INTRO TO UBICOMP

CSE 590 Ubiquitous Computing | Lecture 1 | Mar 29

Jon Froehlich • Liang He (TA)

DESIGN USE BUILD

MAKEABILITY LAB

PAUL G. ALLEN SCHOOL OF COMPUTER SCIENCE & ENGINEERING

UNIVERSITY of WASHINGTON

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Android Studio

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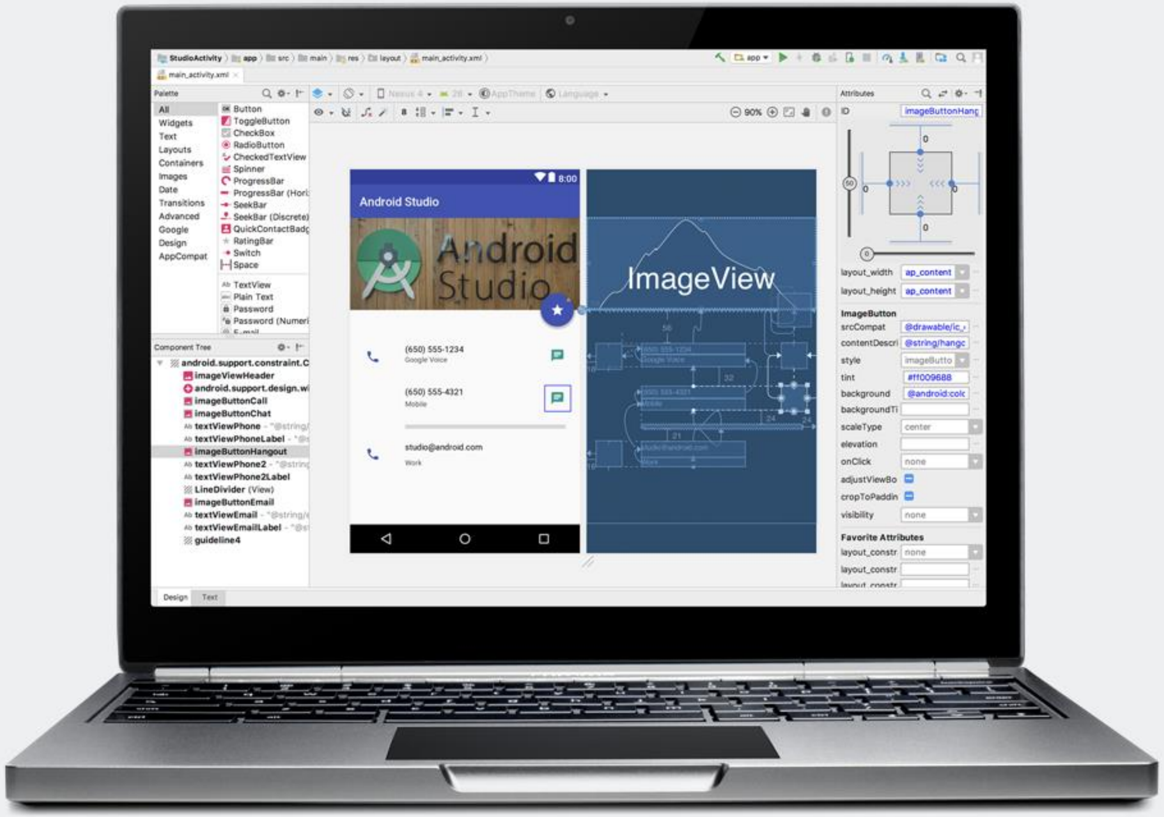
Android Studio provides the fastest tools for building apps on every type of Android device.

World-class code editing, debugging, performance tooling, a flexible build system, and an instant build/deploy system all allow you to focus on building unique and high quality apps.



DOWNLOAD ANDROID STUDIO
3.1 FOR MAC (847 MB)

> Read the docs

> See the release notes

SCHEDULE TODAY: 6:30-9:20

06:30-06:45: Ice breaker

06:45-07:45: Intro to UbiComp

07:45-07:55: Short break

07:55-08:05: This class

08:05-09:20: Intro to Android

CSE590_UbiComp_WhoWeAre_Sp2018

File Edit View Insert Format Slide Arrange Tools Add-ons Help All changes saved in Drive

Background... Layout Theme... Transition...

1 Jon Froehlich

2 Liang He | www.lianghe.me

3 Name | website | Template Do Not Delete

4 Name | website

Name | website | Template Do Not Delete

Picture

Background:

Technical Interests:

Path:

Life:

Contact:

Go Here: https://goo.gl/fbnV87

Click to add speaker notes


MAKEABILITY LAB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DESIGN, BUILD, & STUDY INTERACTIVE TOOLS & TECHNIQUES TO ADDRESS PRESSING SOCIETAL CHALLENGES

MAKEABILITY LAB

FOUR FOCUS AREAS

ENVIRONMENTAL SUSTAINABILITY

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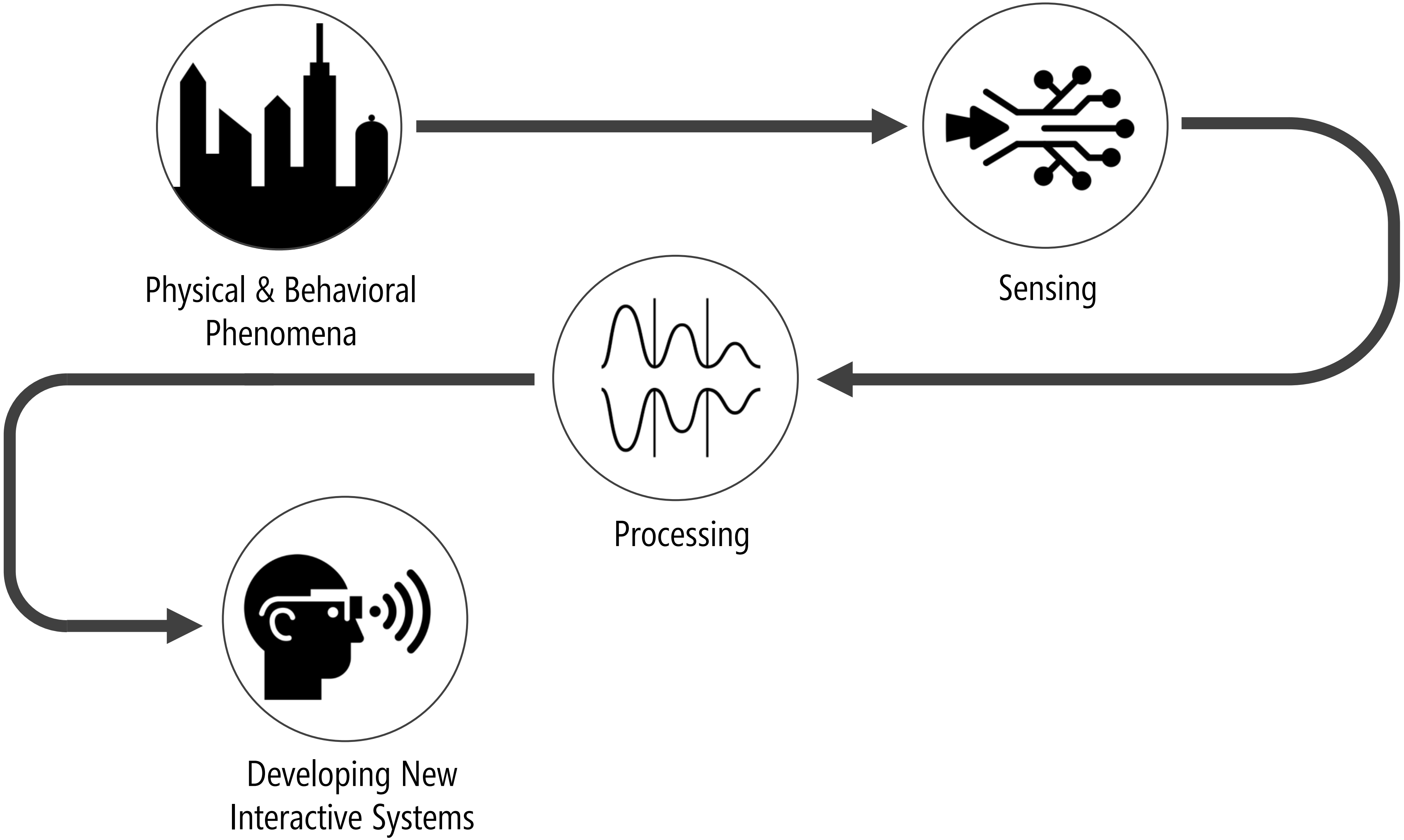
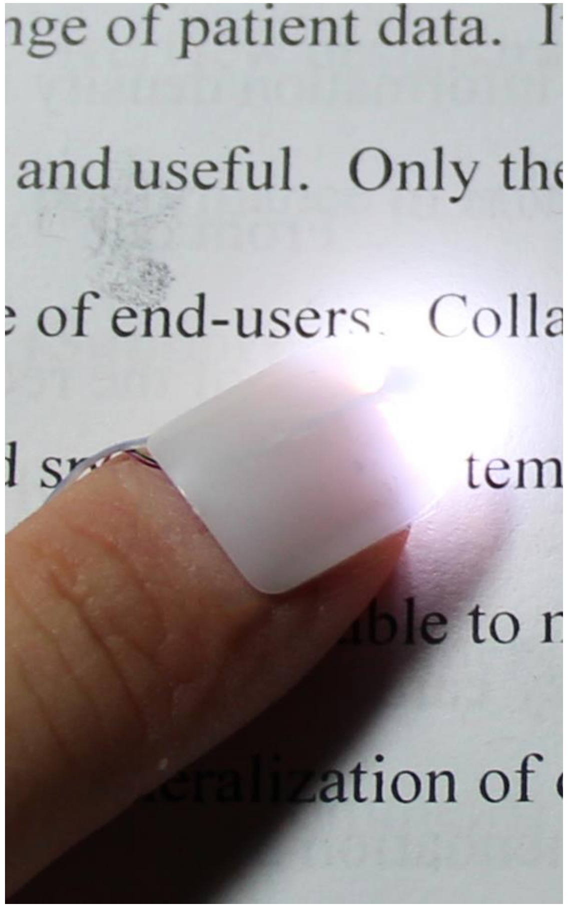
APPROACH



IMPROVING ACCESS TO THE PHYSICAL WORLD

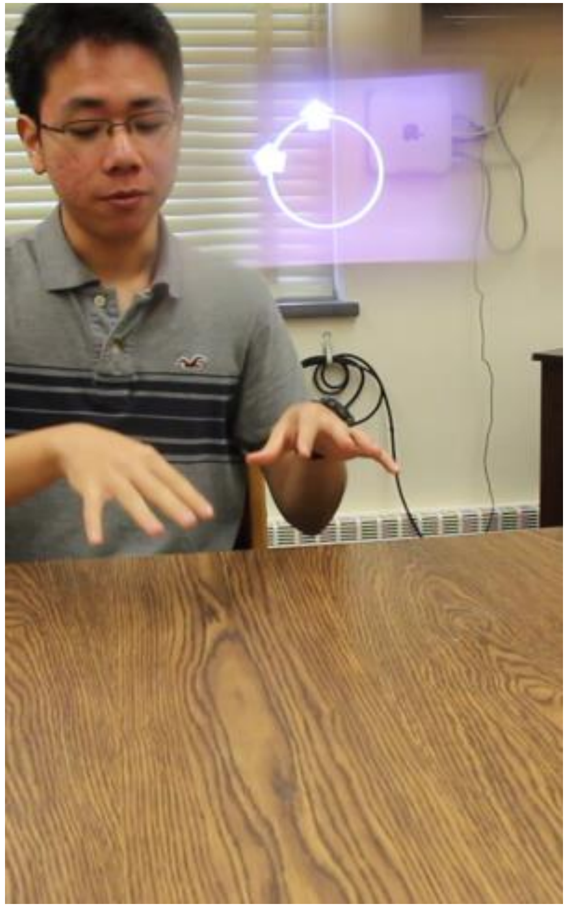
PROJECT SIDEWALK

[ASSETS'12, CHI'13, HCOMP'13, ASSETS'13 Best Paper, UIST'14, TACCESS'15, SIGACCESS'15, CHI'16, ASSETS'17]



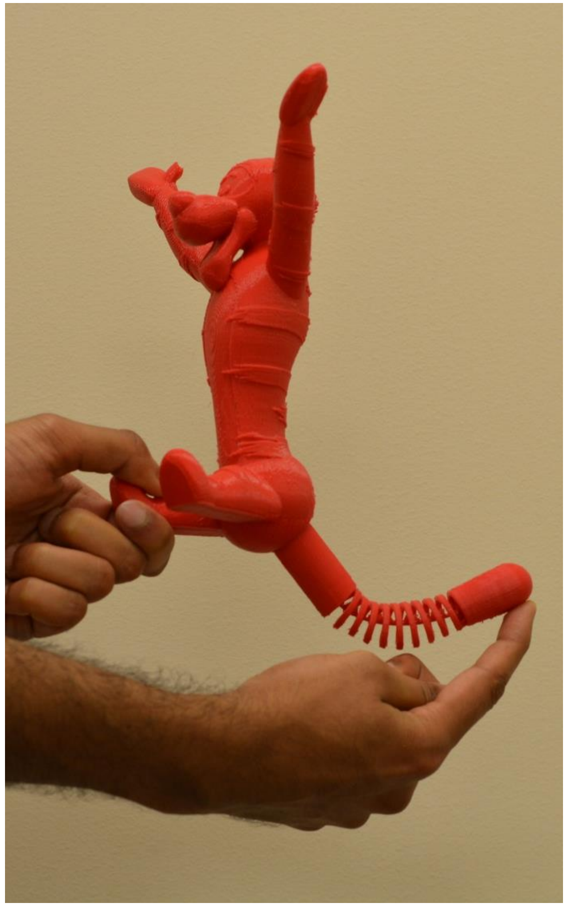
HANDSIGHT

[ACVR'14, ASSETS'15, GI'16, TACCESS'16, ASSETS'17 x4, IMWUT'17]



GLASSEAR

[CHI'15]

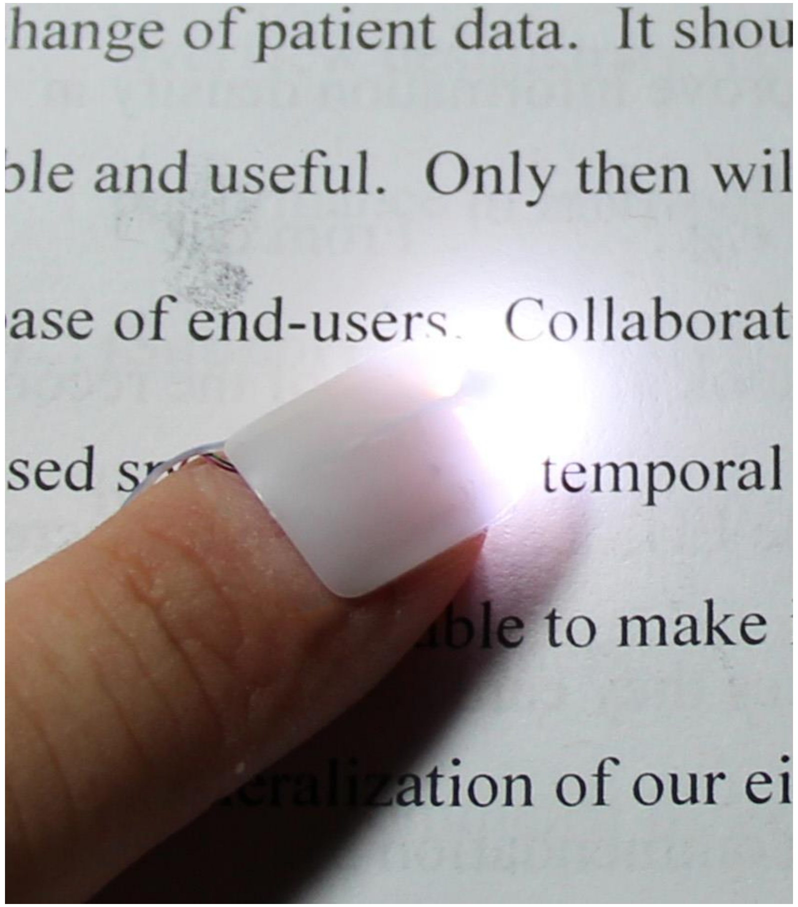


ONDULÉ

[CompFab'17, UIST'17 Poster]

THREAD 1: ACCESSIBILITY

IMPROVING ACCESS TO THE PHYSICAL WORLD

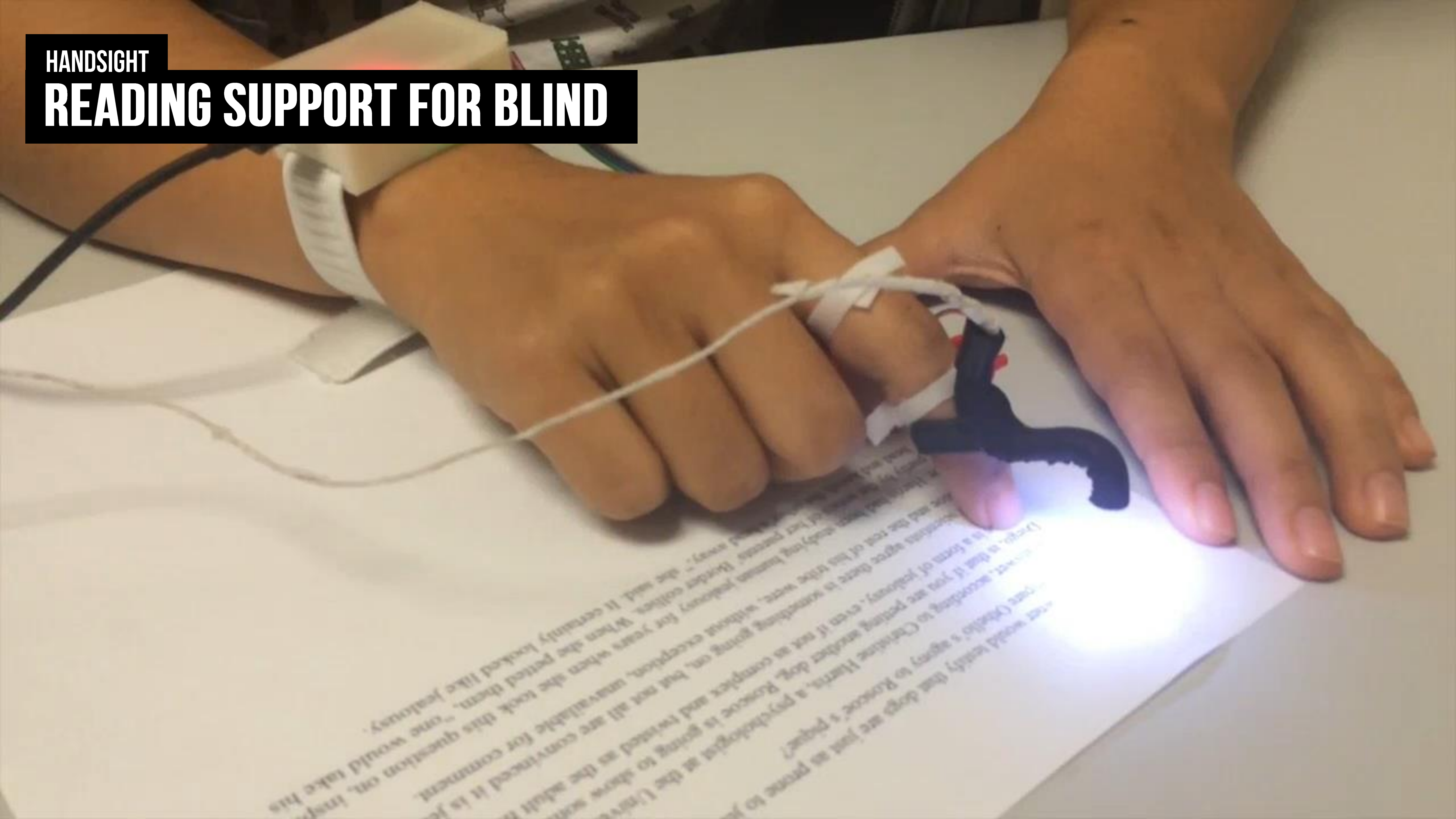


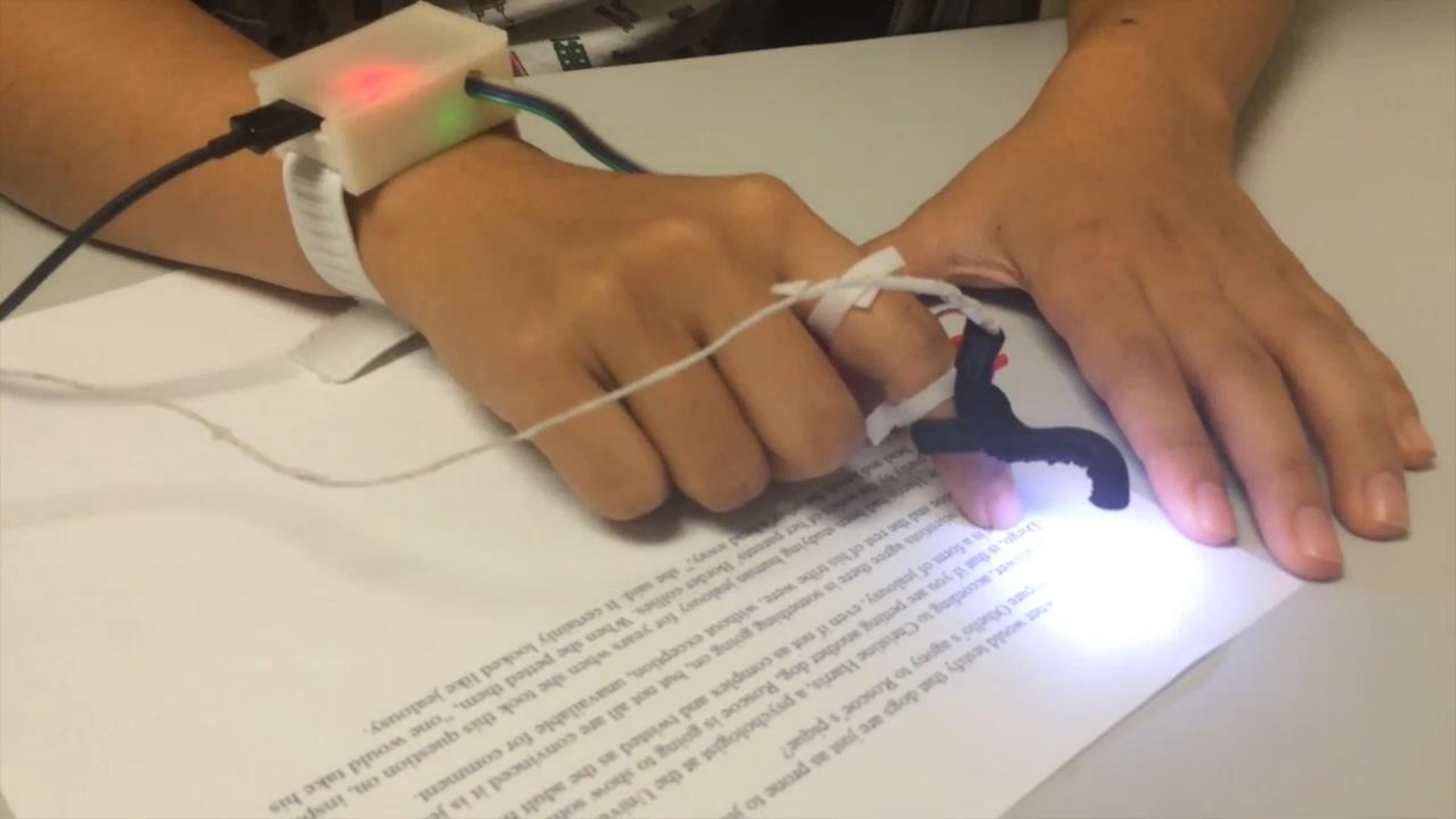
HANDSIGHT

[ACVR'14, ASSETS'15, GI'16, TACCESS'16]

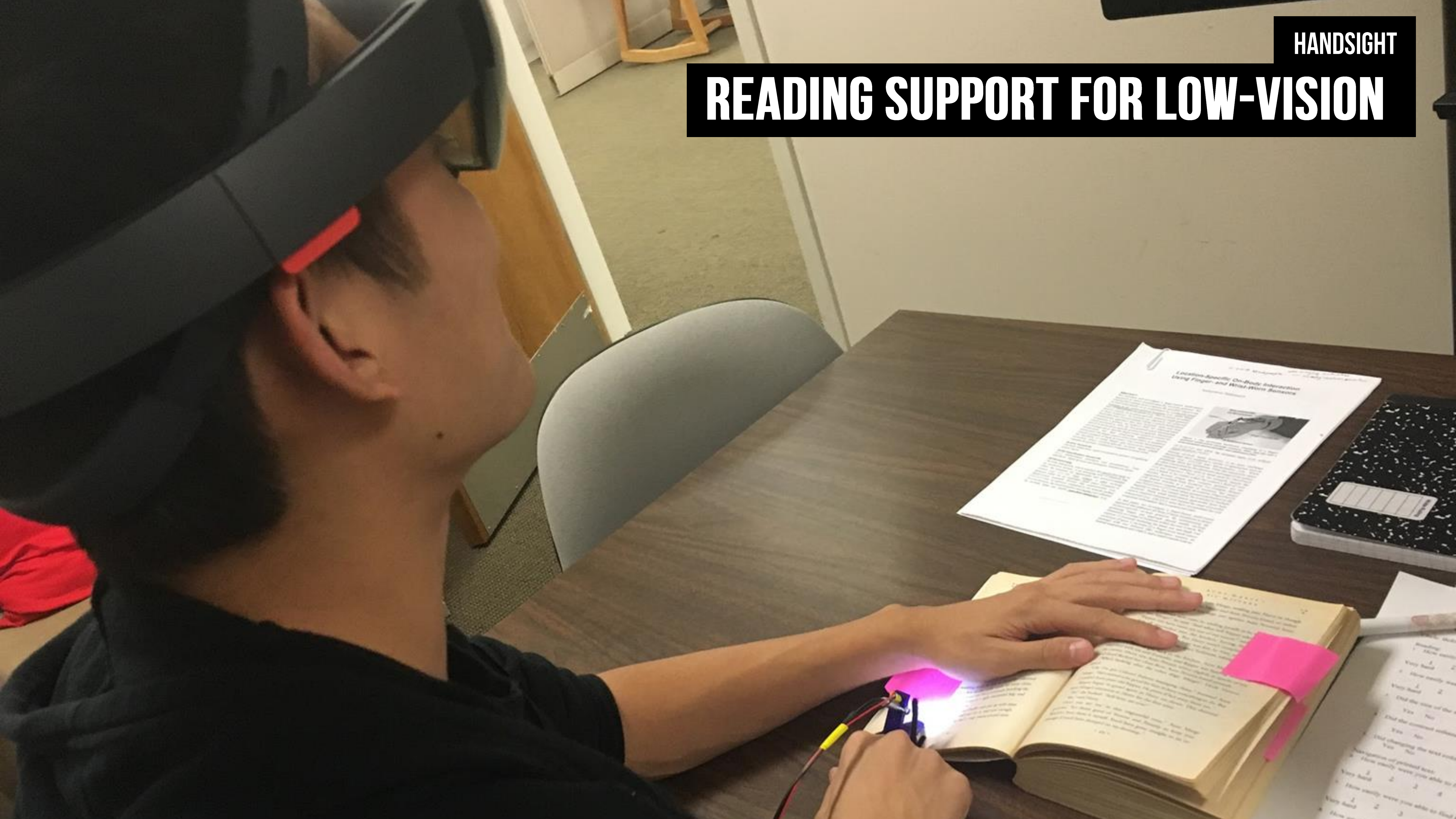
How can we...

