,2]

[1]Electrical Engineering,
[2]Computer Science & Engineering,
DUB Institute, University of Washington
Seattle, WA 98195
{eclarson, mayankg, gaetano, shwetak }@uw.edu

[3]Seattle Children's Hospital
Center for Clinical and Translational Research
4800 Sand Point Way NE
Seattle, WA 98105
{sonya.heltshe, margaret.rosenfeld}@seattlechildrens.org

ABSTRACT

Home spirometry is gaining acceptance in the medical community because of its ability to detect pulmonary exacerbations and improve outcomes of chronic lung ailments. However, cost and usability are significant barriers to its widespread adoption. To this end, we present SpiroSmart, a low-cost mobile phone application that performs spirometry sensing using the built-in microphone. We evaluate SpiroSmart on 52 subjects, showing that the mean error when compared to a clinical spirometer is 5.1% for common measures of lung function. Finally, we show that pulmonologists can use SpiroSmart to diagnose varying degrees of obstructive lung ailments.

Author Keywords

Health sensing, spirometry, mobile phones, signal processing, machine learning.

ACM Classification Keywords

H5.m. Information interfaces and presentation (*e.g.*, HCI): Miscellaneous.

INTRODUCTION

Spirometry is the most widely employed objective measure of lung function [37] and is central to the diagnosis and management of chronic lung diseases, such as asthma, chronic obstructive pulmonary disease (COPD), and cystic fibrosis. During a spirometry test, a patient forcefully exhales through a flow-monitoring device (a tube or mouthpiece), which measures instantaneous flow and cumulative exhaled volume (Figure 1). Spirometry is generally performed in medical offices and clinics using conventional spirometers, but home spirometry with portable devices is slowly gaining acceptance [6,26]. Measurement of spirometry at home allows patients and physicians to more regularly monitor for trends and detect changes in lung function that may need evaluation and/or treatment. Home spirometry has the potential to result in earlier treatment of exacerbations, more rapid recovery, reduced health care costs, and improved outcomes [15,23,34,35]. However, challenges currently faced by home spirometry are cost, patient compliance and usability, and an integrated method for uploading results to physicians [9,12]. Importantly, while office-based spirometry is coached by a trained technician, current home spirometers have no coaching, feedback, or quality control mechanisms to ensure acceptable measurements.

Figure 1. Subjects using SpiroSmart (left) and a clinical spirometer (right) and example curves from each device.

In this paper, we present *SpiroSmart*, a smartphone-based approach that measures lung function using the phone's built-in microphone (*i.e.*, a complete software-enabled solution). SpiroSmart requires the user to hold the smartphone at approximately arm's length, breathe in their full lung volume, and forcefully exhale at the screen of the phone until the entire lung volume is expelled. The phone's microphone records the exhalation and sends the audio data to a server, which calculates the exhaled flow rate by estimating models of the user's vocal tract and the reverberation of sound around the user's head. Flow rate is estimated by calculating the envelope of the sound in the time domain; performing resonance tracking in the frequency domain; while measuring white noise gain through linear prediction. SpiroSmart is able to compute and provide flow rates and graphs similar to those found in home or clinical spirometers (Figure 1).

UbiComp' 12, Sep 5 – Sep 8, 2012, Pittsburgh, USA.

[*] The first two authors are equal contributors to this work.

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Next week

Last Summary + Critique due on **Tuesday**

Panel of Experts on **Tuesday**

Emerging Topics + Talk about Final Exam on **Thursday**