

Scalable Medical Devices: Personal and Social

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Abstract Health and well-being is poised to become more quantitative and connected, with a brand new class of devices. These personalized and population-scale health diagnostics, assessment and analysis devices will be markedly different from the current generation devices in three important attributes: (a) access, (b) affordability, and (c) required operational skill. We discuss the design principles and examples of next generation of medical devices and highlight the potential of this new class of devices to revolutionize health monitoring and eventual health outcomes.

Keywords Medical devices • Measuring behavior • Quantified communities

1 Introduction

Healthcare continues to be a significant and ever-growing challenge for all nations. The healthcare challenge is inherently multi-dimensional: variables such as access, affordability, quality, health behaviors and perception all contributing to the eventual health outcomes in complex ways. Effective healthcare solutions, as a result, require multi-disciplinary solutions. The engineering challenge is that of measurement, how do we measure bio-markers and (yet-to-be-discovered) “behavioral-markers,” accurately. The question thus is *how do we then scale these measurement techniques so that they reach the target population, which in many ways is socially, economically and geographically diverse?*

While past decades have witnessed great advances in our ability to measure clinically relevant parameters, a large part of the design has assumed operation in a diagnostic lab with expert trained technicians. To increase access to healthcare, a

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first crucial challenge is to reduce the cost and expertise barrier to conduct advanced diagnostic tests.

Ideally, a diagnostic test should be designed such that it can be performed by anyone and anywhere. However, some thought immediately reveals there are new challenges in developing diagnostic devices to meet the envisioned anywhere-anyone use. First, the operating conditions cannot be controlled, and hence the design has to fundamentally account for a much larger range of operating conditions. That is, the design has to be *operating-condition-robust*. Second, since the operator expertise is no longer guaranteed, the design should require *zero-training* such that the devices can be operated by almost anyone without any training. Third, the devices should seek to achieve *clinical grade accuracy*, to ensure that the data from the devices is diagnostically relevant. If a medical device achieves the three goals of operating-condition-robustness, zero-training and clinical-grade accuracy, it forms the foundation of a *scalable medical device*.

Adding to the diagnostic challenge, a significant challenge in healthcare is human behavior that impacts all aspects of our health. For example, it is well known that many chronic disease patients find it challenging to adhere to their medical regimens (see e.g. CDC data on chronic diseases like Asthma, COPD, diabetes). Analogously, many individuals find it challenging to adopt healthy lifestyles. Human behavior is complex and multi-dimensional, making it extremely challenging to understand the causal pathways that lead us to make specific choices.

While it is well appreciated in concept that our behavior is heavily influenced by our social context, it is still not possible to measure its strength and overall impact on the health for an individual. Product marketing and public health campaigns have long used social network ties to achieve their aims. However, we still do not have a systematic understanding of how to leverage our social networks to impact positive change for an individual.

Opportunity: The rise of smartphones has led to a multi-faceted opportunity to meet both challenges. First, there is a growing acceptance that more of our world will be smartphone-connected and app-controlled. Second, participation in online social networks has made us increasingly more comfortable with sharing personal data, at least in closed circles of our friends and families. Third, there is an increasingly more acceptance to behavior logging, where more of our actions can be automatically logged. The best example is perhaps activity monitors, like Fitbit and similar products, that automatically log and categorize physical activity and in some cases, related physiological state. Finally, the preponderance and ubiquity of smartphones, in all corners of the world, mean that smartphone-centric solutions may provide the potential to reach a geographically, socially and economically diverse population, resulting in at-scale monitoring and interventions. Our key hope is that the more than billion smartphones being sold world-over today, become the distributing health and wellness infrastructure that ushers in a new era of quantitative, connected and scalable health monitoring, diagnosis and interventions.

In the sequel, we divide our discussion into two classes of medical devices: (i) scaling traditional diagnostics, (ii) measuring social context.

2 Scaling Traditional Diagnostics

The key design goal is enabling measurements by anyone and anywhere. Thus, the devices have to be designed for scalability, to be used in non-ideal conditions and by non-expert operations and yet be clinically accurate. To appreciate the design thought process, we use two examples, CameraVitals and mobileVision, from our recent research that illustrate the concept of developing scalable medical devices. Other examples from our recent research include mobileSpiro for easier spirometry [1, 2], unconstrained gaze estimation for tablets [3], improved methods to manage Asthma [4] and even simplifying mHealth trials [5]. Our ongoing research also addresses zero-effort respiratory health status diagnostics, automated mental health tracking and measuring cognitive engagement.

Case Study 1—Rice CameraVitals: Our first design study targets measuring some of the most basic diagnostics—heart rate and breathing rate—in a manner that is much more scalable than current methods.

Current Practice All common techniques to measure the vital signs are based on contact sensors such as ECG probes, chest straps, pulse oximeters and blood pressure cuffs. Contact-based sensors are so prevalent that we do not stop to think about them. However, they are not convenient in all scenarios, e.g. contact sensors are known to cause skin damage in pre-mature babies during their treatment in a neonatal intensive care unit (NICU). Similarly, elderly may have difficulty time following precise instructions, thereby contributing to lower rates of regular self-monitoring. Finally, one of the challenges of contact-based vital sign measurement that they all require special hardware, thereby limited by the shipping, service and associated costs.

Scalable Design The driving question is how do we create a highly scalable method to measure vital signs. It is well known that software is simply more scalable than hardware, especially when considering all steps in the process, from creation to delivery. Currently, the most accessible computing platform is smartphones, and apps have made nearly everyone comfortable with using software. Ideally, if vital sign measurement was an app on the phone, using only its built-in sensor, then we have the foundation for a highly scalable approach.