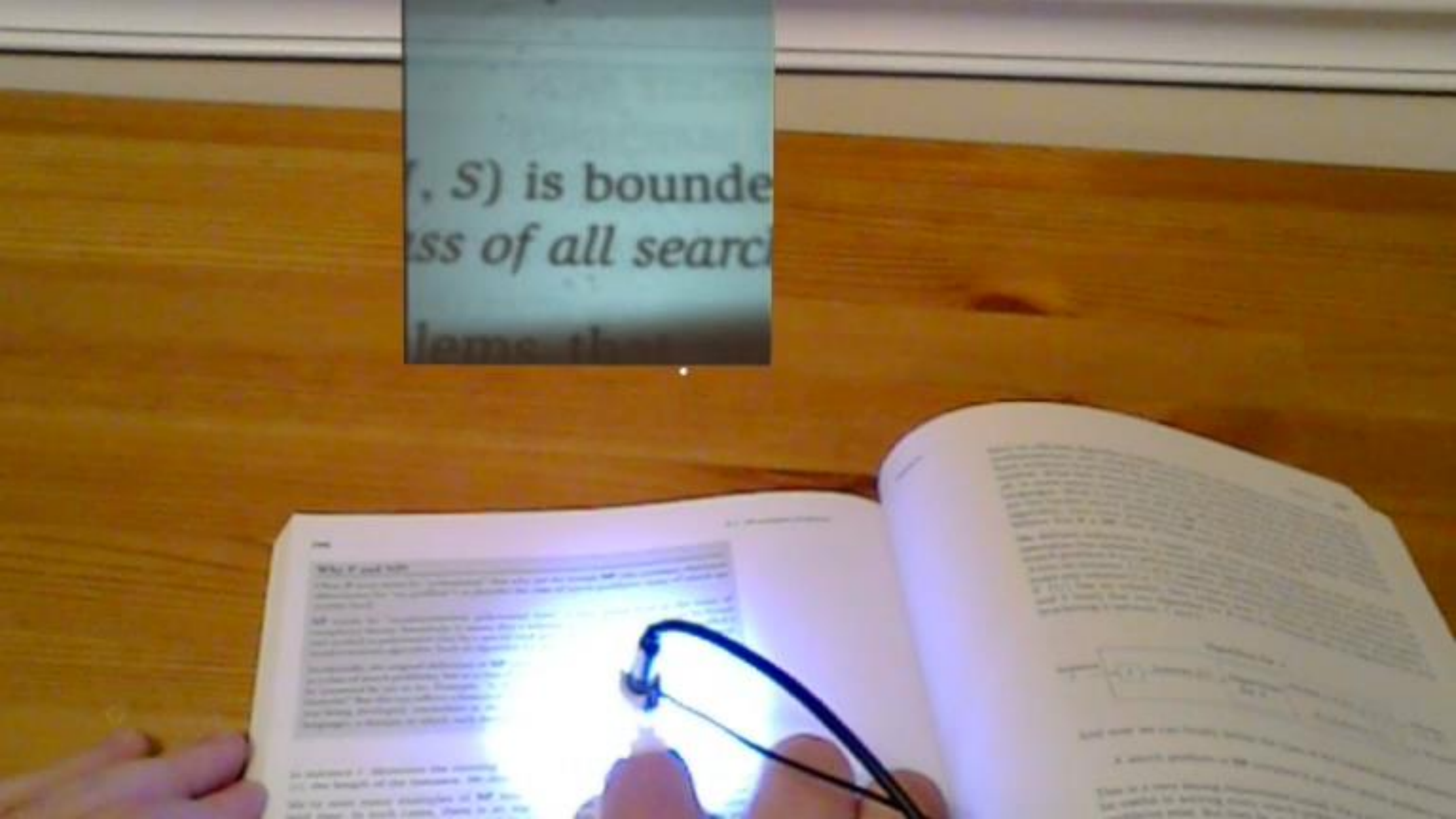
we sense & feed back non-tactile information about the physical world *as it is touched*?


HANDSIGHT
READING SUPPORT FOR BLIND



READING SUPPORT FOR LOW-VISION

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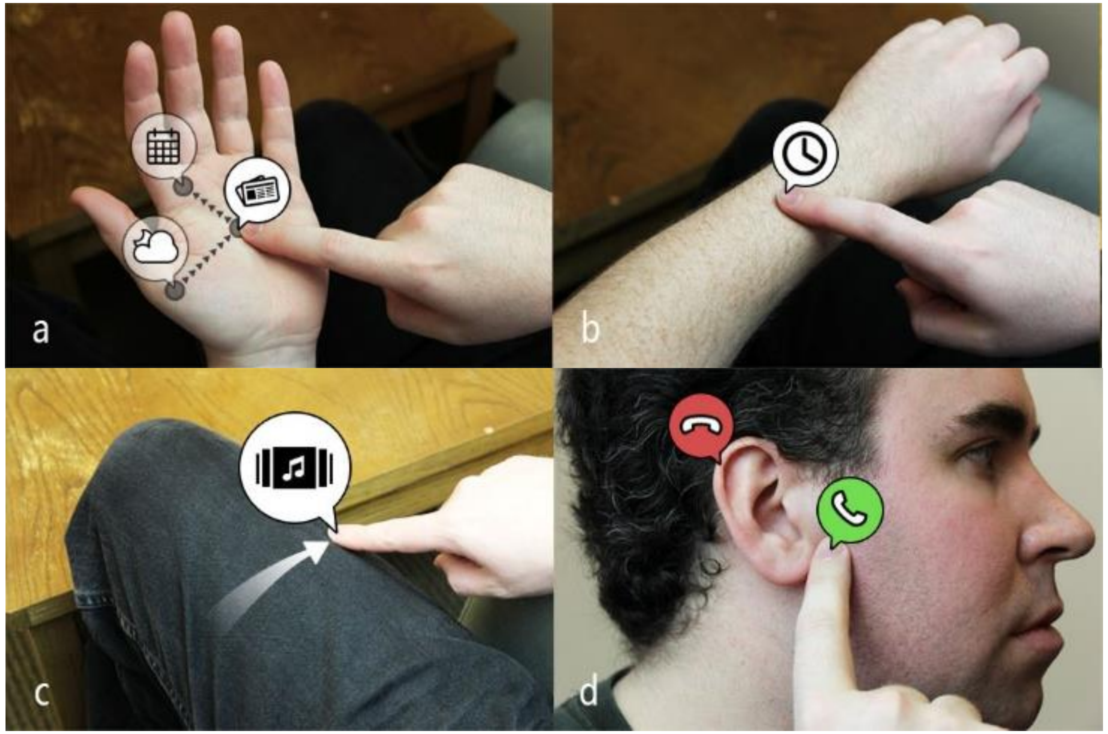
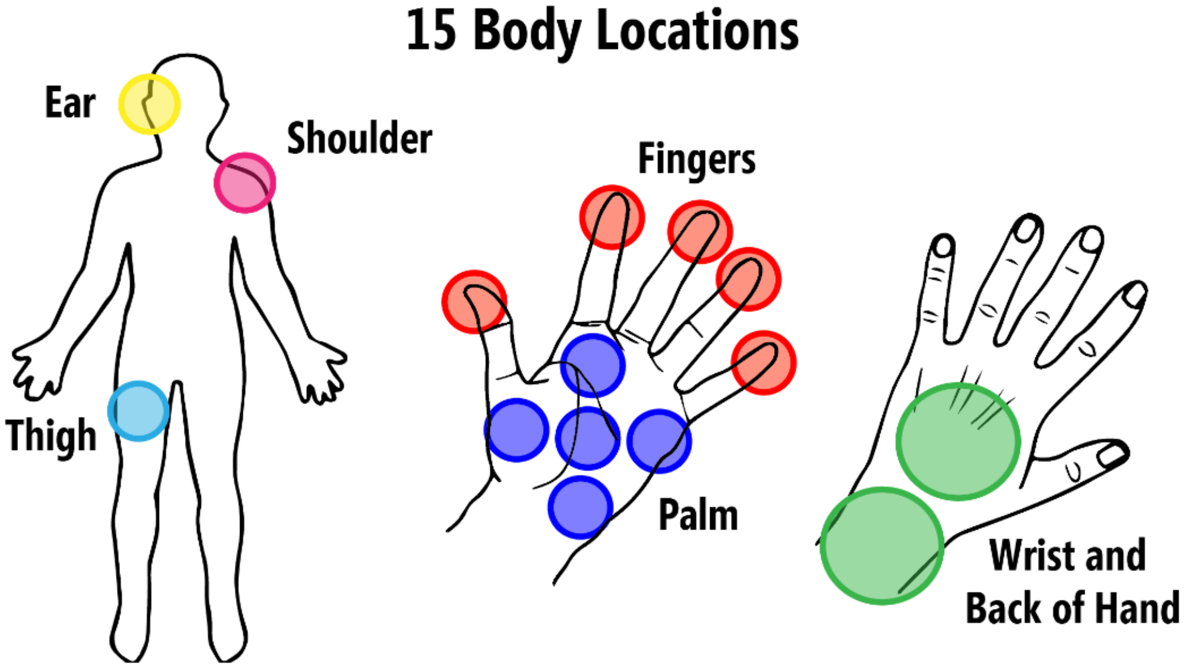
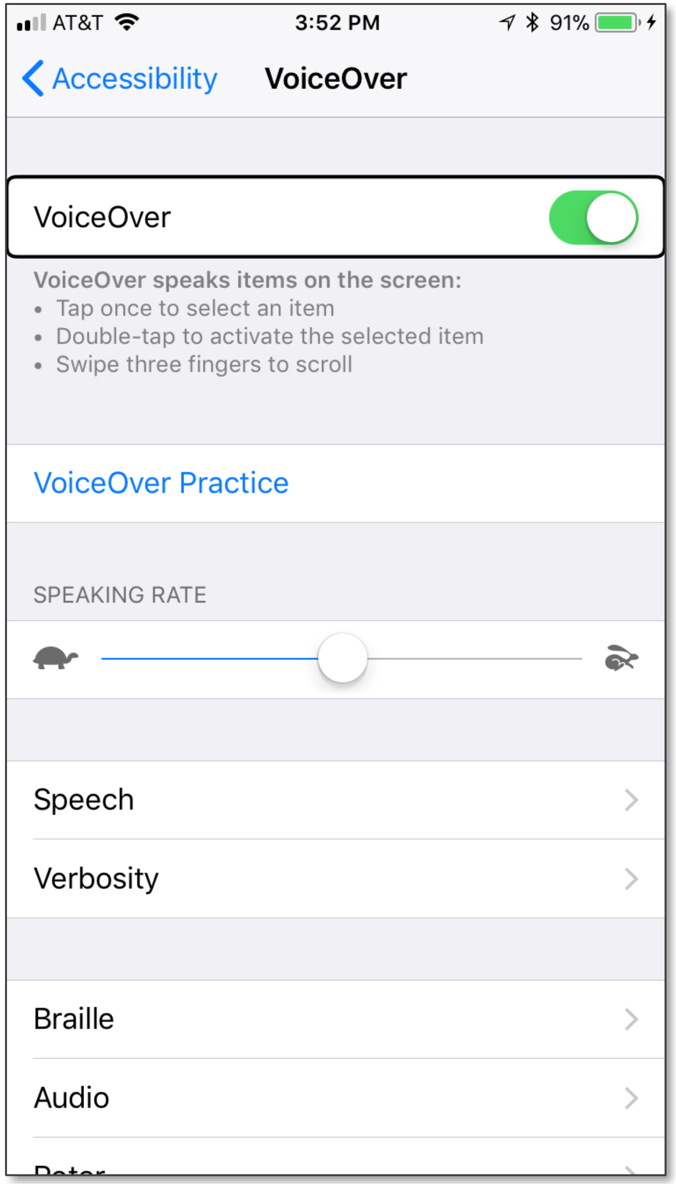
HANDSIGHT

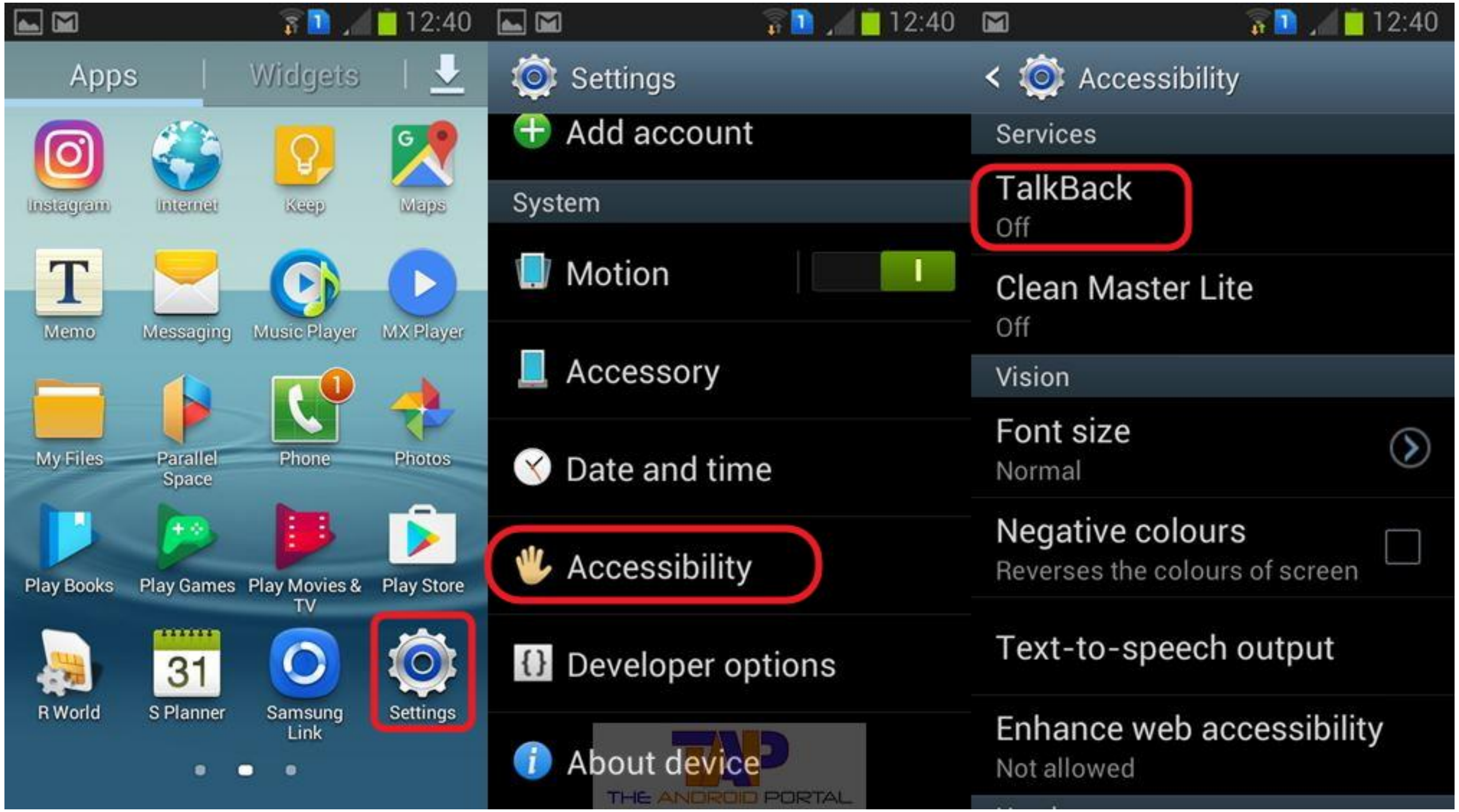
ON-BODY INTERACTION FOR VISUALLY IMPAIRED

ICPR'16, ASSETS'17, IMWUT'17






AT&T 3:52 PM 91%
Accessibility
VoiceOver
VoiceOver
VoiceOver speaks items on the screen:
• Tap once to select an item
• Double-tap to activate the selected item
• Swipe three fingers to scroll
VoiceOver Practice
SPEAKING RATE
Speech
Verbosity
Braille
Audio


12:40
Apps
Widgets
Instagram
Internet
Keep
Maps
Memo
Messaging
Music Player
MX Player
My Files
Parallel Space
Phone
Photos
Play Books
Play Games
Play Movies & TV
Play Store
R World
S Planner
Samsung Link
Settings
12:40
Settings
Add account
System
Motion
Accessory
Date and time
Accessibility
Developer options
About device
THE ANDROID PORTAL
12:40
Accessibility
Services
TalkBack
Off
Clean Master Lite
Off
Vision
Font size
Normal
Negative colours
Reverses the colours of screen
Text-to-speech output
Enhance web accessibility
Not allowed


Daily Summary
Clock
Voice Input


Clock
Voice Input
Health & Activities

THREAD 1: ACCESSIBILITY

IMPROVING ACCESS TO THE PHYSICAL WORLD

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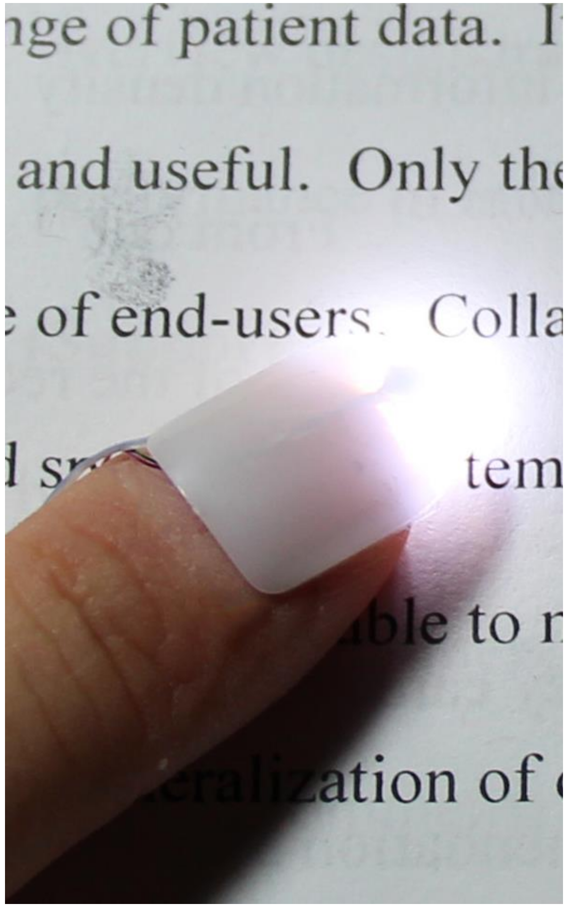
[ASSETS'12, CHI'13, HCOMP'13, ASSETS'13 Best Paper, UIST'14, TACCESS'15, SIGACCESS'15, CHI'16, ASSETS'17]



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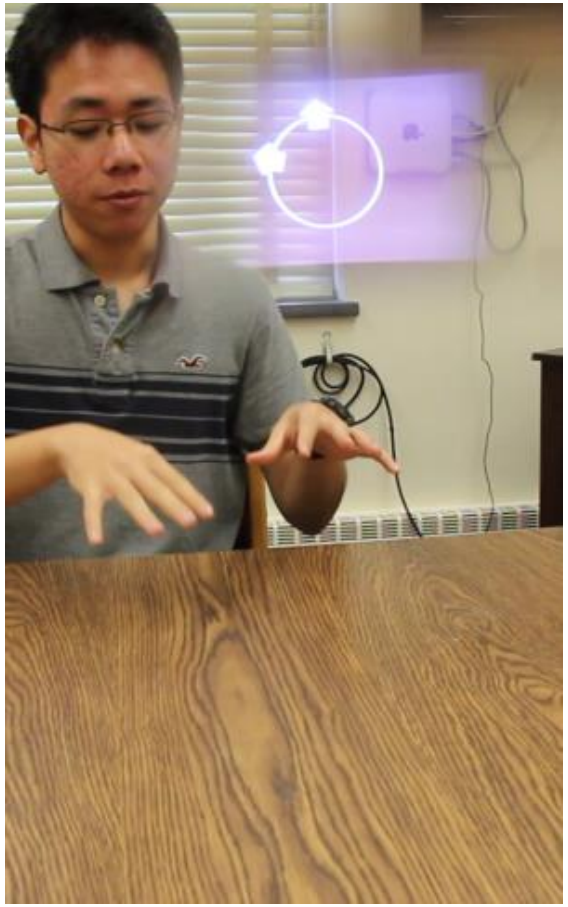
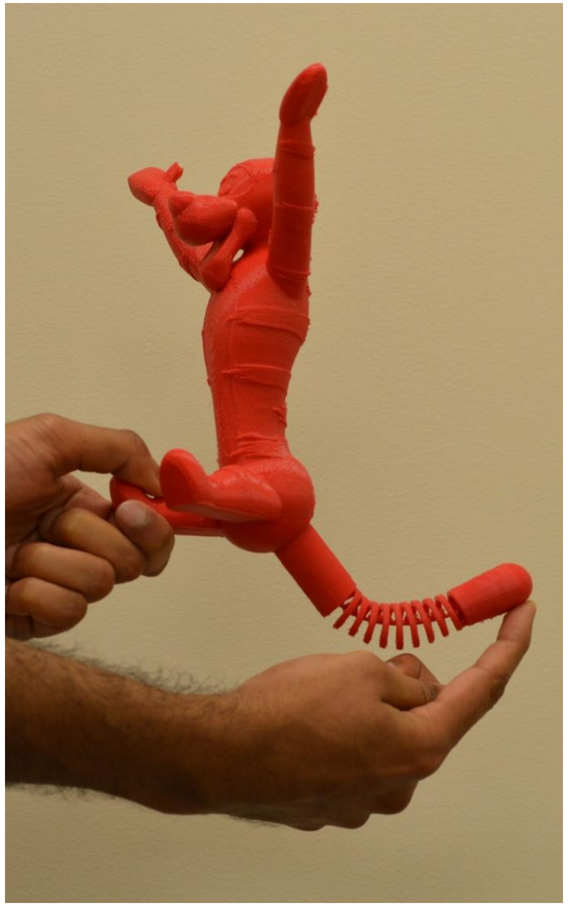


GLASSEAR

[CHI'15]



ONDULÉ

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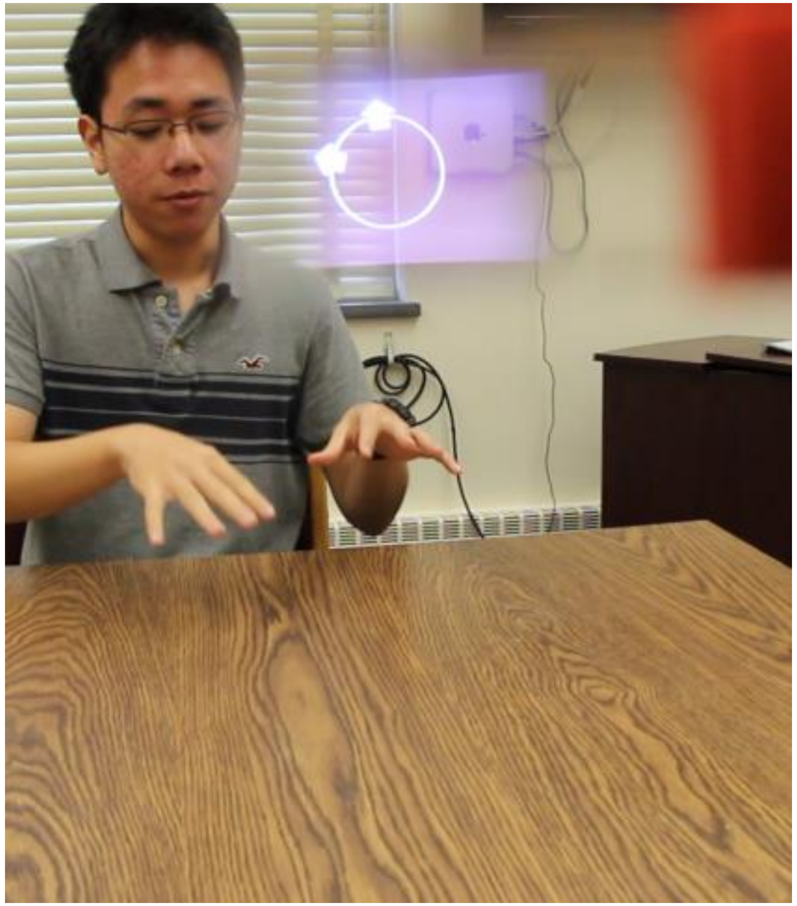


GLASSEAR
[CHI'15]

How can we...

