Beyond Steps: Challenges and Opportunities in Fitness Tracking

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ABSTRACT

The quantified-self is a positive and prevalent aspect of our culture that has progressed during the last decade propelled by technological advances in health and fitness tracking. Prior research has shown that self tracking has a myriad of benefits. And we have the ability to sense and track various aspects of fitness and well-being, however one key challenge that remains is what data needs to be shown to the user, and how to present it to the user. Moreover, when is the right time to deliver key information to the user. Secondly, we have noticed that self-monitoring and tracking research has mostly evolved in isolation *i.e.,* researchers have separately studied or built systems for various aspects of fitness like exercise tracking, diet or sleep monitoring. While in reality many of these areas are intertwined and depend on each other: Poor sleep can lead to overeating and consequently weight gain. In this workshop, we propose to highlight and address these two challenges and explore opportunities to expand beyond the current paradigm of single health factors tracking to a more comprehensive fitness tracking.

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KEYWORDS

fitness, well-being, exercise tracking, diet monitoring, sleep monitoring

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1 INTRODUCTION

In the past decade, the quantified-self culture has become more prevalent and we have witnessed its positive effect on our well-being. Many studies have shown that self-monitoring is one of the most successful methods used to prevent and combat diseases [1, 14]. Self-report is the most common approach to self-monitoring but it suffers from recall errors , low adherence [5, 8].

This problem encouraged many researchers in the Ubicomp community to develop activity tracking systems that mitigate some of the self-monitoring challenges and algorithms to infer more information about the performed actions (*e.g.,* how many repetitions of squats did a user perform? How many hours of REM sleep did a user get? How many calories did a user consume during the day?). For example, GymCam [10], a vision-based **exercise tracking** system that can simultaneously track exercises for 100s of users at the same time and identify the type of exercise from optic flow patterns. Similarly, EarBit [2] is a wearable **diet monitoring** device that utilizes an inertial sensor placed behind the ear to detect chewing activities and use it as a proxy to identify eating episodes. And finally, [4] Chen *et.al.* used a technique called Best Effort Sleep to **track sleeping** hours from smartphone usage (*e.g.,* time and length of smartphone interaction or recharge events) and environment observations (*e.g.,* prolonged silence and darkness).

In this workshop, we would like to highlight some of the key challenges and open research questions for automatic fitness tracking, with a focus on three aspects: monitoring physical exercises, diet and eating habits, and sleep activity.

First, there is an am imbalance between novelty in sensing approach, and the outcomes that would be beneficial for the user to achieve their fitness goals. Prior work has shown that information overload is an outstanding problem due to the multifaceted nature of the data collected for self-tracking [3, 9]. And rightly, there has been research on what information is useful [6, 7], ways to present the data [11], and best methods to draw useful inferences from the sensor data [15] collected by activity trackers. However, even though we have come far in the technological prowess of novel fitness tracking techniques [2, 10], there has been little effort to integrate these approaches and present only the information that is important to the user. Another important aspect is when to deliver this information to the user. Research areas such as interruptiblity detection [12, 13] study the best context (time, place and user preferences) to deliver information to the user. More recently started building models to detect best times to deliver a health intervention. All of these works can potentially enhance the capabilities of the next big fitness tracker and improves lives, but research in these related domains is largely disconnected from each other at the moment.

Secondly, while the advances in sensing techniques for automatic monitoring systems [2, 10] demonstrate the potential of fitness tracking, but the efforts in each area have evolved in isolation. The individual inferences drawn from a diet monitoring system, or an exercise tracker or a sleep-hygiene system are useful and promotes healthy behavior change. However, this disconnect between the approaches in each of the areas leads to a major drawback. Currently there is no way to capture how one aspect of fitness may affect the other. For example, it might be useful for a user to know that they are more likely to over eat if they sleep less than 5 hours the night before. Systems built in isolation are unable to capture the interplay between the data from different sensing signals and convert them into useful inferences. This is an uncharted research area that is a critical part of achieving a user's fitness goals.

In summary, we highlight two key challenges in fitness tracking:

(1) What is the 'right' information to present to the user? How should it be presented, and when is the right time to deliver it?
(2) How to consolidate and draw inferences from multiple sensing systems to achieve an overall fitness goal?

2 WORKSHOP GOALS AND STRUCTURE

This workshop will address critical issues surrounding the integration and unification of data across different devices, systems, and platforms. Discussions and artifacts produced during the workshop will aim to support researchers and designers at tackling this issue of data integration in support of individual users achieving their fitness goals. We therefore aim to bring together researchers from across Ubicomp, including people who focus on novel sensing, interface design, systems architecture, and theoretical strategies for behavior change.

Workshop participants will share their research and experiences working on different facets of the fitness challenge. They will also engage in small group discussions and design activities to envision solutions to high priority challenges of data presentation and integration. These small groups will share their work and the group will be tasked with producing guidelines for researchers and designers of ubiquitous fitness technologies.

Specifically, this one-day workshop will be divided into three sections:

First: We will begin with lightning talks by workshop attendees. Each talk will last for 3 minutes, followed by 1 minute for Q&A. The lightning talks will be based on the participants submitted position papers which will cover topics including, but not limited to, current challenges in fitness tracking, proposals for fitness data integration, and appropriate intervention and feedback techniques. The goal of this session is to develop a shared understanding of the state of the field among attendees.

Second: In this section, we will divide workshop attendees into small teams to ideate and prototype solutions for one of the challenges identified in the first section. We will try to ensure diverse backgrounds and skills in each team to bring varying perspectives. The teams will be allowed to use different tools to prototype and evaluate their designs (e.g. paper prototyping, software simulation, or sketches). Next, each team will share their solutions with the group and discuss its merits and demerits.