Rice CameraVitals In [6], we presented a new method to turn video selfies using cameras into a vital sign estimator with clinical-grade accuracy. While using a camera to estimate vital signs has been known for a decade; see [6] for more details, all prior proposals have found it challenging to measure vital signs accurately for darker skin tones, in low ambient lights and in the presence of unavoidable natural motion. Our method, distancePPG, leveraged ideas from computer vision, motion tracking and wireless communications to develop a composite method that provides a significant gain in measurement accuracy, overcoming nearly all challenges.

Case Study 2—Rice MobileVision: Our second design study is that of retinal imaging, that falls more in the category of advanced diagnostics and hence is often

performed in a dedicated lab or in specialist's office. Retinal imaging is a core diagnostic for diabetic retinopathy and macular degeneration. Beyond the core diagnostic value, retina is one of the few places in human body where we can directly image internal tissue, like blood vessels, with a *non-invasive* procedure, making it particularly suitable for regular screening.

Current Practice Current devices handle the above challenge with a combination of ideas. First, pupil response is removed from the picture by dilating the eyes (which in essence paralyzes the eye muscles). Second, to ensure that adequate light enters the eye, the patient and the imaging system have to be carefully aligned manually. Proper alignment ensures that sufficient light enters the eye. Third, an expert technician manages the whole process and takes the image at the right moment. In summary, all forms of motion (eye's reflex to light and patient's normal movement) and imaging moment are carefully and manually controlled.

Challenge The biggest challenge in imaging the eye is the eye itself. First, there are strict safe limits on the amount of light energy which can be projected into the human eye. Second, the pupillary response to visible light limits the amount of light that enters the eye. Lastly, only about 1 out of 1000 incident photons is reflected by the retina. Thus, not only we cannot project too much light into the eye, very little light comes out of it.

Rice MobileVision In [7], we presented a complete prototype design of a system that requires no user intervention in imaging, is voice activated and employs novel signal processing. The Rice mobileVision system consists of a goggles-like design that the patient wears over his face. The patient's personal smartphone attaches to the device, and acts as the sensor (camera), computing and communication platform. We have designed and developed two prototypes. The first prototype is intended for tracking the degradation in patients already diagnosed with retinal diseases and achieves a 50° field of view at $10\ \mu\text{m}$ resolution but requires the acquisition of multiple images. The second prototype is designed to be a rugged, on-the-field, screening device for diabetic retinopathy and is a first-of-its-kind, self-administered retinal imaging device that achieves a 20° field of view and $20\ \mu\text{m}$ spatial resolution.

3 Measuring Social Context

We start with a definition of social context or more equivalently social environment, put forth in [8]—"Human social environments encompass the immediate physical surroundings, social relationships, and cultural milieus within which defined groups of people function and interact. [...] Social environments are dynamic and change over time as the result of both internal and external forces.[...]"

Social context can have a large impact on our health behaviors. For example, eating healthy requires access to healthy food choices and strategies to manage

nutrition. Healthy food choices can vary significantly from one region to another, and nutritional strategies are often learnt from our social environment (homes, friends, schools). As we repeat our actions, the repetition of our specific behaviors gets coded as habits. That is, we may be inclined to eat a specific type of diet, primarily because it is part of habitual decision making. In short, habits are automatic behaviors, triggered by cues and are believed to form a bulk of our actions on day to day basis.

From public health perspective, it is highly desirable that the population adopts good habits (e.g. regular exercise, healthy foods) and avoids bad habits (e.g. smoking or sugary drinks). The challenge to achieving the desired public health outcome is well captured by the age-old adage “old habits die hard”. Substantial evidence rooted in neuroscience [9] has shown that habitual behavior is supported by strong and stable mental representations, which makes forgetting or unlearning of habits very challenging.

Prior research has studied the role of incentives to change habits. One possible strategy is to offer financial incentives to either reduce or eliminate an undesirable behavior (e.g. smoking) or increase a desirable behavior (e.g. regular exercise). Many recent studies have shown promise with its approach. For example, the studies reported in [10] offered different level of financial incentives to university students to attend the gym. It was found that by requiring some students to attend the gym multiple times for a financial compensation led to increased gym attendance, even *beyond* the period of the study. However, while a later study [11] managed to replicate the results, it also discovered that there was a substantial decay in gym participation after the winter break.

A very promising result was reported in [12], where the researchers obtained a detailed friendship network from the participants, living in the same residence hall, before the start of the study and then provided financial incentives like the prior studies. A key finding was that the gym participation was not only increased by the financial incentive, but its effect was higher for the participants with friends who had also been incentivized. That is, the overall participation was higher for participants if their friends were also in the incentive group, and lower if their friends were in control group. The finding in [12] shows the importance of the social network in enhancing the effect of incentives for habit change.

While the result reported in [12] is highly intuitive and satisfying, the overall evidence to support the role, methods and strength of habit change due to social engagement remains in its infancy. *A key challenge lies in our ability to measure social context, and its impact on our specific health behaviors and outcomes.*

Rice OWlympics¹ At Rice, we are developing the engineering core to measure social context (e.g. our friendship network), health metrics and mental well-being using a combination of (i) sensors mounted throughout the campus that can measure the type of activity, its intensity and its impact on the person’s vitals,

¹OWLS is the name of Rice University’s sports teams. The name, OWlympics, is thus derived from the Rice team name.

(ii) mental well-being using innovative analysis of one's digital footprint, and (iii) social network interactions, both in-person and online. The combined data will enable a unique *Quantified Organization*, complementing the quantified self movement, where we can leverage both the personal and social for our best health outcomes. The project is still in its early stages, and the results from the pilot program were reported in [13].

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