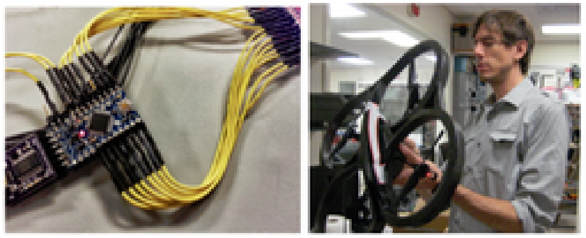
we sense & visualize sound information on an HMD to improve sound awareness for people who are deaf or hard of hearing?

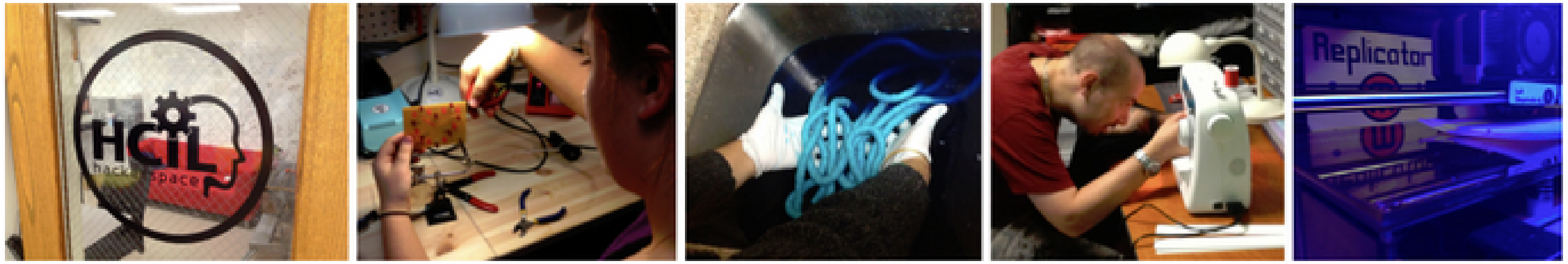

HMD CONVEYS SOUND
DIRECTION & MAGNITUDE


NON-WEARABLE
MICROPHONE ARRAY
HMD DISPLAY

CMSC838f

Tangible Interactive Computing





"Joy is a well-made object, equaled only to the joy of making it."

-a Canadian Native American tribe saying, as quoted by Mark Fraunfelder (author, co-founder of BoingBoing, & editor of MAKE Magazine)

Preamble

This class is about making, being creative, taking risks. We will make to learn and learn to make. We will use materials to help us think and to push our own boundaries of what interactive computing is and could be. I taught this class once before: http://cmsc838f-f12.wikispaces.com. It was, by most accounts, a success (I think!). I learned a lot. The class learned a lot. Most importantly, along the way, we had *fun* together, we *made* interesting things, and we *helped* each other (peer learning ftw).

As another indicator of success, the aforementioned Fall2012 class generated one MS thesis topic, one PhD thesis topic, and two publications (with more to come!). In addition, the instructables posted for the final project have garnered over 74,265 views and have been favorited 317 times (as of Jan. 2014) including HandSight (9,330 views

Course Pages

- Home
- Schedule
- Resources
- HCIL Hackerspace

Individual Assignments

- IA01 Background Survey - 1/29
- IA02 Arduino Graph - 2/13
- IA03 Partner Eval for MPA01 - 3/10
- IA04 Partner Eval for MPA02 - 4/02
- IA05 Partner Eval for MPA03 - 4/21

Mini-Project Assignments

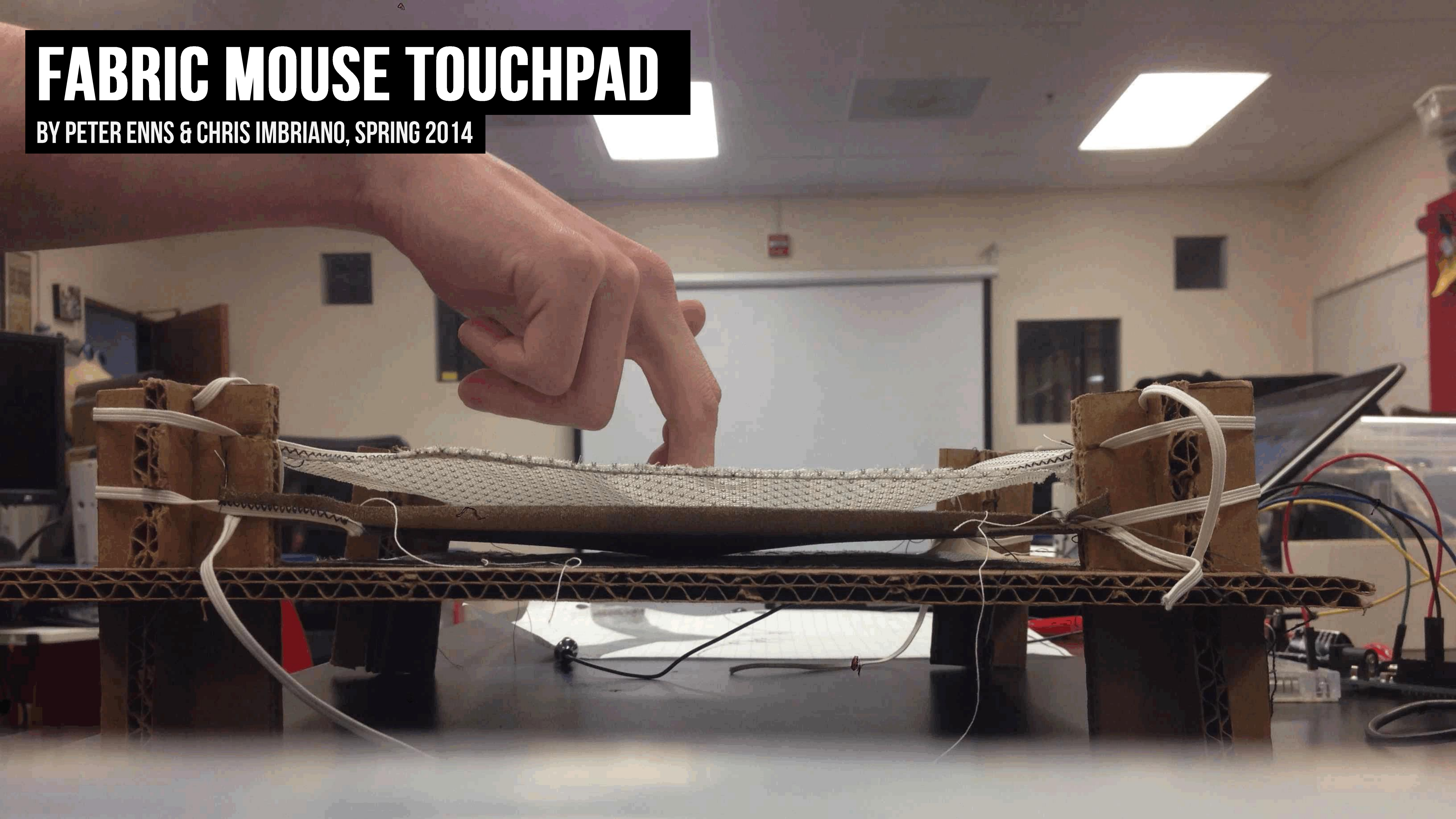
- MPA01 Input Inventions - 3/3
- MPA02 High-Low Tech - 3/26
- MPA03 Kinects & Motors - 4/16

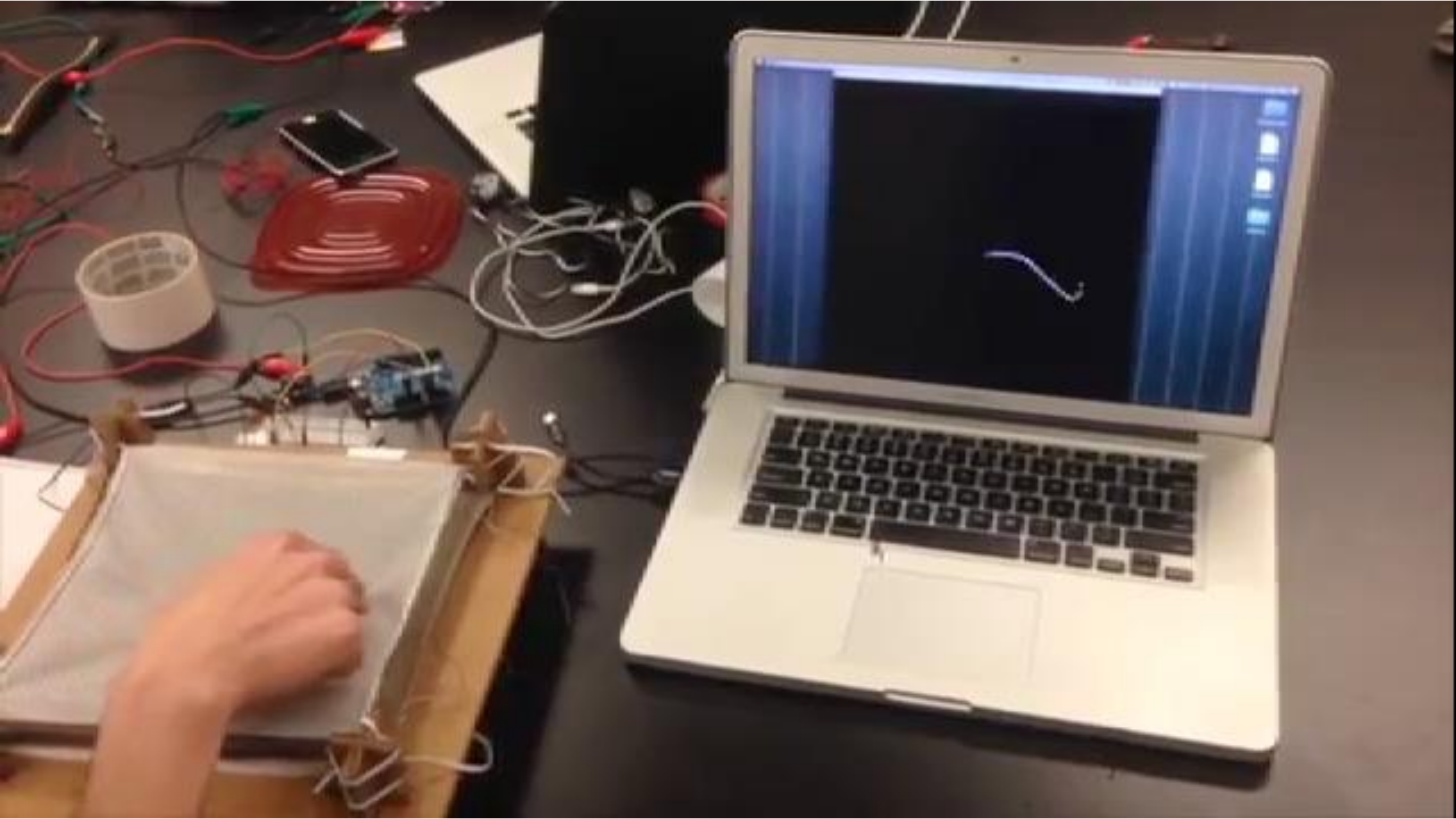
Semester Project Assignments

- SPA01 Project Pitch
- SPA02 Project Presentation
- SPA03 Project Instructable
- SPA04 Project Video
- SPA05 Project Artifact

Reading Assignments

- RA01 Tangible Bits - 1/29
- RA02 Arduino Intro - 2/3
- RA03 Electricity Intro - 2/13
- RA04 Switches (p 39-59) - 2/19
- RA05 Input Technology - 2/26
- RA05 Sensor-Based Input - 2/26
- RA06 Prototyping 3/5


FABRIC MOUSE TOUCHPAD
BY PETER ENNS & CHRIS IMBRIANO, SPRING 2014



MUSICAL SPAGHETTI MADNESS

BY RICHARD JOHNSON, SPRING 2014

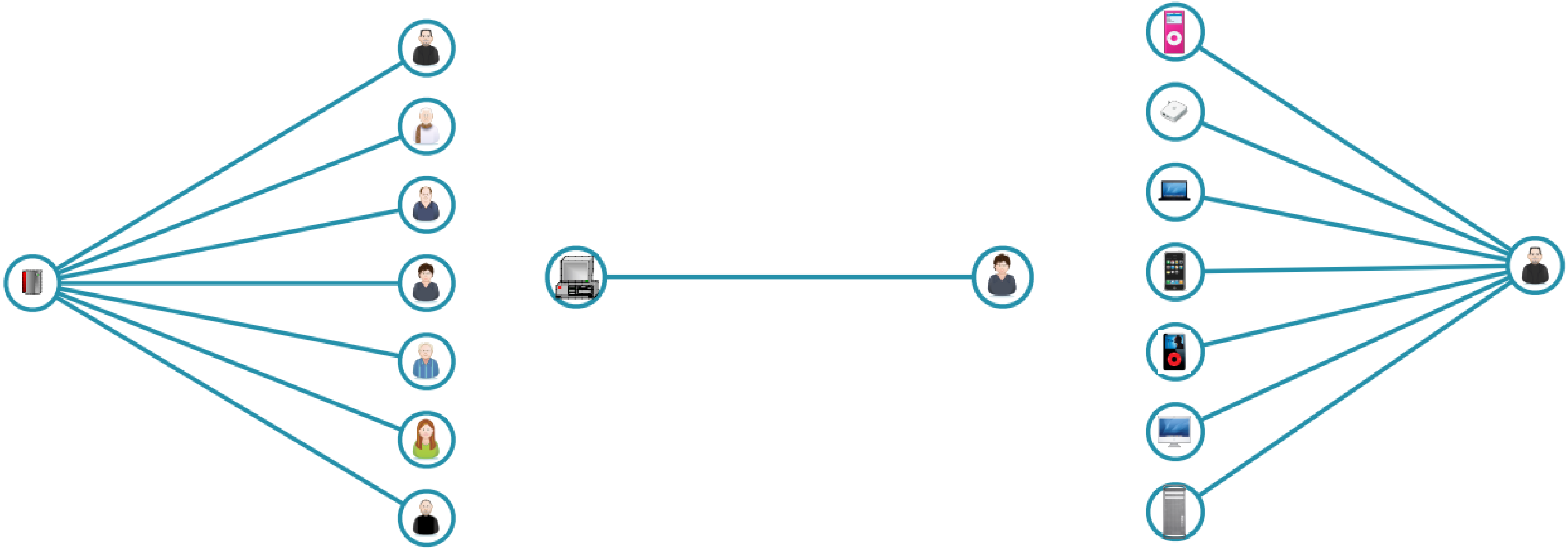
Introduction to Ubiquitous Computing:
Some Background and Context

ORIGINS OF UBICOMP

XEROX PARC
(1970s)

- Laser Printer
- Ethernet local area computer network
- Computer generated bitmap graphics
- Graphical user interface featuring windows and icons
- WYSIWYG text editor

3 ERAS OF COMPUTING



First Wave
1 Computer, Many People

Second Wave
1 Computer, 1 Person

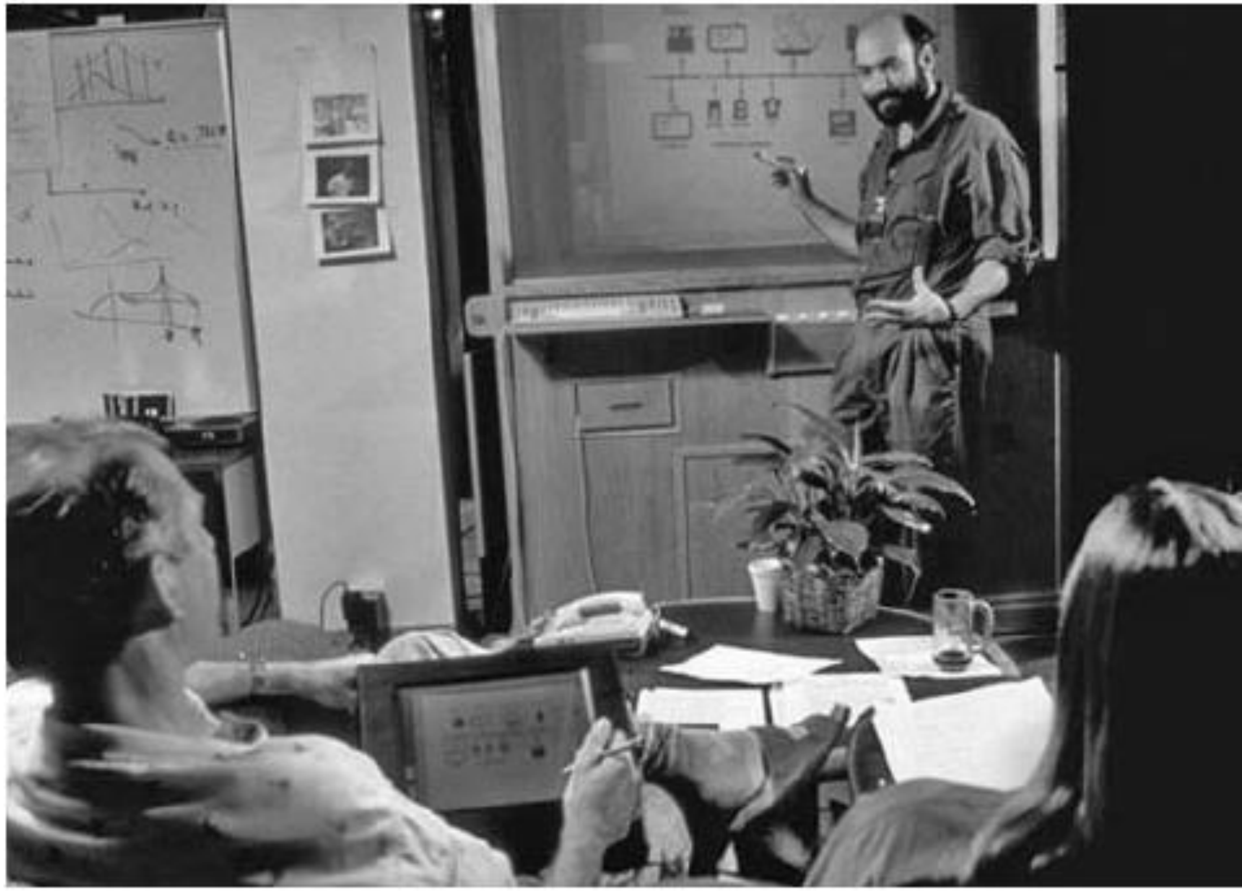
Third Wave
Many Computers, 1+ Person

Based on Don Patterson's INF241 course slides: http://www.ics.uci.edu/~djp3/classes/2012_01_INF241/Lectures/Lecture01.pdf

ORIGINS OF UBICOMP

Late 1980s, **Mark Weiser** became new manager of PARC's Computer Science Lab

Mark felt it was time for a new and radically different paradigm of computing and proposed a new research agenda termed "ubiquitous computing."



The Computer for the 21st Century

Specialized elements of hardware and software, connected by wires, radio waves and infrared, will be so ubiquitous that no one will notice their presence

by Mark Weiser

The most profound technologies are those that disappear. They weave themselves into the fabric of everyday life until they are indistinguishable from it.

Consider writing, perhaps the first information technology. The ability to represent spoken language symbolically for long-term storage freed information from the limits of individual memory. Today this technology is ubiquitous in industrialized countries. Not only do books, magazines and newspapers convey written information, but so do street signs, billboards, shop signs and even graffiti. Candy wrappers are covered in writing. The constant background presence of these products of "literacy technology" does not require active attention, but the information to be transmitted is ready for use at a glance. It is difficult to imagine modern life otherwise.

Silicon-based information technology, in contrast, is far from having become part of the environment. More than 50 million personal computers have been sold, and the computer nonetheless remains largely in a world of its own. It is approachable only through complex jargon that has nothing to do with the tasks for which people use computers. The state of the art is perhaps analogous to the period when scribes had to know as much about making ink or baking clay as they did about writing.

The arcane aura that surrounds personal computers is not just a "user interface" problem. My colleagues and I at the Xerox Palo Alto Research Center think that the idea of a "personal" computer itself is misplaced and that the vision of laptop machines, dynabooks and "knowledge navigators" is only a transitional step toward achieving the real potential of information technology. Such machines cannot truly make computing an integral, invisible part of people's lives. We are therefore trying to conceive a new way of thinking about computers, one that takes into account the human world and allows the computers themselves to vanish into the background.

Such a disappearance is a fundamental consequence not of technology but of human psychology. Whenever people learn something sufficiently well, they cease to be aware of it. When you look at a street sign, for example, you absorb its information without consciously performing the act of reading. Computer scientist, economist and Nobelist Herbert A. Simon calls this phenomenon "compiling"; philosopher Michael Polanyi calls it the "tacit dimension"; psychologist J. J. Gibson calls it "visual invariants"; philosophers Hans Georg Gadamer and Martin Heidegger call it the "horizon" and the "ready-to-hand"; John Seely Brown of PARC calls it the "periphery." All say, in essence, that only when things disappear in this way are we freed to use them without thinking and so to focus beyond them on new goals.