Third: Finally, we will have a group discussion and prioritize design recommendations for integrated fitness systems. A sample schedule for the workshop follows:

8:30 am	Registration / Doors Open
9:00 am - 10:30 am	Lightning Talks
10:30 am - 11:00 am	Coffee Break
11:00 am -12:30 pm	Design Session 1
12:30 pm - 2:00 pm	Lunch
2:00 pm - 3:30 pm	Design Session 2 & Sharing
3:30 pm - 4:00 pm	Coffee Break
4:00 pm - 5:30 pm	Priorities Discussion and Wrap-up

Figure 1: GymCam is a camera-based exercise tracking system that uses optical flow to track, detect and recognize activities for 100s of users at the same time.

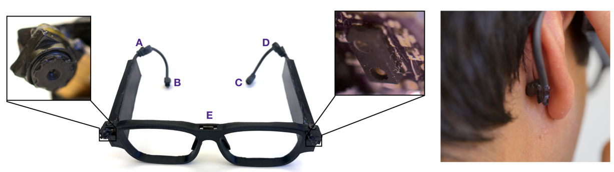

Figure 2: FitByte is an automatic diet monitoring system. It has a glass form-factor that has one camera, one proximity sensor, and six IMUs.

3 PRE-WORKSHOP PLANS

We will advertise the call for papers in various relevant communities: ubicomp, sensing, health and well-being, personal informatics, and quantified self. Besides posting the call for papers on the workshop website, we will also post the call for papers on various mailing lists, and shared calendars that are popular within these communities (*e.g.,* WikiCfP). We will also advertise on social media (*e.g.* Twitter and Facebook). We will also reach out to relevant researchers and practitioners individually and encourage them to submit position papers. We expect that the workshop would be of interest to both academics and industry practitioners and we plan to advertise accordingly. Our goal for pre-workshop plans is to ensure diverse representation in the workshop attendees.

4 POST WORKSHOP PLANS

We will create a mailing list of all workshop participants to facilitate easier communication between researchers in the community interested in engaging and collaborating on the subject matter in the future.

In a further effort to encourage future research and collaborations in this space, we will also summarize the outcomes, discussions and key takeaways from our workshop and post them on the workshop website.

5 CALL FOR PARTICIPATION

Fitness tracking has become a growing culture all around the world. In the past decade, academic and industrial research have offered a plethora of solutions enabling users to track their exercise, diet, and sleep activities. While they aim to help users achieve their fitness goals, yet in practice these fitness trackers operate independently from each other. This disconnect can lead to incomplete or contradicting feedback to the user. In this workshop we focus on three aspects of fitness:

(1) Physical exercise.
(2) Diet.
(3) Sleeping activity.

We invite submissions for position papers that address fitness-tracking challenging questions, including but not limited to:

(1) Which activities should we design tools to sense, and how?
(2) What information is appropriate and useful to present?
(3) When is the right time for feedback and intervention?
(4) How to consolidate and draw inferences from multiple sensing systems to achieve an overall fitness goal?

This workshop represents an opportunity for academics and practitioners to exchange knowledge and brainstorm ideas for novel solutions addressing the present fitness tracking challenges. We encourage submissions of **Work in Progress** papers that highlight potential preliminary research and thought-provoking ideas. We also invite authors to submit **Challenge** papers that identify and discuss new challenges in the field.

All submissions will be reviewed by at least two members of the workshop organizing committee. Papers will be accepted based on their quality, novelty, relevance to the workshop topic, and their potential to spark a fruitful discussion. For more details about the workshop and how to submit, please visit our workshop website: <website link>

6 ORGANIZERS

The organizing team consists of experts in novel sensing, personal informatics, and ubiquitous computing with a focus on well-being and fitness.

Rushil Khurana is a PhD student at Carnegie Mellon University. His research interests include building novel unobtrusive sensing technologies driven by machine learning and computer vision. He also values how design impacts technological use and interactions.

Abdelkareem Bedri is a PhD student at Carnegie Mellon University. His research interests include activity recognition, novel sensing technologies, and mobile health. His current research focuses on developing wearable tracking solutions for fitness activities.

Patrick Carrington is an Assistant Professor at Carnegie Mellon University. His interests include exploring how technology can be used to understand human ability and support empowerment, independence, and improved quality of life. His research focuses on understanding user needs and designing technology systems that enhance and leverage the full potential of users with diverse abilities.

Daniel Epstein is an Assistant Professor in Informatics at the University of California, Irvine. He studies and designs personal informatics systems, understanding and addressing the challenges people face when using self-tracking technology in everyday life.

Rúben Gouveia is an Assistant Professor in Design, Production, and Management at University of Twente. His work examines and designs tools to support health and wellbeing, evaluating how these tools augment abilities to reflect and to identify opportunities for change.

Jochen Meyer is the director of R&D Health at OFFIS Institute for Information Technology. His research interests are particularly in the areas of technologies for prevention and well-being, ambient assisted living and personal media use.

Julian Ramos is a PhD student at Carnegie Mellon University. His interests include building systems and methods with the goal of understanding human behavior and improving people's well-being. He is currently focused on personalization of health interventions using machine learning, wearables and a smartphone.

Jason Wiese is an Assistant Professor at the University of Utah. His interests include developing approaches for interpreting personal data. He uses mixed approaches to understand challenges in dealing with unified data, and understand the perspectives of both users and application developers.

Paweł Woźniak is an Assistant Professor at Utrecht University. He is interested in mobile interactions, designing technology for sports and persuasive technology.

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