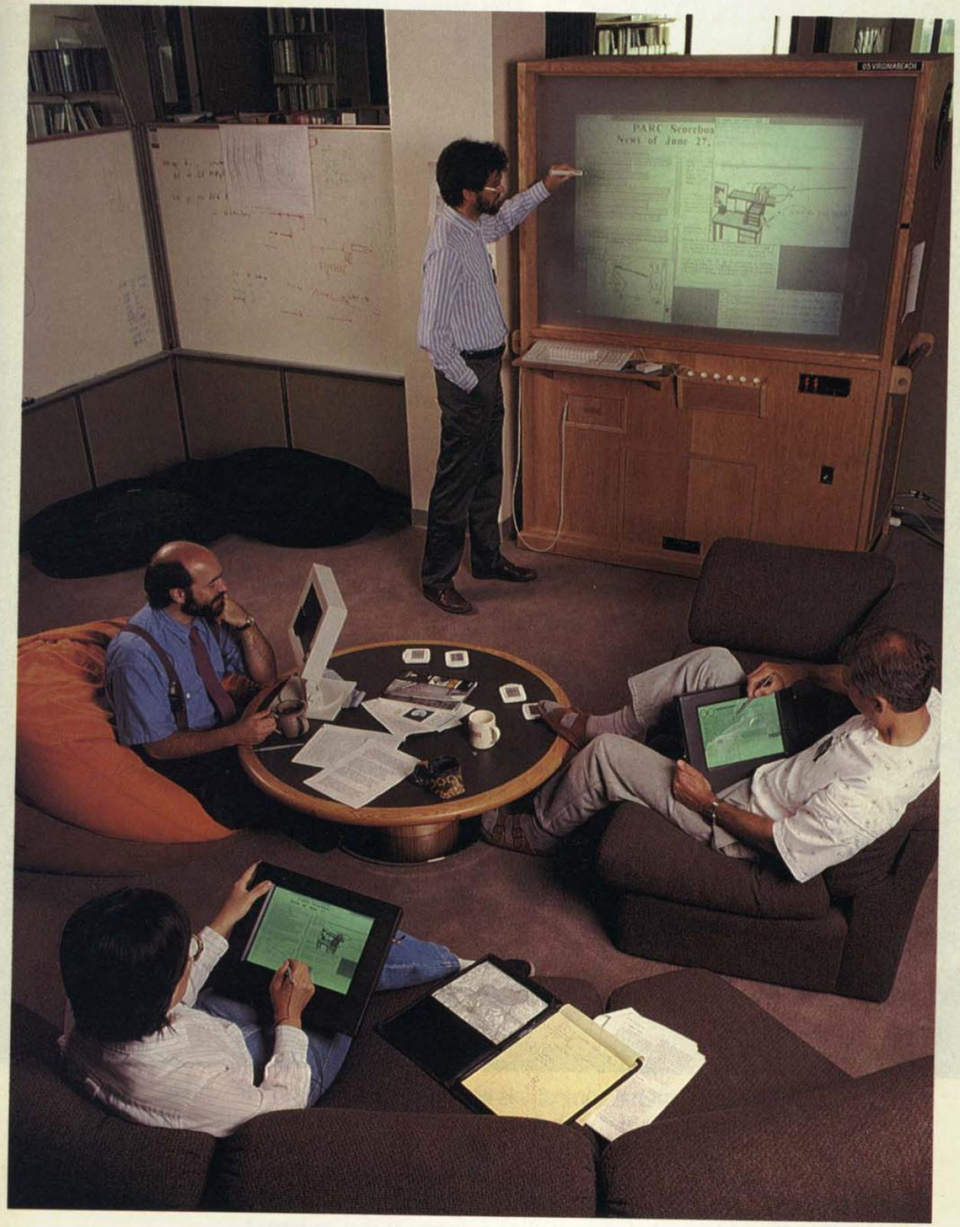
The idea of integrating computers seamlessly into the world at large runs counter to a number of present-day trends. "Ubiquitous computing" in this context does not mean just computers that can be carried to the beach, jungle or airport. Even the most powerful notebook computer, with access to a worldwide information network, still focuses attention on a single box. By analogy with writing, carrying a super-laptop is like owning just one very important book. Customizing this book, even writing millions of other books, does not begin to capture the real power of literacy.

Furthermore, although ubiquitous computers may use sound and video in addition to text and graphics, that does not make them "multimedia computers." Today's multimedia machine makes the computer screen into a demanding focus of attention rather than allowing it to fade into the background.

Perhaps most diametrically opposed to our vision is the notion of virtual reality, which attempts to make a world inside the computer. Users don special goggles that project an artificial scene onto their eyes; they wear gloves or even bodysuits that sense their motions and gestures so that they can move about and manipulate virtual objects. Although it may have its purpose in allowing people to explore realms otherwise inaccessible—the insides of cells, the surfaces of distant planets, the information web of data bases—virtual reality is only a map, not a territory. It excludes desks, offices, other people not wearing goggles and bodysuits, weather, trees, walks, chance encounters and, in general, the infinite richness of the universe. Virtual reality focuses an enormous apparatus on simulating the world rather than on invisibly enhancing the world that already exists.

Indeed, the opposition between the

MARK WEISER is head of the Computer Science Laboratory at the Xerox Palo Alto Research Center. He is working on the next revolution of computing after workstations, variously known as ubiquitous computing or embodied virtuality. Before working at PARC, he was a professor of computer science at the University of Maryland; he received his Ph.D. from the University of Michigan in 1979. Weiser also helped found an electronic publishing company and a video arts company and claims to enjoy computer programming "for the fun of it." His most recent technical work involved the implementation of new theories of automatic computer memory reclamation, known in the field as garbage collection.



UBIQUITOUS COMPUTING begins to emerge in the form of live boards that replace chalkboards as well as in other devices at the Xerox Palo Alto Research Center. Computer scientists gather around a live board for discussion. Building boards and integrating them with other tools has helped researchers understand better the eventual shape of ubiquitous computing. In conjunction with active badges, live boards can customize the information they display.

The most profound technologies are those that disappear. They weave themselves into the fabric of everyday life until they are indistinguishable from it.

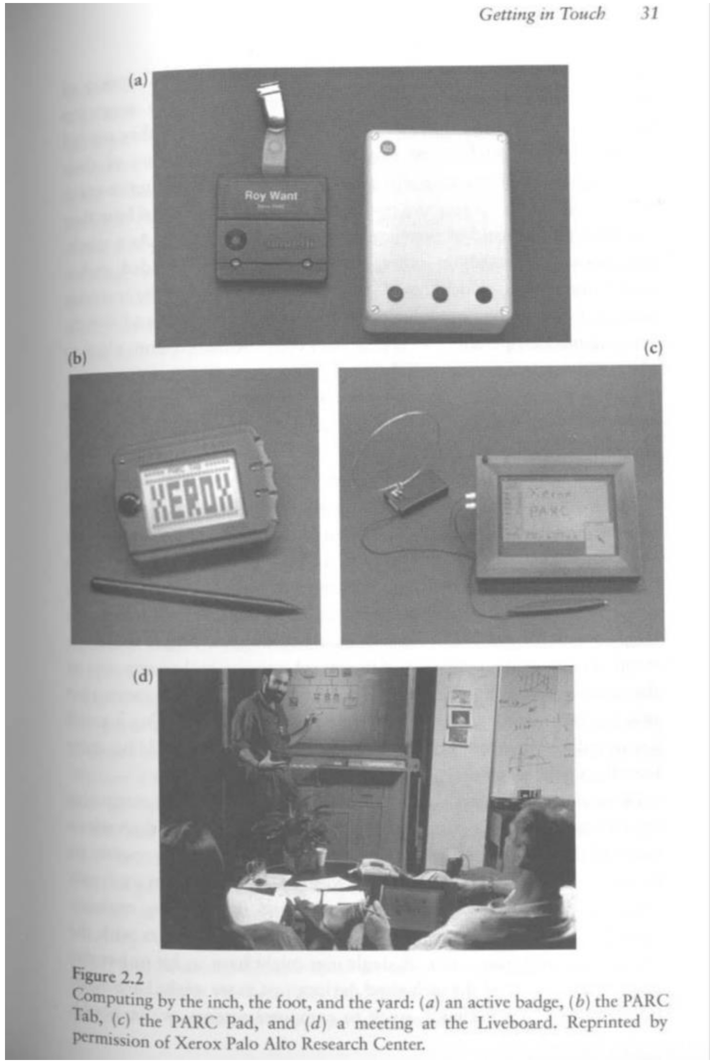
Mark Weiser
Father of Ubiquitous Computing
Xerox PARC Manager

Source:: Weiser, Scientific American'91

COMPUTATION BY THE INCH, FOOT, & YARD

Research agenda focused on addressing the problems of *everyday life* (away from the desk).

Developed a computational agenda around computing by the inch (small devices like the Active Badge), by the foot (tablets like the PARC Tab), and by the yard (interactive whiteboards).



Getting in Touch 31

Figure 2.2
Computing by the inch, the foot, and the yard: (*a*) an active badge, (*b*) the PARC Tab, (*c*) the PARC Pad, and (*d*) a meeting at the Liveboard. Reprinted by permission of Xerox Palo Alto Research Center.

MULTI-DISCIPLINARY FOCI

Studying human behavior to inform technology design (*i.e.*, design ethnography, sociological studies)

Designing new sensing and inference systems (both at hardware and software layers)

Building novel applications enabled by such systems (*e.g.*, pervasive health applications)

Field deployments to study and validate applications

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Designing new sensing and inference systems (both at hardware and software layers)

Building novel applications enabled by such systems (*e.g.*, pervasive health applications)

Field deployments to study and validate applications

Sensing and Inference Systems

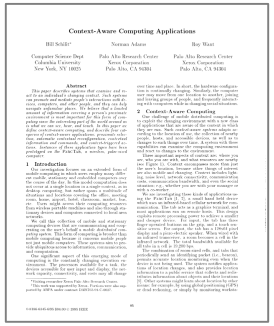
CONTEXT AWARE COMPUTING

> One challenge of mobile distributed computing is to **exploit the changing environment** with a new class of applications that are aware of the context in which they are run. Such **context-aware applications adapt according** to the **location** of use, the **collection** of **nearby people**, hosts, and accessible **devices**, as well as to changes to such things over **time**.

Bill Schilit, Norman Adams, Roy Want

Context-Aware Computing Applications

WMCSA'94



Context-Aware Computing Applications

Bill Schilit* — Computer Science Dept, Columbia University, New York, NY 10025

Norman Adams — Palo Alto Research Center, Xerox Corporation, Palo Alto, CA 94304

Roy Want — Palo Alto Research Center, Xerox Corporation, Palo Alto, CA 94304

Abstract

This paper describes systems that examine and react to an individual's changing context. Such systems can promote and mediate people's interactions with devices, computers, and other people, and they can help navigate unfamiliar places. We believe that a limited amount of information covering a person's proximate environment is most important for this form of computing since the interesting part of the world around us is what we can see, hear, and touch. In this paper we define context-aware computing, and describe four categories of context-aware applications: proximate selection, automatic contextual reconfiguration, contextual information and commands, and context-triggered actions. Instances of these application types have been prototyped on the PARCTAB*, a wireless, palm-sized computer.*

1 Introduction

Our investigation focuses on an extended form of ...

... over time and place. In short, the hardware configuration is continually changing. Similarly, the computer user may move from one location to another, joining and leaving groups of people, and frequently interacting with computers while in changing social situations.

2 Context-Aware Computing

One challenge of mobile distributed computing is to exploit the changing environment with a new class of applications that are aware of the context in which they are run. Such *context-aware systems* adapts according to the location of use, the collection of nearby people, hosts, and accessible devices, as well as to changes to such things over time. A system with these capabilities can examine the computing environment and react to changes to the environment.

Three important aspects of context are: where you are, who you are with, and what resources are nearby (see Figure 1). Context encompasses more than just the user's location, because other things of interest ...

WHAT ARE SOME EXAMPLES OF CONTEXT?

Location

Biometrics

Time

Conversational context

Environmental context (e.g., temperature)

Identity (i.e., who is using it)

Proximity to other devices

Human behavioral patterns

Interests and beliefs

Emotional context

A GOOD MINIMAL SET…

What are we doing?

Where are we doing it?

Who are we and who are we doing it with?

When are we doing it? Have we done it before?

Based, in part, on Abowd & Mynatt, ACM Trans on CHI'00

AN EXPANDED SET…

What are we doing?

Where are we doing it?

Who are we and who are we doing it with?

When are we doing it? Have we done it before?

EASIER

Why are we doing it?

How are we doing it?

How do we feel? Why do we feel that way?

What do we want to do but cannot?

HARDER

Based, in part, on Abowd & Mynatt, ACM Trans on CHI'00

BUT EVEN "SIMPLE" CONTEXT CAN BE HARD…

Re: location. Does the system need to sense/infer:

- Lat/long?
- A physical address (123 Cherry St, Seattle)
- The room I'm in?
- A semantic place (*e.g.*, my home, my work, a friend's house)
- What's near me?
- Which way I'm facing?
- ….

UBICOMP INFERENCE SYSTEMS

CONTEXT AWARE COMPUTING

Context-Aware Computing Applications
Schilit *et al.*, WMCSA'94
4,707 citations

Developing a Context-Aware Electronic Tourist Guide: Some Issues and Experiences
Cheverst *et al.*, CHI'00
1,323 citations

Understanding and Using Context
Anind Dey, Pers. & UbiComp'01
5,690 citations

What We Talk About When We Talk About Context
Paul Dourish, Pers. & UbiComp'04
1,688 citations

CORE CONTEXT INFERENCE AREAS: A RAPID TOUR

Location

Movement

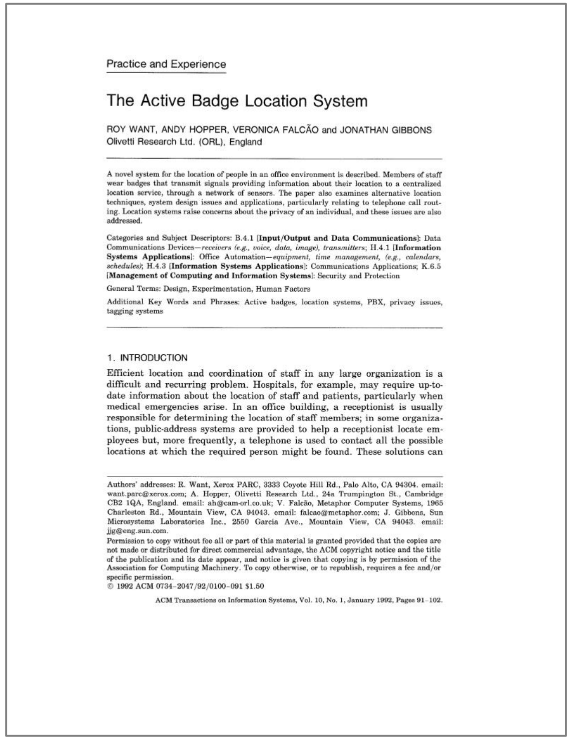
Activity

Social interaction

Emotion

Rapidly cover the seminal work & the influential people & places. I’m gonna go fast. We’ll dive deeper throughout quarter.

LOCATION INFERENCE: THE EARLY DAYS



Practice and Experience

The Active Badge Location System

ROY WANT, ANDY HOPPER, VERONICA FALCÃO and JONATHAN GIBBONS
Olivetti Research Ltd. (ORL), England

A novel system for the location of people in an office environment is described. Members of staff wear badges that transmit signals providing information about their location to a centralized location service, through a network of sensors. The paper also examines alternative location techniques, system design issues and applications, particularly relating to telephone call routing. Location systems raise concerns about the privacy of an individual, and these issues are also addressed.

Categories and Subject Descriptors: B.4.1 [**Input/Output and Data Communications**]: Data Communications Devices—*receivers (e.g., voice, data, image), transmitters*; H.4.1 [**Information Systems Applications**]: Office Automation—*equipment, time management, (e.g., calendars, schedules)*; H.4.3 [**Information Systems Applications**]: Communications Applications; K.6.5 [**Management of Computing and Information Systems**]: Security and Protection

General Terms: Design, Experimentation, Human Factors

Additional Key Words and Phrases: Active badges, location systems, PBX, privacy issues, tagging systems

1. INTRODUCTION

Efficient location and coordination of staff in any large organization is a difficult and recurring problem. Hospitals, for example, may require up-to-date information about the location of staff and patients, particularly when medical emergencies arise. In an office building, a receptionist is usually responsible for determining the location of staff members; in some organizations, public-address systems are provided to help a receptionist locate employees but, more frequently, a telephone is used to contact all the possible locations at which the required person might be found. These solutions can

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© 1992 ACM 0734-2047/92/0100-091 $1.50

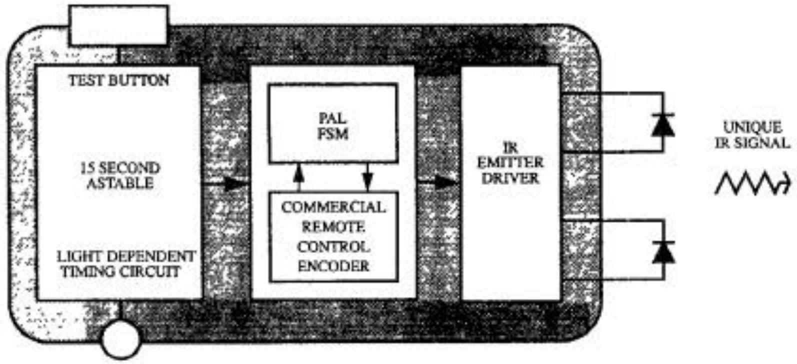
ACM Transactions on Information Systems, Vol. 10, No. 1, January 1992, Pages 91-102.

The Active Badge Location System
Want *et al.,* ACM Trans. InfoSys'92
5,252 citations

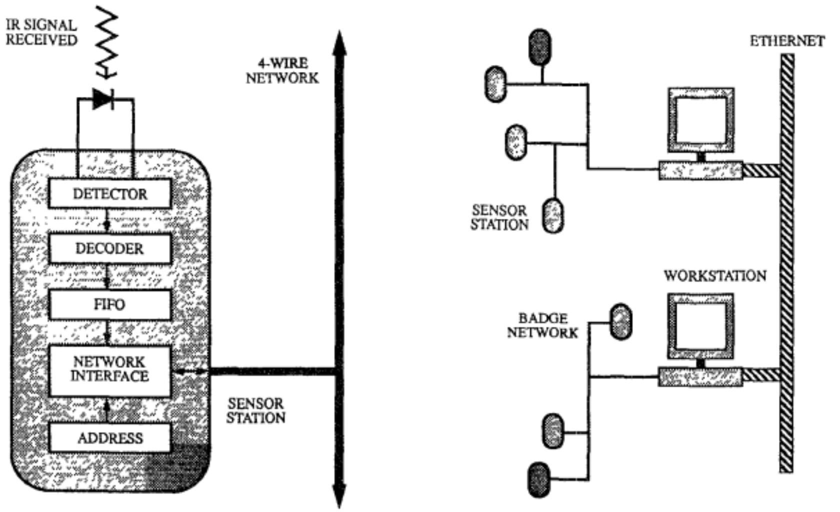
LOCATION INFERENCE: ACTIVE BADGE

The *Active Badge* emits a unique IR code every 15 secs, which are picked up by a sensor network placed throughout a building, which communicates with a centralized server and provides a social location API. IR was chosen because ultrasonic too expensive.

Active Badge



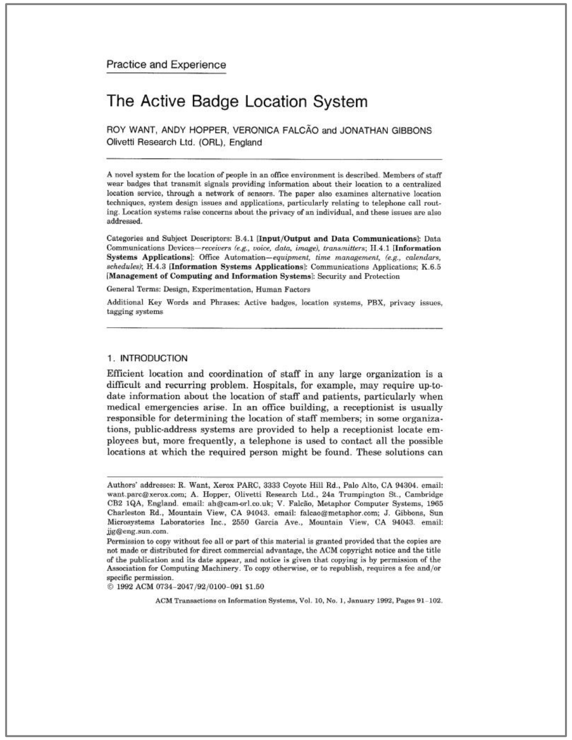
Active Badge Schematic



Back End Schematic

LOCATION INFERENCE: THE EARLY DAYS

IR	Ultrasonic + RF	RF	Survey Paper



Practice and Experience

The Active Badge Location System

ROY WANT, ANDY HOPPER, VERONICA FALCÃO and JONATHAN GIBBONS
Olivetti Research Ltd. (ORL), England

The Active Badge Location System

Want *et al.*, ACM Trans. InfoSys'92

5,252 citations

The Cricket Location-Support System

Nissanka B. Priyantha, Anit Chakraborty, and Hari Balakrishnan
MIT Laboratory for Computer Science
Cambridge, MA 02139
{bodhi, achakra, hari}@lcs.mit.edu

The Cricket Location-Support System

Priyantha *et al.*, MobiCom'00

4,934 citations

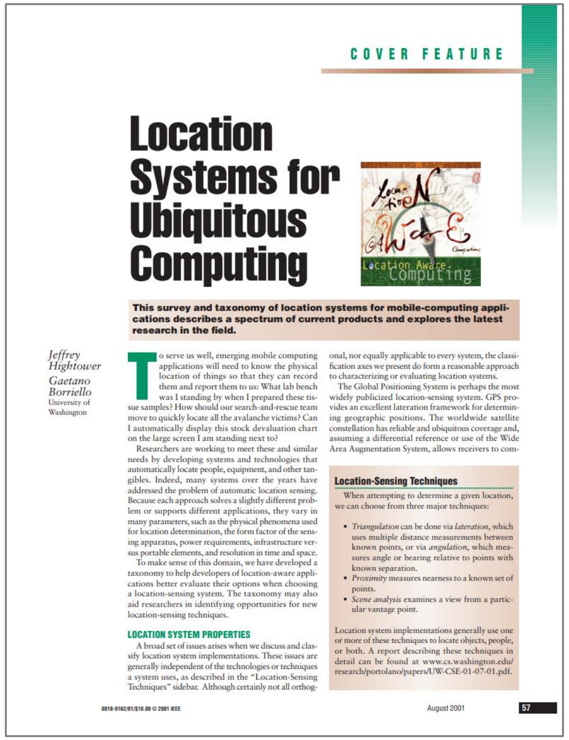
RADAR: An In-Building RF-based User Location and Tracking System

Paramvir Bahl and Venkata N. Padmanabhan
Microsoft Research
{bahl, padmanab}@microsoft.com

RADAR: An In-Building RF-Based User Location and Tracking System

Bahl & Padmanabhan, INFOCOM'00

9,653 citations



COVER FEATURE

Location Systems for Ubiquitous Computing

This survey and taxonomy of location systems for mobile-computing applications describes a spectrum of current products and explores the latest research in the field.

Jeffrey Hightower
Gaetano Borriello
University of Washington

Location Systems for Ubiquitous Computing

Hightower & Boriello, IEEE Computer'01

4,284 citations

UBICOMP INFERENCE SYSTEMS

LOCATION INFERENCE: PIGGYBACKING ON INFRASTRUCTURE

FM Radio

WiFi (& Bluetooth)

GSM Cells

UbiComp 2003, October 2003

RightSPOT: A Novel Sense of Location for a Smart Personal Object

John Krumm, Gerry Cermak, and Eric Horvitz

Microsoft Research
Microsoft Corporation
One Microsoft Way
Redmond, WA USA

RightSPOT: A Novel Sense of Location for a Smart Personal Object
Krumm *et al.*, UbiComp'03
173 citations

To appear at Mobiquitous 2004 (First Annual International Conference on Mobile and Ubiquitous Systems: Networking and Services), August 22-26, 2004, Boston, MA, USA

LOCADIO: Inferring Motion and Location from Wi-Fi Signal Strengths

John Krumm and Eric Horvitz
Microsoft Research
Microsoft Corporation
One Microsoft Way
Redmond, WA USA
{jckrumm, horvitz}@microsoft.com

LOCADIO: Inferring Motion and Location from WiFi Signal Strengths
Krumm & Horvitz, Mobiquitous'04
333 citations

Place Lab: Device Positioning Using Radio Beacons in the Wild

Anthony LaMarca[1], Yatin Chawathe[1], Sunny Consolvo[1], Jeffrey Hightower[1], Ian Smith[1], James Scott[2], Timothy Sohn[3], James Howard[4], Jeff Hughes[4], Fred Potter[4], Jason Tabert[5], Pauline Powledge[1], Gaetano Borriello[4], and Bill Schilit[1]

[1] Intel Research Seattle
[2] Intel Research Cambridge
[3] Department of Computer Science, UC San Diego
[4] Department of Computer Science & Engineering, University of Washington
[5] Information School, University of Washington

H.W. Gellersen et al. (Eds.): PERVASIVE 2005, LNCS 3468, pp. 116 – 133, 2005.
© Springer-Verlag Berlin Heidelberg 2005

Place Lab: Device Positioning Using Radio Beacons in the Wild
LaMarca *et al.*, Pervasive Comp'05
1,337 citations

Accurate GSM Indoor Localization

Accurate GSM Indoor Localization
Otsason *et al.*, UbiComp'05
542 citations

BEACON-BASED POSITIONING

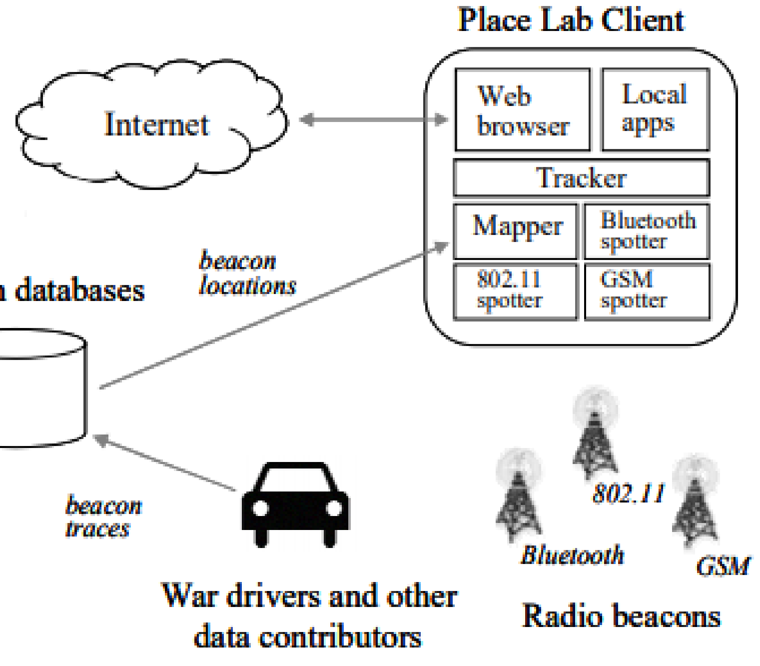


Fig.1. Key components in the Place Lab architecture

1. Collect "ground truth" location of beacons by driving/walking with GPS+radios (GSM, WiFi, Bluetooth).
2. Radio signatures at each location are distinct and thus referred to as fingerprints. Fingerprints tagged by GPS or manual entry.
3. Client (which may not have GPS) simply uploads radio signature at current place and server triangulates location.

See: LaMarca *et al.*, Pervasive Computing'05

ANDROID LOCATION TRACKING

Bluetooth beacons: the MAC address, identifier, type, and (two) measures of signal strength for all nearby Bluetooth devices

WiFi beacons: the MAC address, signal strength, and frequency of nearby WiFi access points (including the connected network)

Cell beacons: cell-id, signal strength measures

GPS coordinates, elevation, and accuracy estimates

Other: Barometric pressure and inferred activity states (e.g., moving, stationary).

Source: https://developer.android.com/guide/topics/location/strategies.html; https://qz.com/1183559/if-youre-using-an-android-phone-google-may-be-tracking-every-move-you-make/

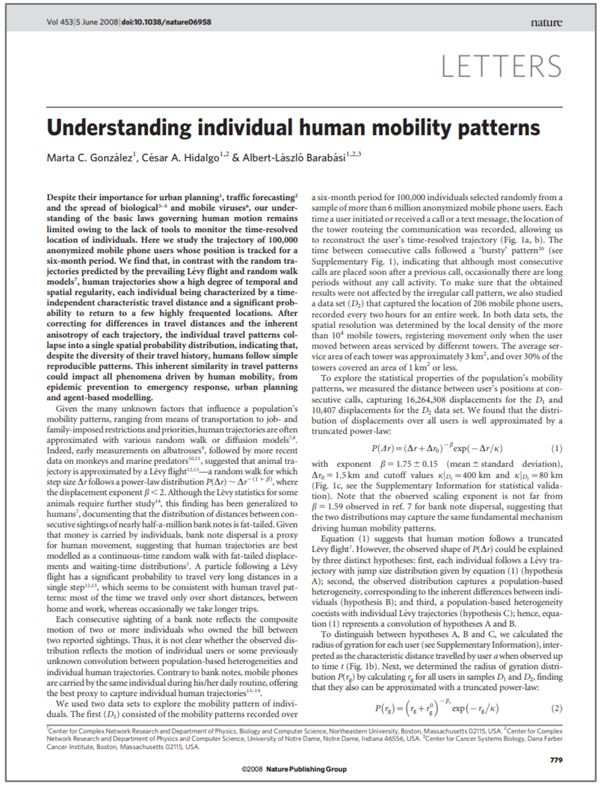
UBICOMP INFERENCE SYSTEMS

HUMAN TRAJECTORY PREDICTION

Trajectory Pattern Mining
Giannotti *et al.,* KDD'07
965 citations

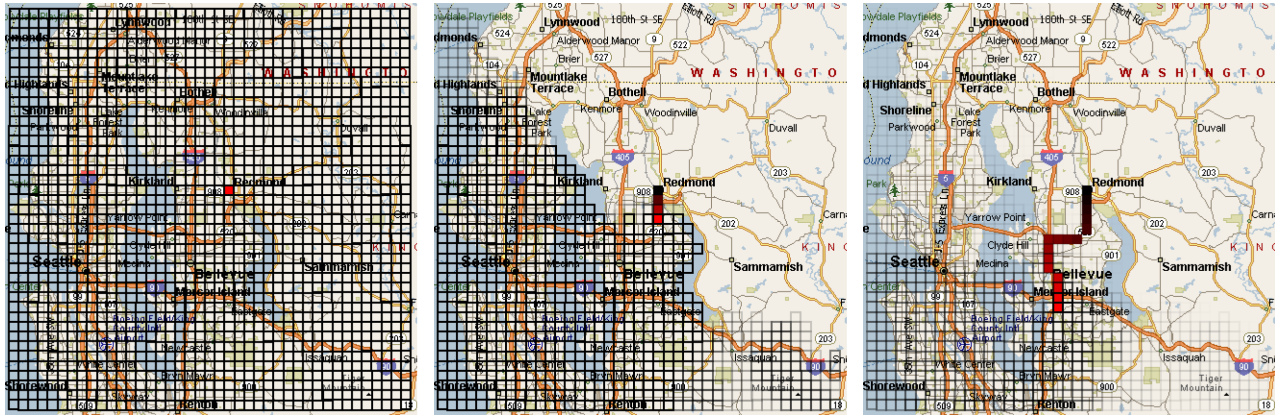
Predestination: Inferring Destinations from Partial Trajectories
Krumm & Horvitz, UbiComp'06
463 citations

Route Prediction from Trip Observations
Froehlich & Krumm, SAE W. Congress'08
231 citations



Understanding Individual Human Mobility Patterns
Gonzalez *et al.,* Nature'08
4,163 citations

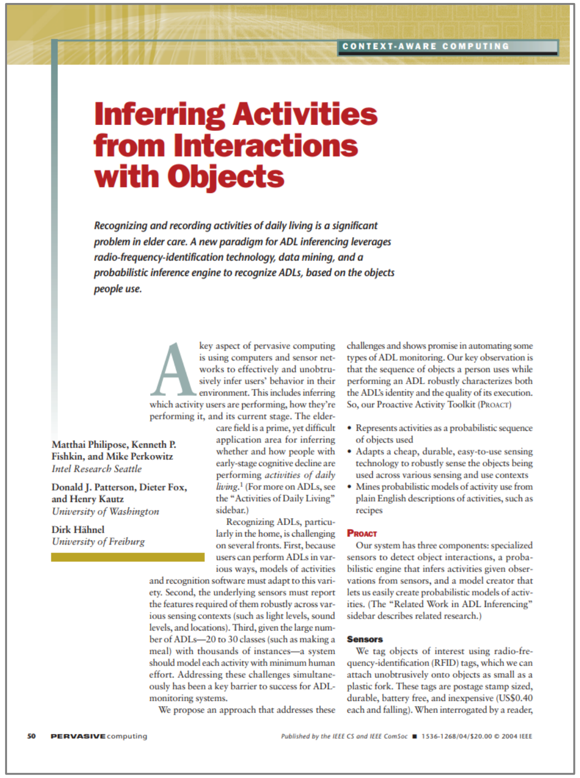
PREDESTINATION (2006)



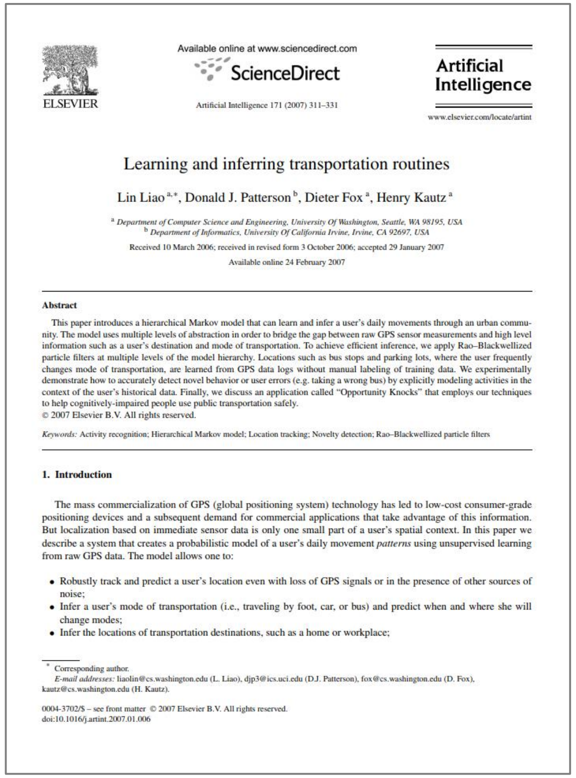
Discretizes city into cells
Use Bayesian inference to predict destination
Can even predict places previously not visited
Result: predicts 2km median error at halfway point of trip

ACTIVITY RECOGNITION WITH WEARABLES

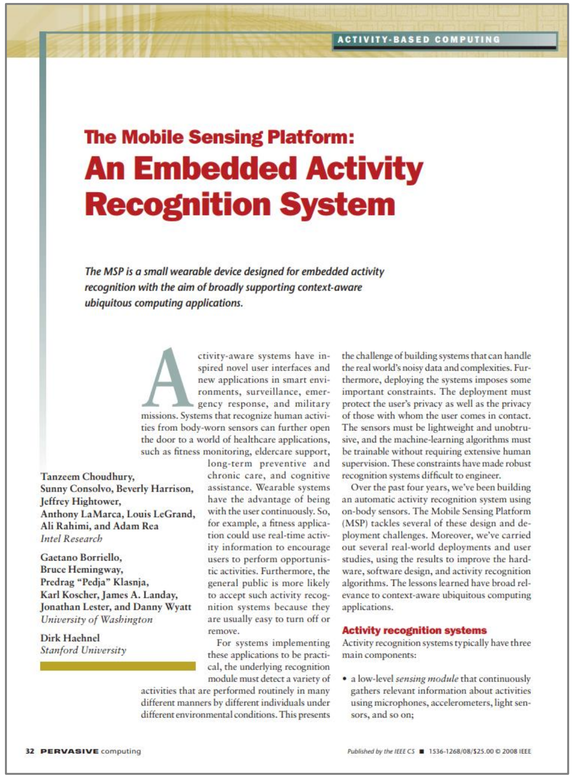
Activity Recognition from User-Annotated Acceleration Data
Bao & Intille, Pervasive'04
2,795 citations



Inferring Activities from Interactions with Objects
Philipose *et al.*, Pervasive Comp'04
987 citations

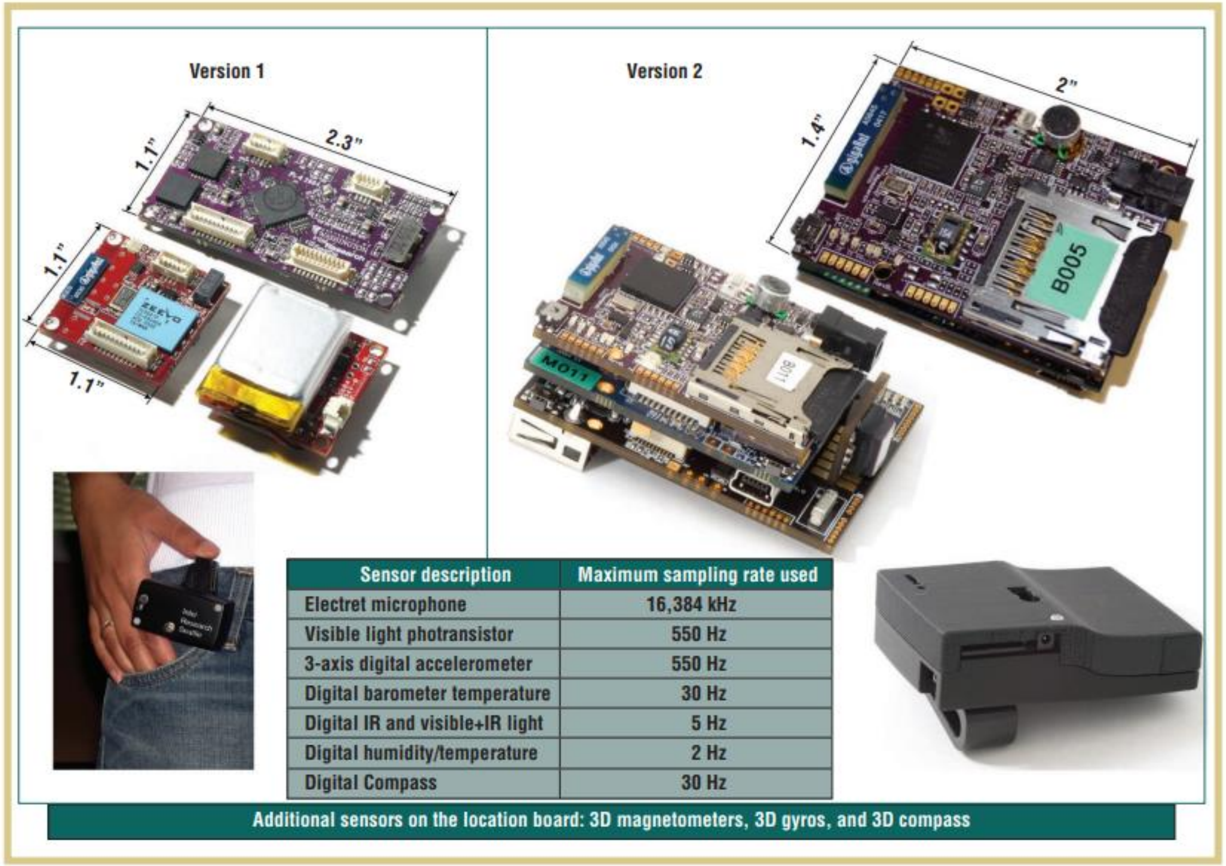


Learning and Inferring Transportation Routines
Liao *et al.*, Artificial Intelligence'07
987 citations



The Mobile Sensing Platform: An Embedded Activity Recognition System
Choudhury *et al.*, Pervasive Computing'08
562 citations

MOBILE SENSING PLATFORM (~2005-2009)



Sensor description	Maximum sampling rate used
Electret microphone	16,384 kHz
Visible light photransistor	550 Hz
3-axis digital accelerometer	550 Hz
Digital barometer temperature	30 Hz
Digital IR and visible+IR light	5 Hz
Digital humidity/temperature	2 Hz
Digital Compass	30 Hz

Figure 1. The Mobile Sensing Platform hardware, versions 1.0 and 2.0., with and without cases. Both MSP versions support seven sensors. In addition, version 2.0 offers a location daughterboard that includes additional 3D sensors. The MSP can communicate wirelessly with other devices in real time or store raw sensor data, features, or activity recognition results for offline use.

The beginning of "activity recognition" as a service.

Hardware/software platform for activity recognition.

Multi-sensor, belt-worn device.

Can log sensor data for offline experiments or perform real-time recognition.

Source: Choudury *et al.*, Pervasive Computing 2008

MOBILE SENSING PLATFORM (~2005-2009)

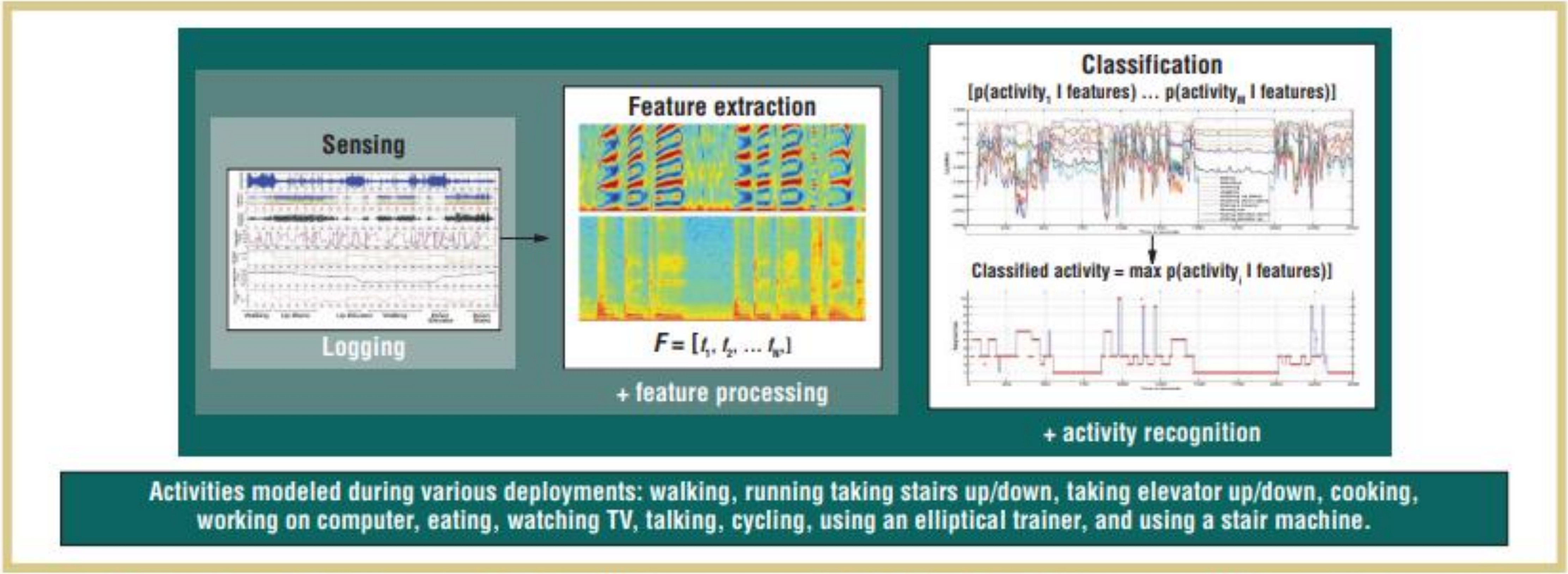


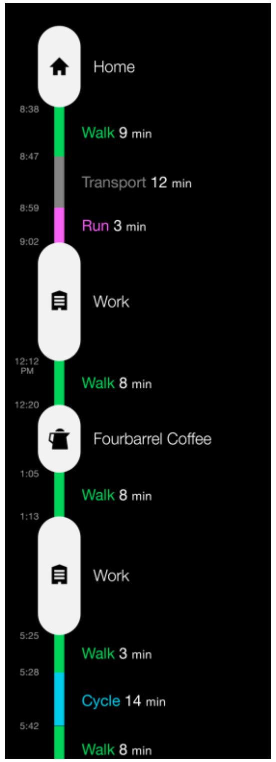
Figure 2. MSP software flow diagram for the classification system. The MSP has a flexible usage model that includes logging, feature processing, and activity recognition.

Source: Choudury *et al.*, Pervasive Computing 2008

ACTIVITY RECOGNITION: COMMERCIAL SYSTEMS

Apple M-Series Coprocessors

First released in 2013 for the iPhone 5S, the M-series coprocessors collect, process, and store sensor data even if the device is asleep. Includes: accelerometer, gyroscope, compass, barometer, & w/the M9, even the microphone.



Moves App

Automatically recognizes **walking, cycling, running**, and counts **steps.** Can manually record other activities.

https://moves-app.com/

Apple Watch

Watch automatically recognizes movement—categorizes into low- and high-intensity. Measures steps, heartrate, & integrates with 3rd party apps.

LAUNCHED MARCH'18

FITBIT IONIC

fitbit ionic™

Source: https://www.fitbit.com/ionic

fitbit ionic™

ACTIVITY RECOGNITION APIS: COMMERCIAL EXAMPLE

Developer · Discover · Design · Develop · Distribute · Support · Account

Documentation › Core Motion › CMMotionActivity   Language: Swift   API Changes: Show

Class

CMMotionActivity

The data for a single motion update event.

SDKs
iOS 7.0+
watchOS 2.0+

Framework
Core Motion

On This Page
Overview
Topics
Relationships
See Also

Overview

On devices that support motion, you can use a `CMMotionActivityManager` object to request updates when the current type of motion changes. When a change occurs, the update information is packaged into a `CMMotionActivity` object and sent to your app.

The motion-related properties of this class are not mutually exclusive. In other words, it is possible for more than one of the motion-related properties to contain the value `true`. For example, if the user was driving in a car and the car stopped at a red light, the update event associated with that change in motion would have both the `cycling` and `stationary` properties set to `true`. It is also possible for all of the properties to be set to `false` when the device is in motion but the movement does not correlate to walking, running, cycling or automotive travel.

You do not create instances of this class yourself. The `CMMotionActivityManager` object creates them and sends them to the handler block you registered. For more information about how to initiate the delivery of motion activity updates to your app, see `CMMotionActivityManager`.

Topics

Getting the Type of Motion

`var stationary: Bool`
A Boolean indicating whether the device is stationary.

`var walking: Bool`
A Boolean indicating whether the device is on a walking person.

`var running: Bool`
A Boolean indicating whether the device is on a running person.

`var automotive: Bool`
A Boolean indicating whether the device is in an automobile.

`var cycling: Bool`
A Boolean indicating whether the device is in an bicycle.

`var unknown: Bool`
A Boolean indicating whether the type of motion is unknown.

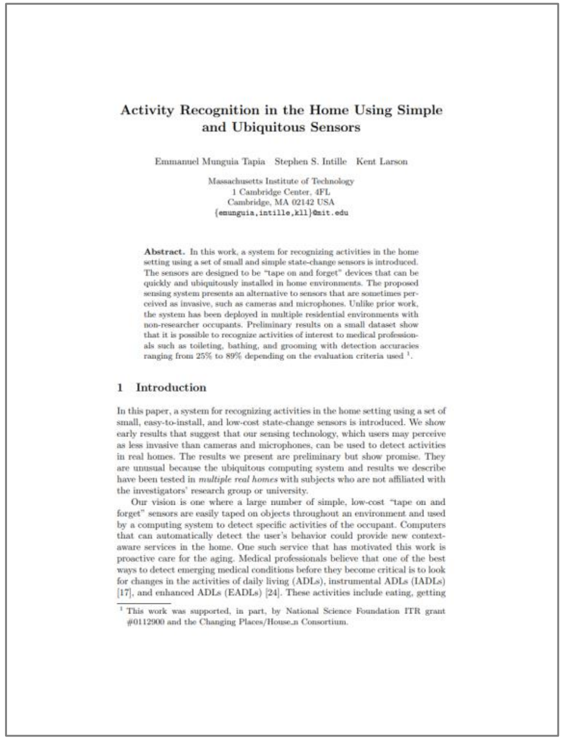
Getting Metadata for the Motion

`var startDate: Date`
The time at which the change in motion occurred.

`var confidence: CMMotionActivityConfidence`
The confidence in the assessment of the motion type.

`enum CMMotionActivityConfidence`
The confidence that the motion data is accurate.

ACTIVITY RECOGNITION VIA INSTRUMENTED SPACES



Activity Recognition in the Home Using Simple and Ubiquitous Sensors

Emmanuel Munguia Tapia Stephen S. Intille Kent Larson

Massachusetts Institute of Technology
1 Cambridge Center, 4FL
Cambridge, MA 02142 USA
{emunguia,intille,kll}@mit.edu

Abstract. In this work, a system for recognizing activities in the home setting using a set of small and simple state-change sensors is introduced. The sensors are designed to be "tape on and forget" devices that can be quickly and ubiquitously installed in home environments. The proposed sensing system presents an alternative to sensors that are sometimes perceived as invasive, such as cameras and microphones. Unlike prior work, the system has been deployed in multiple residential environments with non-researcher occupants. Preliminary results on a small dataset show that it is possible to recognize activities of interest to medical professionals such as toileting, bathing, and grooming with detection accuracies ranging from 25% to 89% depending on the evaluation criteria used [1].

1 Introduction

In this paper, a system for recognizing activities in the home setting using a set of small, easy-to-install, and low-cost state-change sensors is introduced. We show early results that suggest that our sensing technology, which users may perceive as less invasive than cameras and microphones, can be used to detect activities in real homes. The results we present are preliminary but show promise. They are unusual because the ubiquitous computing system and results we describe have been tested in *multiple real homes* with subjects who are not affiliated with the investigators' research group or university.

Our vision is one where a large number of simple, low-cost "tape on and forget" sensors are easily taped on objects throughout an environment and used by a computing system to detect specific activities of the occupant. Computers that can automatically detect the user's behavior could provide new context-aware services in the home. One such service that has motivated this work is proactive care for the aging. Medical professionals believe that one of the best ways to detect emerging medical conditions before they become critical is to look for changes in the activities of daily living (ADLs), instrumental ADLs (IADLs) [17], and enhanced ADLs (EADLs) [24]. These activities include eating, getting

[1] This work was supported, in part, by National Science Foundation ITR grant #0112900 and the Changing Places/House_n Consortium.

Activity Recognition in the Home Using Simple and Ubiquitous Sensors
Tapia *et al.*, Pervasive'04
1,406 citations

UBICOMP INFERENCE SYSTEMS

ACTIVITY RECOGNITION IN THE HOME (2004)

(a)

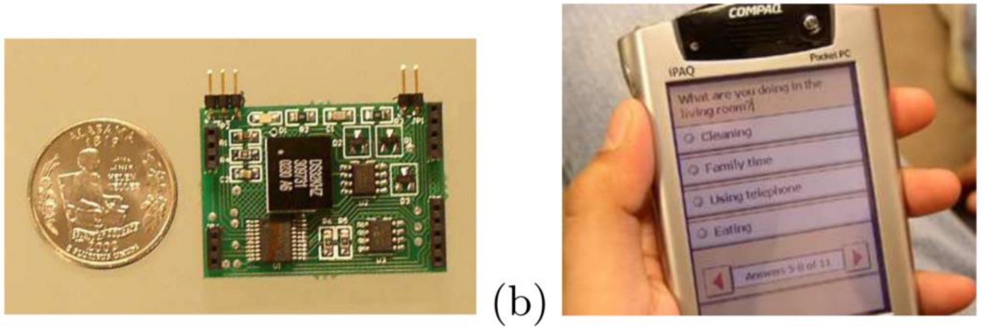


Fig. 1. (a) The state-change sensors that can be installed ubiquitously throughout an environment. Each device consists of a data collection board (shown) and a small sensor. (b) One screenshot from the ESM tool used in this work to collect training data on activities in the home setting.

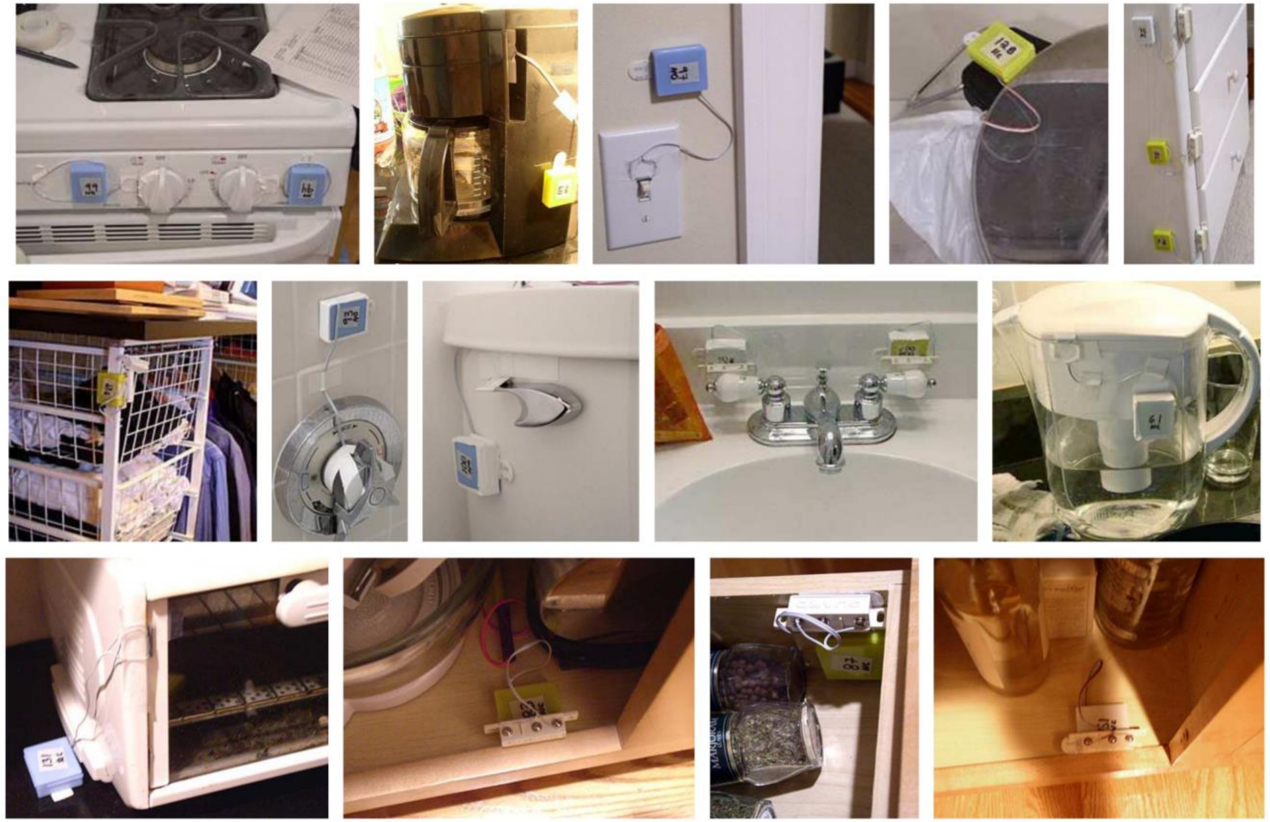
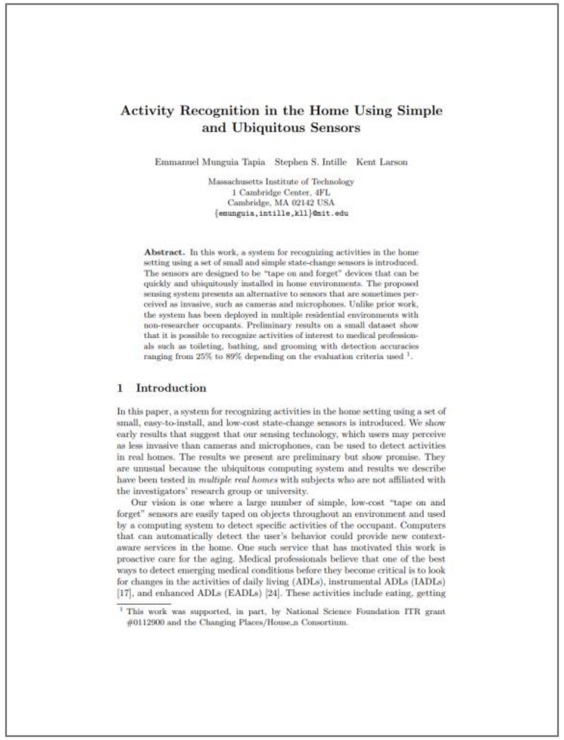


Fig. 2. Examples of some of the 77 sensors that were installed in the home of the first subject. The sensors and data collection boards were literally taped to objects and surfaces for the duration of the data collection period.

Source: Tapia *et al.*, Pervasive '04

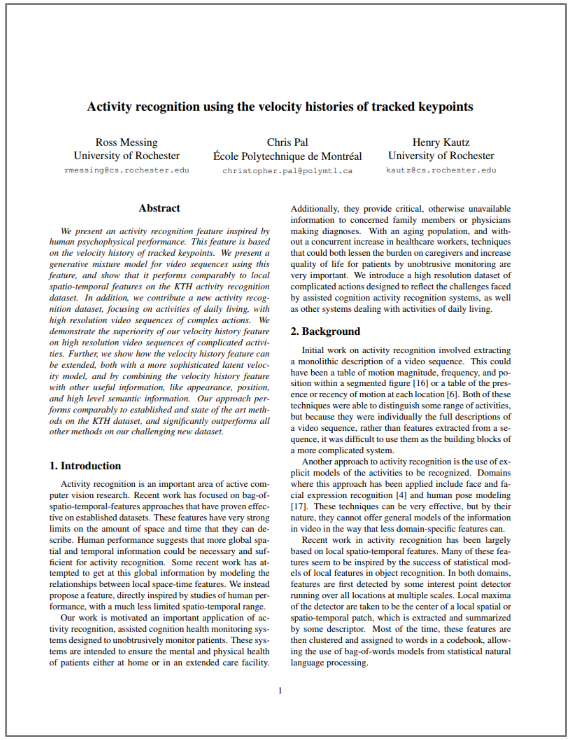
ACTIVITY RECOGNITION VIA INSTRUMENTED SPACES



Activity Recognition in the Home Using Simple and Ubiquitous Sensors

Emmanuel Munguia Tapia Stephen S. Intille Kent Larson

Activity Recognition in the Home Using Simple and Ubiquitous Sensors
Tapia *et al.*, Pervasive'04
1,406 citations



Activity recognition using the velocity histories of tracked keypoints

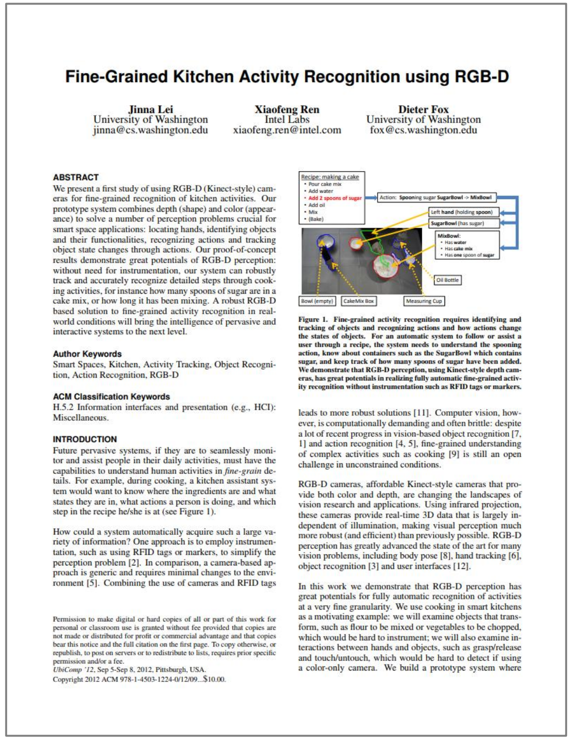
Ross Messing, University of Rochester; Chris Pal, École Polytechnique de Montréal; Henry Kautz, University of Rochester

Activity Recognition Using the Velocity Histories of Tracked Keypoints
Messing *et al.*, ICCV'09
461 citations

At the Flick of a Switch: Detecting and Classifying Unique Electrical Events on the Residential Power Line (Nominated for the Best Paper Award)

Shwetak N. Patel, Thomas Robertson, Julie A. Kientz, Matthew S. Reynolds, and Gregory D. Abowd

Detecting and Classifying Unique Electrical Events on the Residential Power Line
Patel *et al.*, UbiComp'07
450 citations

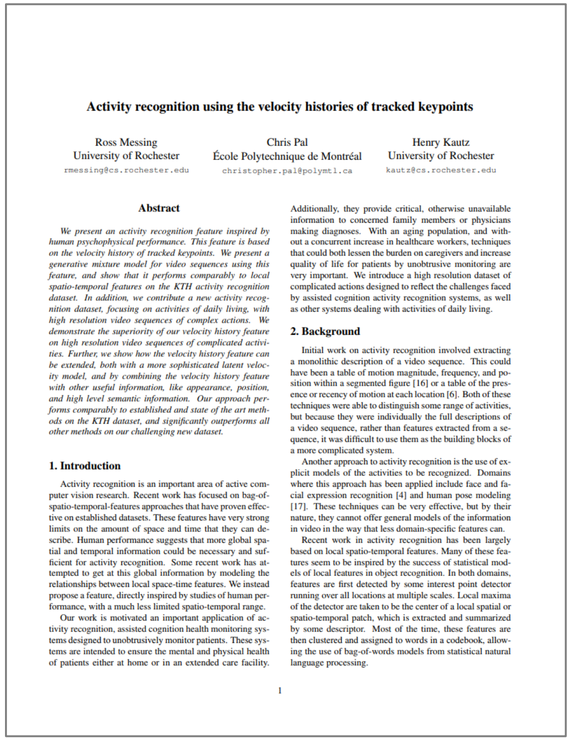


Fine-Grained Kitchen Activity Recognition using RGB-D

Jinna Lei, University of Washington; Xiaofeng Ren, Intel Labs; Dieter Fox, University of Washington

Fine-Grained Kitchen Activity Recognition using RGB-D
Lei *et al.*, UbiComp'12
99 citations

ACTIVITY RECOGNITION VIA INSTRUMENTED SPACES


Activity recognition using the velocity histories of tracked keypoints

Ross Messing, University of Rochester, rmessing@cs.rochester.edu
Chris Pal, École Polytechnique de Montréal, christopher.pal@polymtl.ca
Henry Kautz, University of Rochester, kautz@cs.rochester.edu

Abstract

1. Introduction

2. Background

Activity Recognition Using the Velocity Histories of Tracked Keypoints
Messing *et al.*, ICCV'09
461 citations


At the Flick of a Switch: Detecting and Classifying Unique Electrical Events on the Residential Power Line (Nominated for the Best Paper Award)

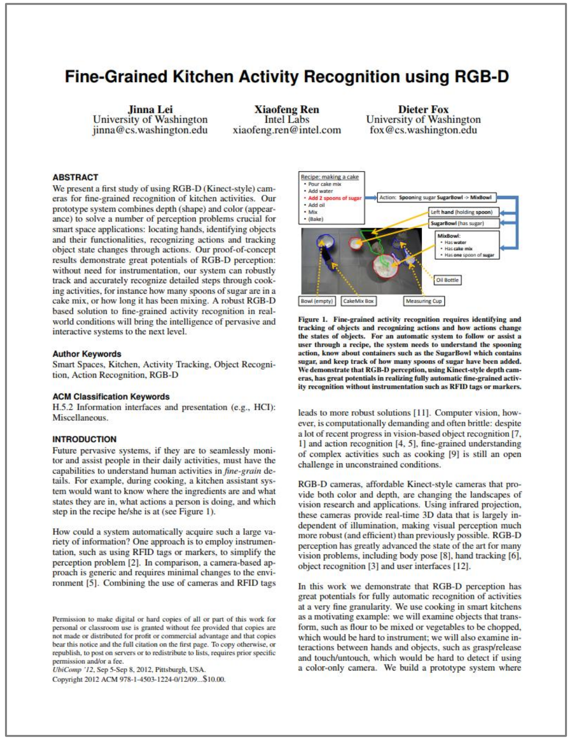
Shwetak N. Patel, Thomas Robertson, Julie A. Kientz, Matthew S. Reynolds, and Gregory D. Abowd

College of Computing, School of Interactive Computing, & GVU Center, Georgia Institute of Technology

1 Introduction and Motivation

J. Krumm et al. (Eds.): UbiComp 2007, LNCS 4717, pp. 271–288, 2007.
© Springer-Verlag Berlin Heidelberg 2007

Detecting and Classifying Unique Electrical Events on the Residential Power Line
Patel *et al.*, UbiComp'07
450 citations


Fine-Grained Kitchen Activity Recognition using RGB-D

Jinna Lei, University of Washington, jinna@cs.washington.edu
Xiaofeng Ren, Intel Labs, xiaofeng.ren@intel.com
Dieter Fox, University of Washington, fox@cs.washington.edu

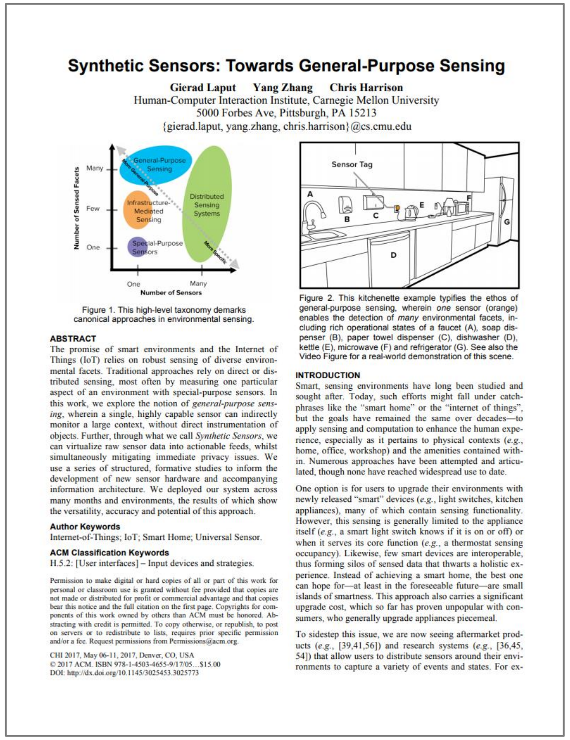
ABSTRACT

Author Keywords

ACM Classification Keywords

INTRODUCTION

Fine-Grained Kitchen Activity Recognition using RGB-D
Lei *et al.*, UbiComp'12
99 citations


Synthetic Sensors: Towards General-Purpose Sensing

Gierad Laput, Yang Zhang, Chris Harrison
Human-Computer Interaction Institute, Carnegie Mellon University
5000 Forbes Ave, Pittsburgh, PA 15213

ABSTRACT

Author Keywords

ACM Classification Keywords

INTRODUCTION

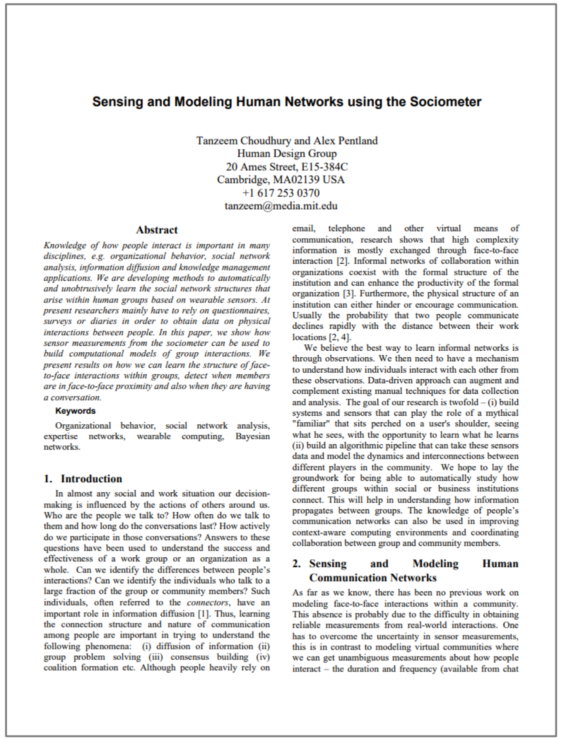
Synthetic Sensors: Towards General-Purpose Sensing
Laput *et al.*, CHI'17
9 citations

LAPUT ET AL., CHI'17

SYNTHETIC SENSORS: TOWARDS GENERAL-PURPOSE SENSING

Source: http://www.gierad.com/projects/supersensor/

SOCIAL INTERACTION INFERENCE



Sensing and Modeling Human Networks using the Sociometer

Tanzeem Choudhury and Alex Pentland
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Cambridge, MA02139 USA
+1 617 253 0370
tanzeem@media.mit.edu

Abstract

Knowledge of how people interact is important in many disciplines, e.g. organizational behavior, social network analysis, information diffusion and knowledge management applications. We are developing methods to automatically and unobtrusively learn the social network structures that arise within human groups based on wearable sensors. At present researchers mainly have to rely on questionnaires, surveys or diaries in order to obtain data on physical interactions between people. In this paper, we show how sensor measurements from the sociometer can be used to build computational models of group interactions. We present results on how we can learn the structure of face-to-face interactions within groups, detect when members are in face-to-face proximity and also when they are having a conversation.

Keywords

Organizational behavior, social network analysis, expertise networks, wearable computing, Bayesian networks.

1. Introduction

In almost any social and work situation our decision-making is influenced by the actions of others around us. Who are the people we talk to? How often do we talk to them and how long do the conversations last? How actively do we participate in those conversations? Answers to these questions have been used to understand the success and effectiveness of a work group or an organization as a whole. Can we identify the differences between people's interactions? Can we identify the individuals who talk to a large fraction of the group or community members? Such individuals, often referred to the *connectors*, have an important role in information diffusion [1]. Thus, learning the connection structure and nature of communication among people are important in trying to understand the following phenomena: (i) diffusion of information (ii) group problem solving (iii) consensus building (iv) coalition formation etc. Although people heavily rely on email, telephone and other virtual means of communication, research shows that high complexity information is mostly exchanged through face-to-face interaction [2]. Informal networks of collaboration within organizations coexist with the formal structure of the institution and can enhance the productivity of the formal organization [3]. Furthermore, the physical structure of an institution can either hinder or encourage communication. Usually the probability that two people communicate declines rapidly with the distance between their work locations [2, 4].

We believe the best way to learn informal networks is through observations. We then need to have a mechanism to understand how individuals interact with each other from these observations. Data-driven approach can augment and complement existing manual techniques for data collection and analysis. The goal of our research is twofold – (i) build systems and sensors that can play the role of a mythical "familiar" that sits perched on a user's shoulder, seeing what he sees, with the opportunity to learn what he learns (ii) build an algorithmic pipeline that can take these sensors data and model the dynamics and interconnections between different players in the community. We hope to lay the groundwork for being able to automatically study how different groups within social or business institutions connect. This will help in understanding how information propagates between groups. The knowledge of people's communication networks can also be used in improving context-aware computing environments and coordinating collaboration between group and community members.

2. Sensing and Modeling Human Communication Networks

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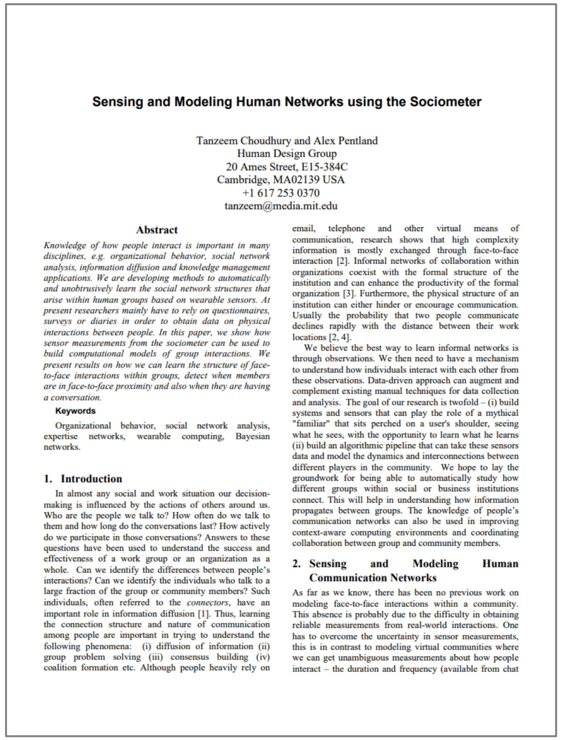
Sensing and Modeling Human Networks using the Sociometer

Choudury *et al.*, Wearable Comp'03

197 citations

SOCIAL INTERACTION INFERENCE



Sensing and Modeling Human Networks using the Sociometer

Tanzeem Choudhury and Alex Pentland
Human Design Group
20 Ames Street, E15-384C
Cambridge, MA02139 USA
+1 617 253 0370
tanzeem@media.mit.edu

Abstract

Knowledge of how people interact is important in many disciplines, e.g. organizational behavior, social network analysis, information diffusion and knowledge management applications. We are developing methods to automatically and unobtrusively learn the social network structures that arise within human groups based on wearable sensors. At present researchers mainly have to rely on questionnaires, surveys or diaries in order to obtain data on physical interactions between people. In this paper, we show how sensor measurements from the sociometer can be used to build computational models of group interactions. We present results on how we can learn the structure of face-to-face interactions within groups, detect when members are in face-to-face proximity and also when they are having a conversation.

Keywords

Organizational behavior, social network analysis, expertise networks, wearable computing, Bayesian networks.

1. Introduction

In almost any social and work situation our decision-making is influenced by the actions of others around us. Who are the people we talk to? How often do we talk to them and how long do the conversations last? How actively do we participate in those conversations? Answers to these questions have been used to understand the success and effectiveness of a work group or an organization as a whole. Can we identify the differences between people's interactions? Can we identify the individuals who talk to a large fraction of the group or community members? Such individuals, often referred to the *connectors*, have an important role in information diffusion [1]. Thus, learning the connection structure and nature of communication among people are important in trying to understand the following phenomena: (i) diffusion of information (ii) group problem solving (iii) consensus building (iv) coalition formation etc. Although people heavily rely on email, telephone and other virtual means of communication, research shows that high complexity information is mostly exchanged through face-to-face interaction [2]. Informal networks of collaboration within organizations coexist with the formal structure of the institution and can enhance the productivity of the formal organization [3]. Furthermore, the physical structure of an institution can either hinder or encourage communication. Usually the probability that two people communicate declines rapidly with the distance between their work locations [2, 4].

We believe the best way to learn informal networks is through observations. We then need to have a mechanism to understand how individuals interact with each other from these observations. Data-driven approach can augment and complement existing manual techniques for data collection and analysis. The goal of our research is twofold – (i) build systems and sensors that can play the role of a mythical "familiar" that sits perched on a user's shoulder, seeing what he sees, with the opportunity to learn what he learns (ii) build an algorithmic pipeline that can take these sensors data and model the dynamics and interconnections between different players in the community. We hope to lay the groundwork for being able to automatically study how different groups within social or business institutions connect. This will help in understanding how information propagates between groups. The knowledge of people's communication networks can also be used in improving context-aware computing environments and coordinating collaboration between group and community members.

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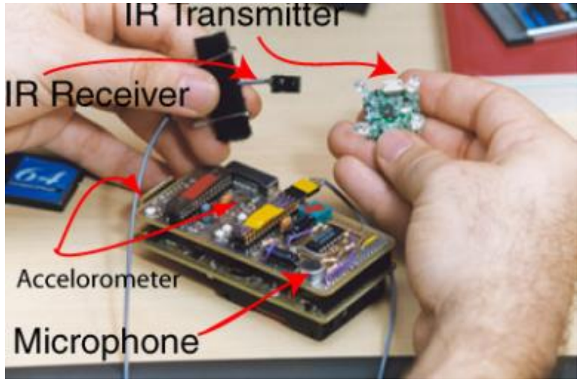
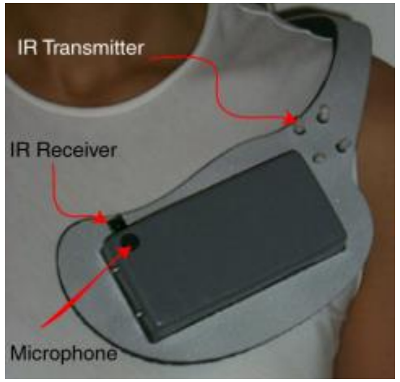
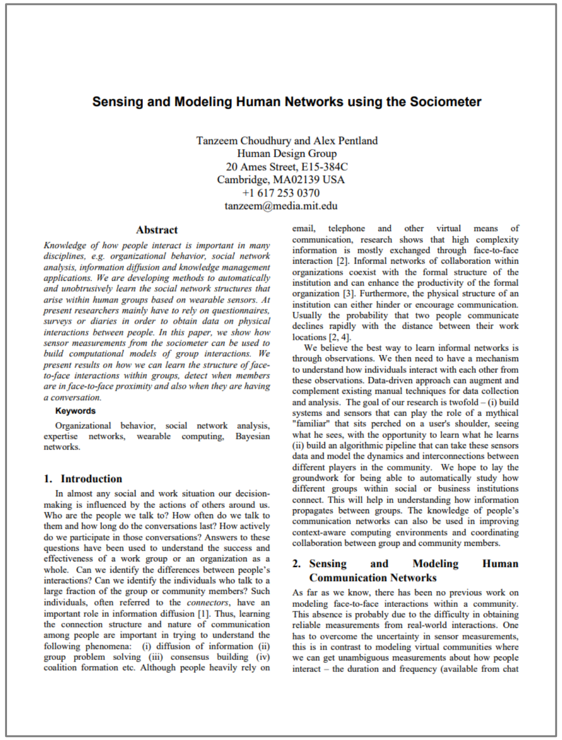




Custom wearable measured information about people nearby using IR, motion information using accel, & speech info using mic.

Physical social interaction data for a single participant.

SOCIAL INTERACTION INFERENCE



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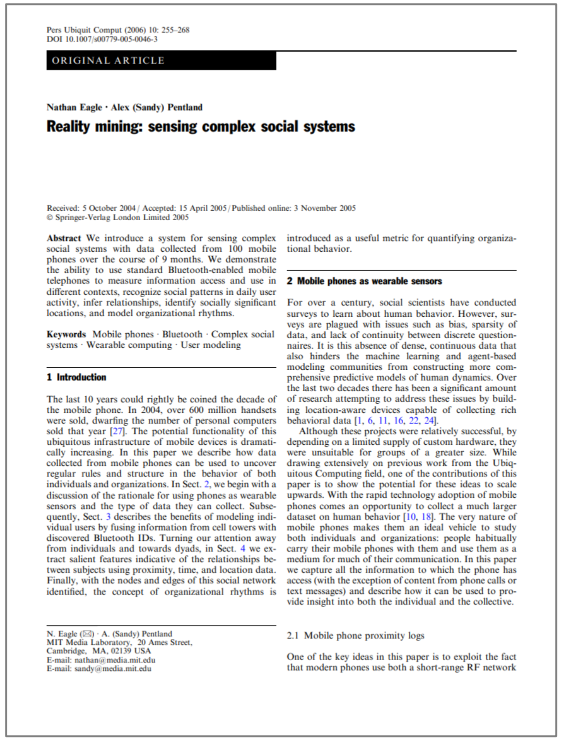

Pers Ubiquit Comput (2006) 10: 255–268
DOI 10.1007/s00779-005-0046-3

ORIGINAL ARTICLE

Nathan Eagle · Alex (Sandy) Pentland

Reality mining: sensing complex social systems

Received: 5 October 2004 / Accepted: 15 April 2005 / Published online: 3 November 2005
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Abstract We introduce a system for sensing complex social systems with data collected from 100 mobile phones over the course of 9 months. We demonstrate the ability to use standard Bluetooth-enabled mobile telephones to measure information access and use in different contexts, recognize social patterns in daily user activity, infer relationships, identify socially significant locations, and model organizational rhythms.

Keywords Mobile phones · Bluetooth · Complex social systems · Wearable computing · User modeling

1 Introduction

The last 10 years could rightly be coined the decade of the mobile phone. In 2004, over 600 million handsets were sold, dwarfing the number of personal computers sold that year [27]. The potential functionality of this ubiquitous infrastructure of mobile devices is dramatically increasing. In this paper we describe how data collected from mobile phones can be used to uncover regular rules and structure in the behavior of both individuals and organizations. In Sect. 2, we begin with a discussion of the rationale for using phones as wearable sensors and the type of data they can collect. Subsequently, Sect. 3 describes the benefits of modeling individual users by fusing information from cell towers with discovered Bluetooth IDs. Turning our attention away from individuals and towards dyads, in Sect. 4 we extract salient features indicative of the relationships between subjects using proximity, time, and location data. Finally, with the nodes and edges of this social network identified, the concept of organizational rhythms is introduced as a useful metric for quantifying organizational behavior.

N. Eagle (✉) · A. (Sandy) Pentland
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2 Mobile phones as wearable sensors

For over a century, social scientists have conducted surveys to learn about human behavior. However, surveys are plagued with issues such as bias, sparsity of data, and lack of continuity between discrete questionnaires. It is this absence of dense, continuous data that also hinders the machine learning and agent-based modeling communities from constructing more comprehensive predictive models of human dynamics. Over the last two decades there has been a significant amount of research attempting to address these issues by building location-aware devices capable of collecting rich behavioral data [1, 6, 11, 16, 22, 24].

Although these projects were relatively successful, by depending on a limited supply of custom hardware, they were unsuitable for groups of a greater size. While drawing extensively on previous work from the Ubiquitous Computing field, one of the contributions of this paper is to show the potential for these ideas to scale upwards. With the rapid technology adoption of mobile phones comes an opportunity to collect a much larger dataset on human behavior [10, 18]. The very nature of mobile phones makes them an ideal vehicle to study both individuals and organizations: people habitually carry their mobile phones with them and use them as a medium for much of their communication. In this paper we capture all the information to which the phone has access (with the exception of content from phone calls or text messages) and describe how it can be used to provide insight into both the individual and the collective.

2.1 Mobile phone proximity logs

One of the key ideas in this paper is to exploit the fact that modern phones use both a short-range RF network

Reality Mining: Sensing Complex Social Systems
Eagle & Pentland, Pers & UbiComp'06
2,644 citations

SOCIAL INTERACTION INFERENCE: “REALITY MINING”

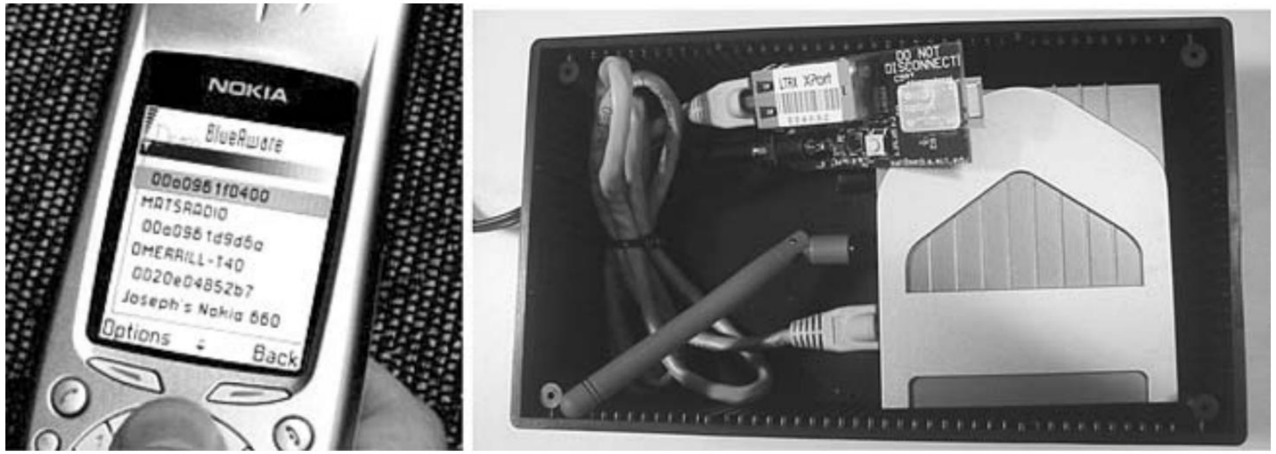

Fig. 1 Methods of detecting Bluetooth devices—BlueAware and Bluedar. BlueAware (*left*) is running in the foreground on a Nokia 3650. BlueAware is an application that runs on Symbian Series 60 phones. It runs in the background and performs repeated Bluetooth scans of the environment every 5 min. Bluedar (*right*) is comprised of a Bluetooth beacon coupled with a WiFi bridge. It also performs cyclic Bluetooth scans and sends the resulting BTIDs over the 802.11b network to the Reality Mining server

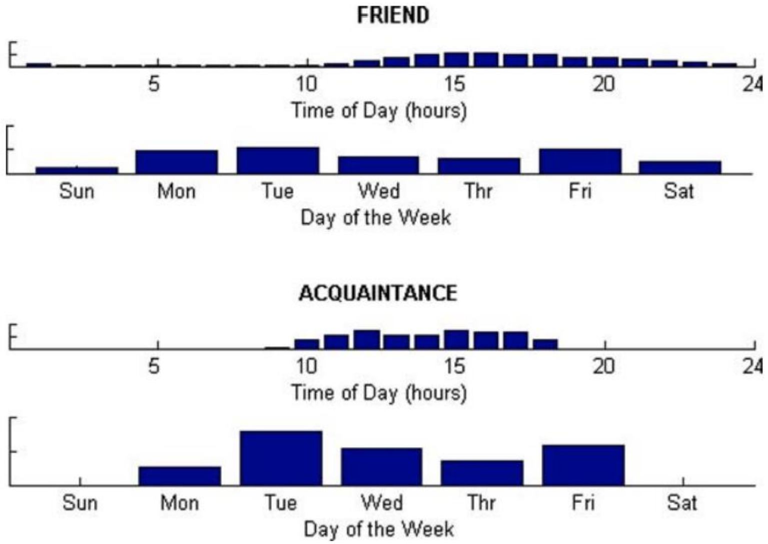

Fig. 12 Proximity frequency data for a friend and a workplace acquaintance. The top two plots are the times (time of day and day of the week, respectively) when this particular subject encounters another subject he has labeled as a “friend.” Similarly, the subsequent two plots show the same information for another individual the subject has labeled as “office acquaintance.” It is clear that while the office acquaintance is encountered more often, the distribution is constrained to weekdays during typical working hours. In contrast, the subject encounters his friend during the workday, but also in the evening and on weekends

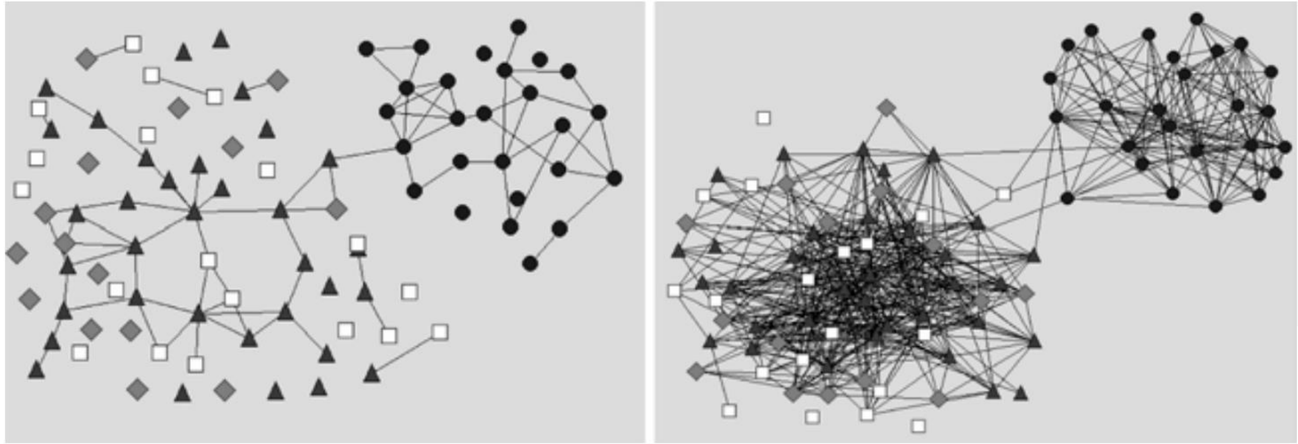

Fig. 11 Friendship (*left*) and daily proximity (*right*) networks. *Circles* represent incoming Sloan business school students. *Triangles*, *diamonds* and *squares* represent senior students, incoming students, and faculty/staff/freshman at the Media Lab. While the two networks share similar structure, inferring friendship from proximity requires the additional information about the context (location and time) of the proximity

UBICOMP INFERENCE SYSTEMS

SOCIAL INTERACTION INFERENCE

Sensing and Modeling Human Networks using the Sociometer
Choudury *et al.*, Wearable Comp'03
197 citations

Reality Mining: Sensing Complex Social Systems
Eagle & Pentland, Pers & UbiComp'06
2,644 citations

Using the Influence Model to Recognize Functional Roles in Meetings
Dong *et al.*, ICMI'07
92 citations

Inferring Friendship Network Structure By Using Mobile Phone Data
Eagle *et al.*, PNSA'09
1,756 citations

UBICOMP INFERENCE SYSTEMS

EMOTION INFERENCE

Affective Computing
Rosalind Picard, Book '97
7,596 citations

How can emotions be generated in computers, be recognized by computers, and be expressed by computers?

Rosalind Picard
Affective Computing Pioneer
MIT Professor

Source:: Picard, Affective Computing

UBICOMP INFERENCE SYSTEMS

EMOTION INFERENCE

Affective Computing
Rosalind Picard, Book '97
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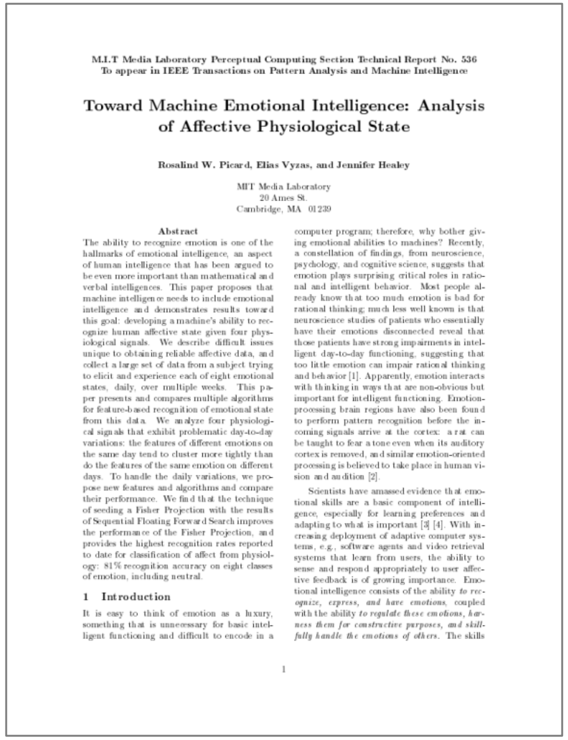
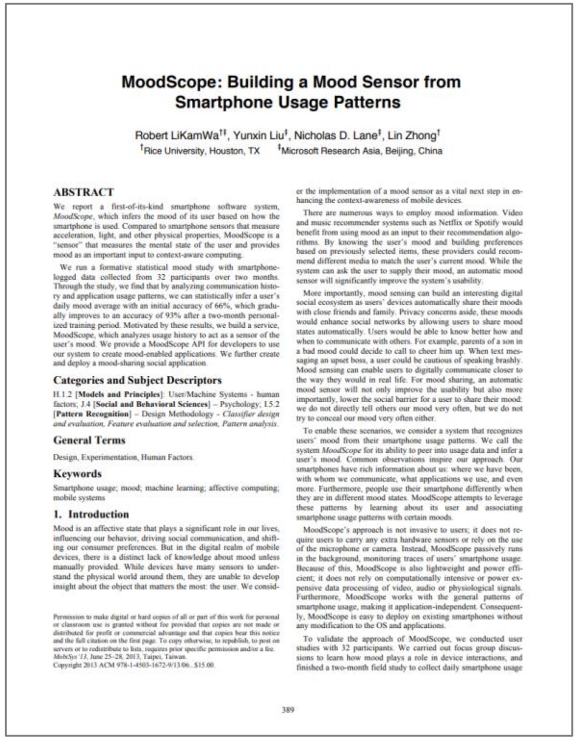
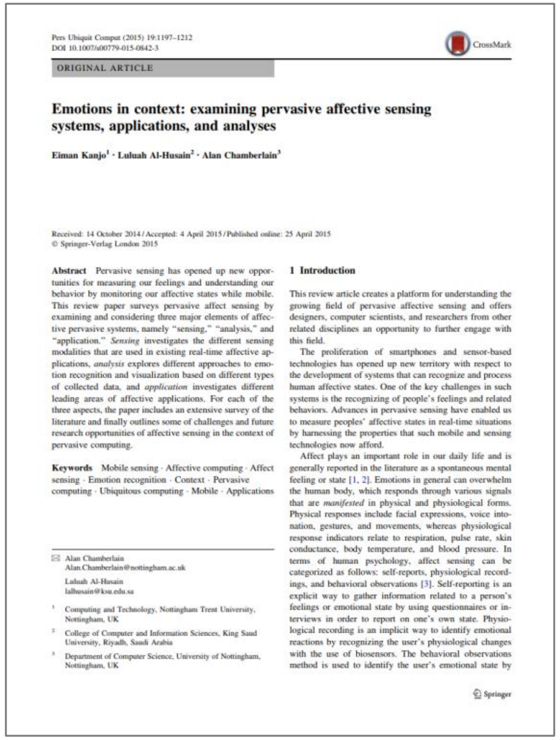


Toward Machine Emotional Intelligence: Analysis of Affective Physiological State
Picard *et al.*, IEEE Trans on PAMI
1,841 citations



Moodscope: Building a Mood Sensor from Smartphone Usage Patterns
LiKamWa *et al.*, MobiSys'13
250 citations



Emotions in Context: Examining Pervasive Affective Sensing Systems, Applications, & Analyses
Kanjo *et al.*, Pers & UbiComp'15
36 citations

UbiComp Application Areas

CORE APPLICATION AREAS

Health & Fitness

Health Diagnostics

Environmental Sustainability

Elder Care (aka Aging in Place)

Accessibility

…

UBICOMP APPLICATION AREAS

WHAT COMES FIRST?

THE APPLICATIONS

THE SENSING & INFERENCE SYSTEMS

WHAT COMES FIRST?

THE APPLICATIONS

THE SENSING & INFERENCE SYSTEMS

Sort of a trick question…

They are very interwoven. Sometimes applications drive sensing + inference systems. Other times, new sensing + inference systems drive new applications. Use HCI/UX methods to explore future…

UBICOMP APPLICATION AREAS

HEALTH & FITNESS

Fish'n'Steps: Encouraging Physical Activity with an Interactive Computer Game

James J. Lin, Lena Mamykina, Silvia Lindtner, Gregory Delajoux, and Henry B. Strub

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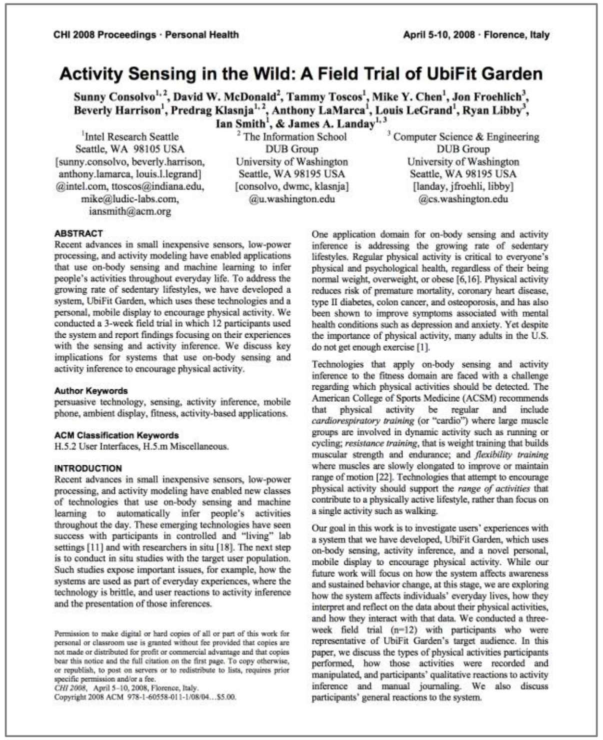
Abstract. A sedentary lifestyle is a contributing factor to chronic diseases, and it is often correlated with obesity. To promote an increase in physical activity, we created a social computer game, Fish'n'Steps, which links a player's daily foot step count to the growth and activity of an animated virtual character, a fish in a fish tank. As further encouragement, some of the players' fish tanks included other players' fish, thereby creating an environment of both cooperation and competition. In a fourteen-week study with nineteen participants, the game served as a catalyst for promoting exercise and for improving game players' attitudes towards physical activity. Furthermore, although most player's enthusiasm in the game decreased after the game's first two weeks, analyzing the results using Prochaska's Transtheoretical Model of Behavioral Change suggests that individuals had, by that time, established new routines that led to healthier patterns of physical activity in their daily lives. Lessons learned from this study underscore the value of such games to encourage rather than provide negative reinforcement, especially when individuals are not meeting their own expectations, to foster long-term behavioral change.

1 Introduction

In recent decades, obesity has become a problem on the scale of a world-wide epidemic. The 1999 National Health and Nutrition survey (NHANES) estimated that 61% of US adults are either overweight or obese. These people suffer from both deleterious health consequences and the corresponding psychological stigma [1] . Epidemiologic studies have identified several environmental factors that contribute to this continual gain of weight over recent decades. Lifestyles have become increasingly *sedentary* (e.g. less physical activity, commonly combined with more time spent watching television) and *energy-dense foods* (high-fat, concentrated-sugar, low-fiber) have become the common components of individuals' diets [2] .

The most effective approaches to treating people for being overweight or obese are similar to those for other chronic diseases. They begin with lifestyle improvements, and continue to more invasive treatments such as pharmaceuticals and even surgery.

P. Dourish and A. Friday (Eds.): Ubicomp 2006, LNCS 4206, pp. 261–278, 2006.



Activity Sensing in the Wild: A Field Trial of UbiFit Garden

Sunny Consolvo[1,2], David W. McDonald[2], Tammy Toscos[1], Mike Y. Chen[1], Jon Froehlich[3], Beverly Harrison[1], Predrag Klasnja[1,2], Anthony LaMarca[1], Louis LeGrand[1], Ryan Libby[3], Ian Smith[1], & James A. Landay[1,3]

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[2] The Information School, DUB Group, University of Washington, Seattle, WA 98195 USA, [consolvo, dwmc, klasnja]@u.washington.edu

[3] Computer Science & Engineering, DUB Group, University of Washington, Seattle, WA 98195 USA, [landay, jfroehli, libby]@cs.washington.edu

ABSTRACT

Recent advances in small inexpensive sensors, low-power processing, and activity modeling have enabled applications that use on-body sensing and machine learning to infer people's activities throughout everyday life. To address the growing rate of sedentary lifestyles, we have developed a system, UbiFit Garden, which uses these technologies and a personal, mobile display to encourage physical activity. We conducted a 3-week field trial in which 12 participants used the system and report findings focusing on their experiences with the sensing and activity inference. We discuss key implications for systems that use on-body sensing and activity inference to encourage physical activity.

Author Keywords

persuasive technology, sensing, activity inference, mobile phone, ambient display, fitness, activity-based applications.

ACM Classification Keywords

H.5.2 User Interfaces, H.5.m Miscellaneous.

INTRODUCTION

Recent advances in small inexpensive sensors, low-power processing, and activity modeling have enabled new classes of technologies that use on-body sensing and machine learning to automatically infer people's activities throughout the day. These emerging technologies have seen success with participants in controlled and "living" lab settings [11] and with researchers in situ [18]. The next step is to conduct in situ studies with the target user population. Such studies expose important issues, for example, how the systems are used as part of everyday experiences, where the technology is brittle, and user reactions to activity inference and the presentation of those inferences.

One application domain for on-body sensing and activity inference is addressing the growing rate of sedentary lifestyles. Regular physical activity is critical to everyone's physical and psychological health, regardless of their being normal weight, overweight, or obese [6,16]. Physical activity reduces risk of premature mortality, coronary heart disease, type II diabetes, colon cancer, and osteoporosis, and has also been shown to improve symptoms associated with mental health conditions such as depression and anxiety. Yet despite the importance of physical activity, many adults in the U.S. do not get enough exercise [1].

Technologies that apply on-body sensing and activity inference to the fitness domain are faced with a challenge regarding which physical activities should be detected. The American College of Sports Medicine (ACSM) recommends that physical activity be regular and include *cardiorespiratory training* (or "cardio") where large muscle groups are involved in dynamic activity such as running or cycling; *resistance training*, that is weight training that builds muscular strength and endurance; and *flexibility training* where muscles are slowly elongated to improve or maintain range of motion [22]. Technologies that attempt to encourage physical activity should support the *range of activities* that contribute to a physically active lifestyle, rather than focus on a single activity such as walking.

Our goal in this work is to investigate users' experiences with a system that we have developed, UbiFit Garden, which uses on-body sensing, activity inference, and a novel personal, mobile display to encourage physical activity. While our future work will focus on how the system affects awareness and sustained behavior change, at this stage, we are exploring how the system affects individuals' everyday lives, how they interpret and reflect on the data about their physical activities, and how they interact with that data. We conducted a three-week field trial (n=12) with participants who were representative of UbiFit Garden's target audience. In this paper, we discuss the types of physical activities participants performed, how those activities were recorded and manipulated, and participants' qualitative reactions to activity inference and manual journaling. We also discuss participants' general reactions to the system.

Fish'n'Steps: Encouraging Physical Activity with an Interactive Computer Game
Lin *et al.*, UbiComp'06
724 citations

Activity Sensing in the Wild: A Field Trial of UbiFit Garden
Consolvo *et al.*, CHI'08
989 citations

UBICOMP APPLICATION AREAS

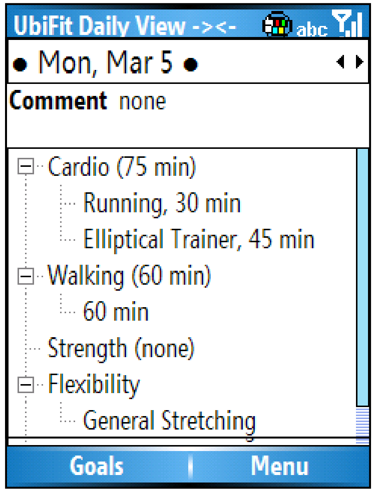
HEALTH & FITNESS: UBIFIT

collects data about physical activities

activity recognition device

+

interactive application



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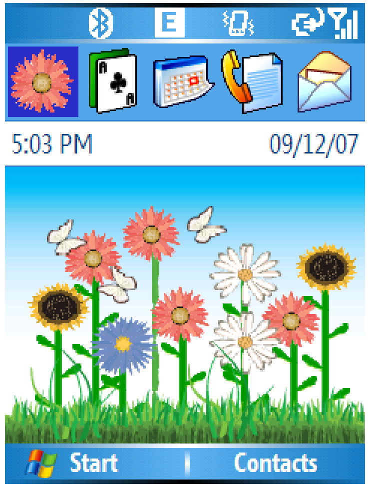
glanceable display



communicates data about physical activities

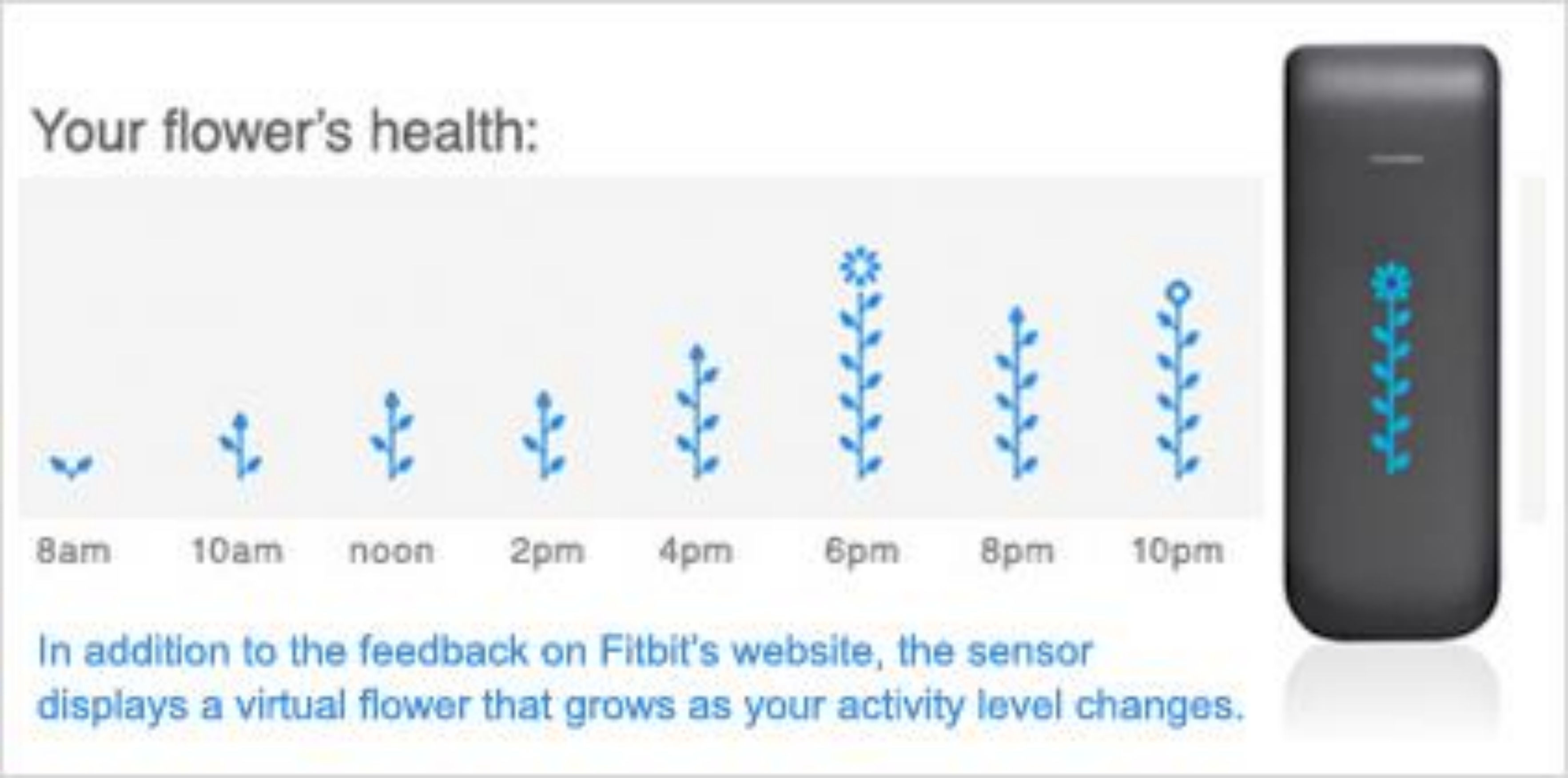
Source: Consolvo *et al.*, CHI'08

UBICOMP APPLICATION AREAS

HEALTH & FITNESS: UBIFIT

Source: Consolvo *et al.*, CHI'08

HEALTH & FITNESS: COMMERCIAL SYSTEMS



UBICOMP APPLICATION AREAS

HEALTH & FITNESS

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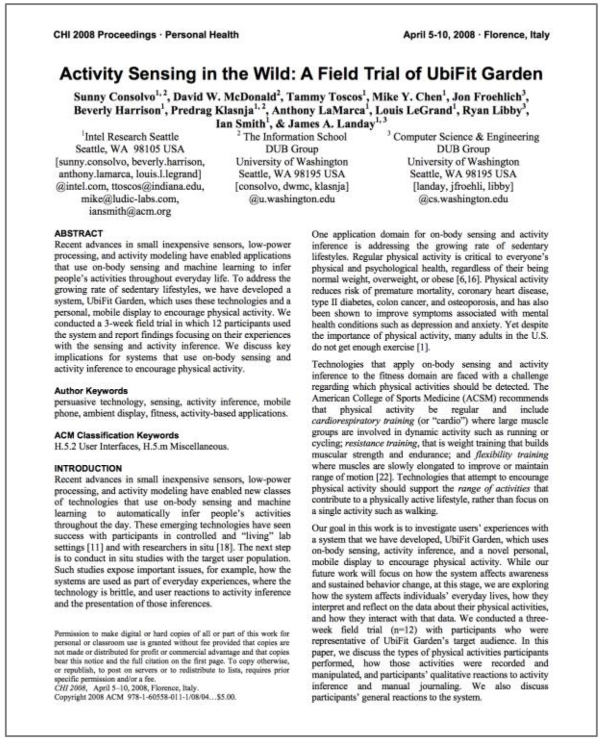

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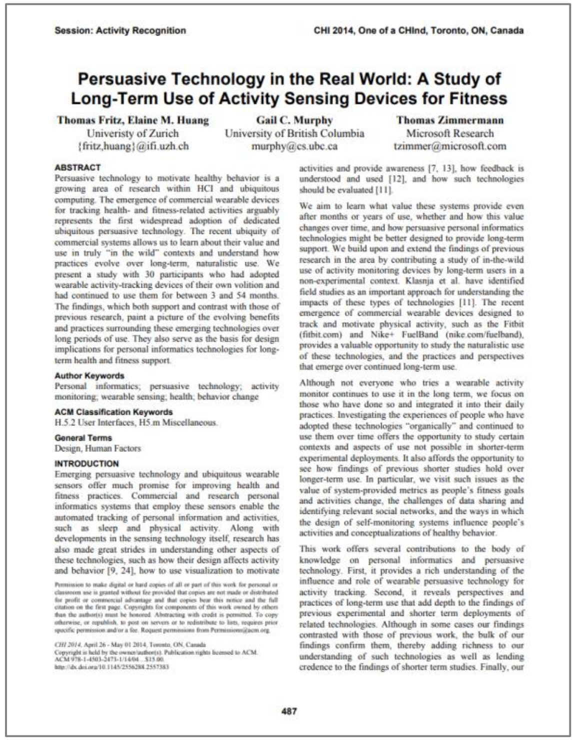
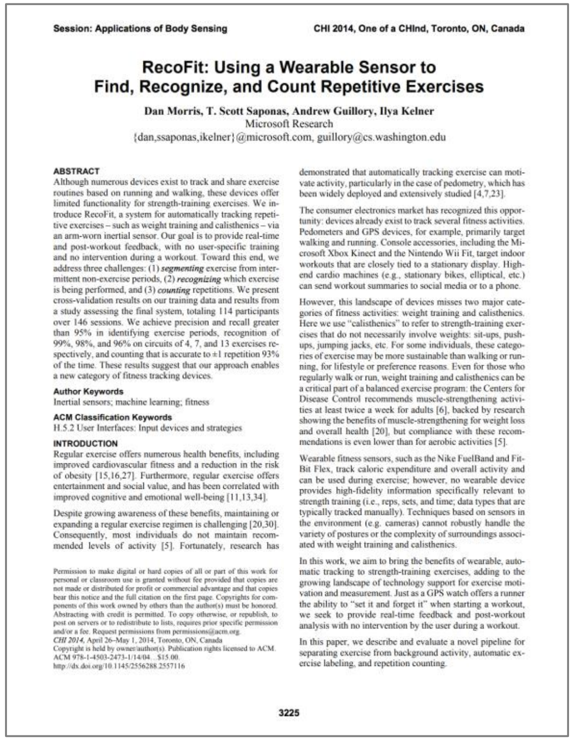


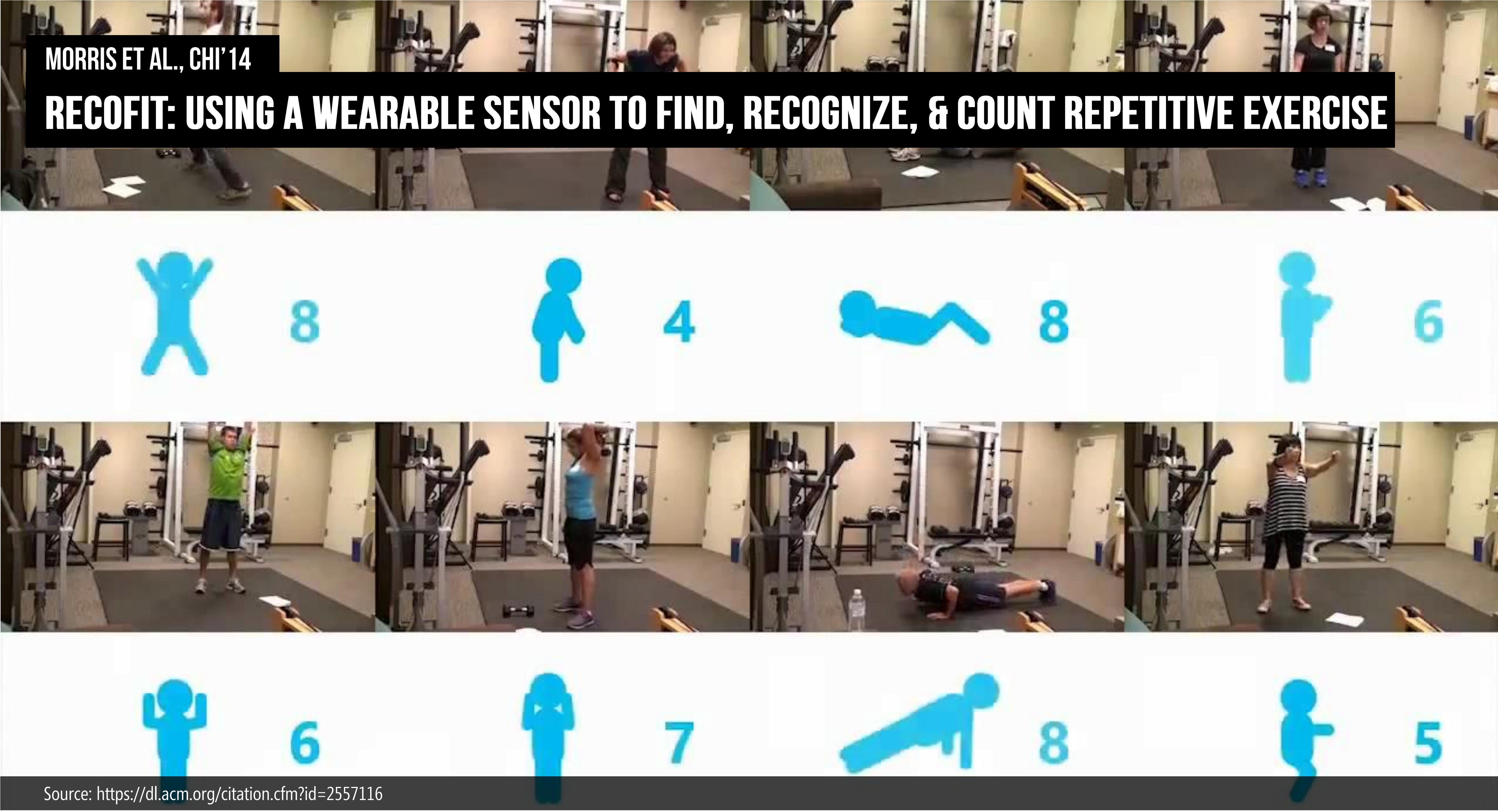
Persuasive Technology in the Real World: A Study of Long-Term Use of Activity Sensing Devices for Fitness
Fritz *et al.*, CHI'14
214 citations



RecoFit: Using a Wearable Sensor to Find, Recognize, & Count Repetitive Exercise
Morris *et al.*, CHI'14
69 citations

MORRIS ET AL., CHI'14

RECOFIT: USING A WEARABLE SENSOR TO FIND, RECOGNIZE, & COUNT REPETITIVE EXERCISE



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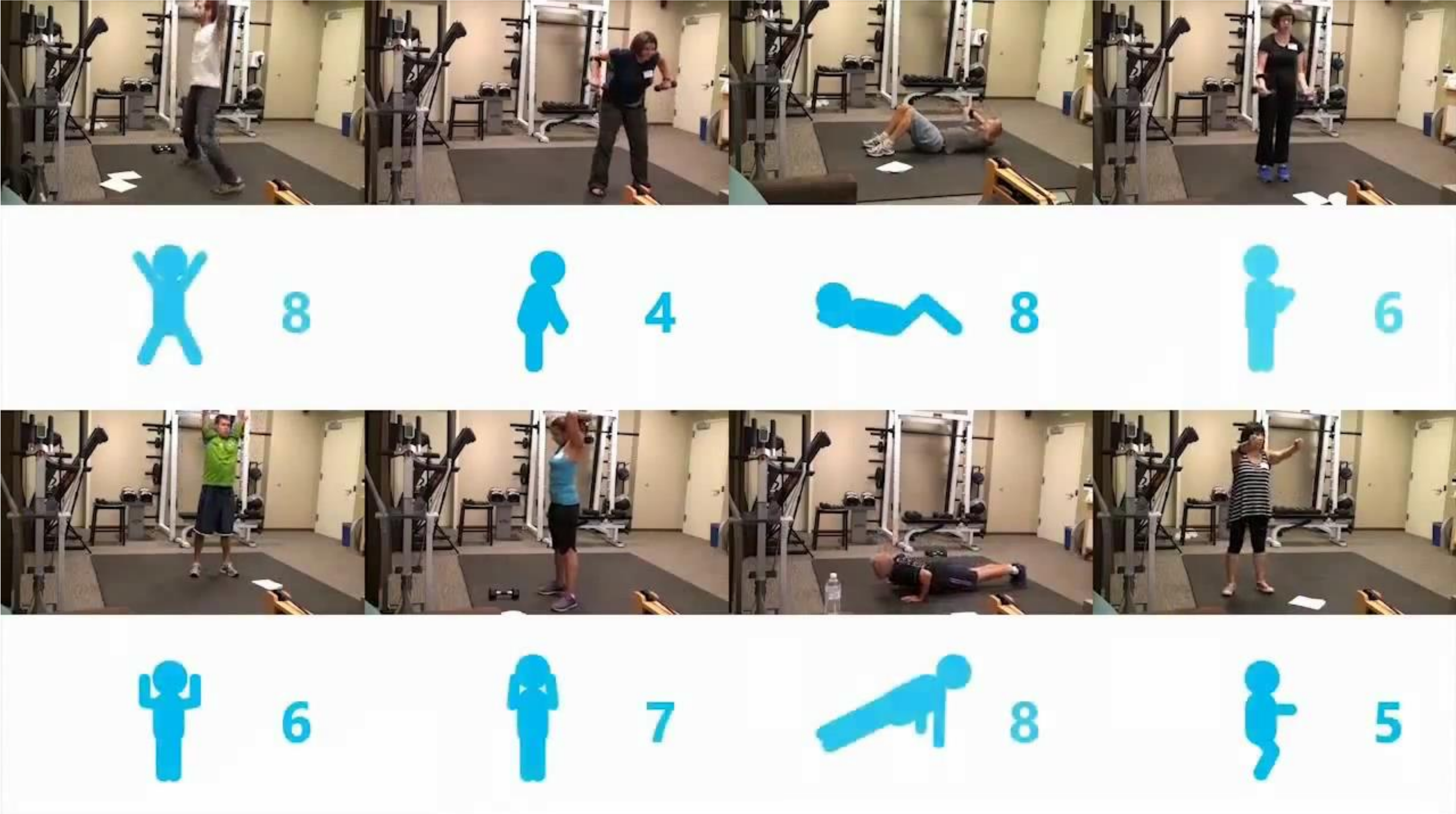
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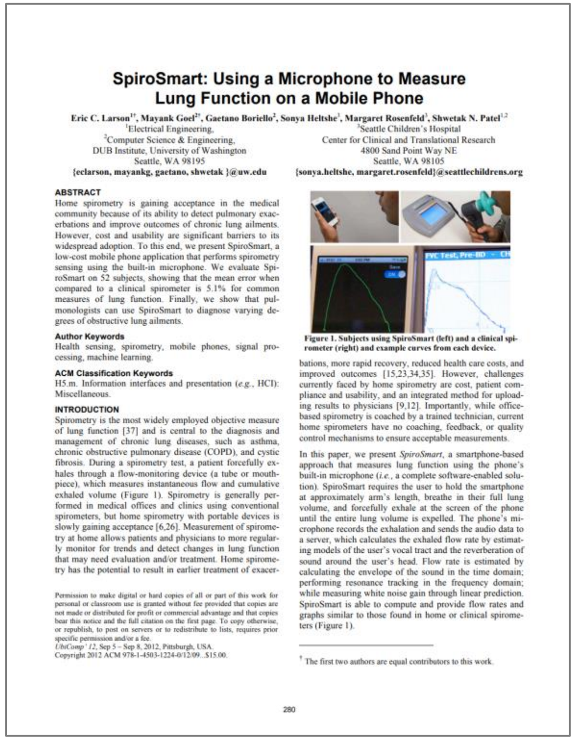
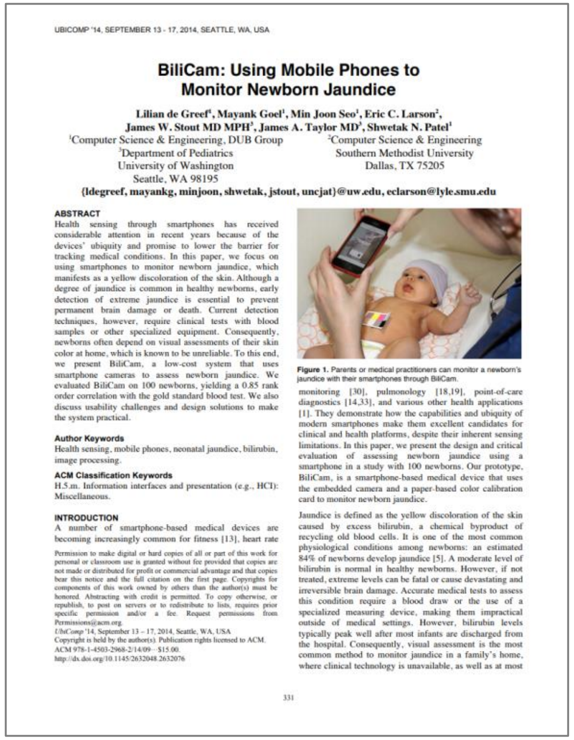
HEALTH MONITORING & DIAGNOSTICS



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

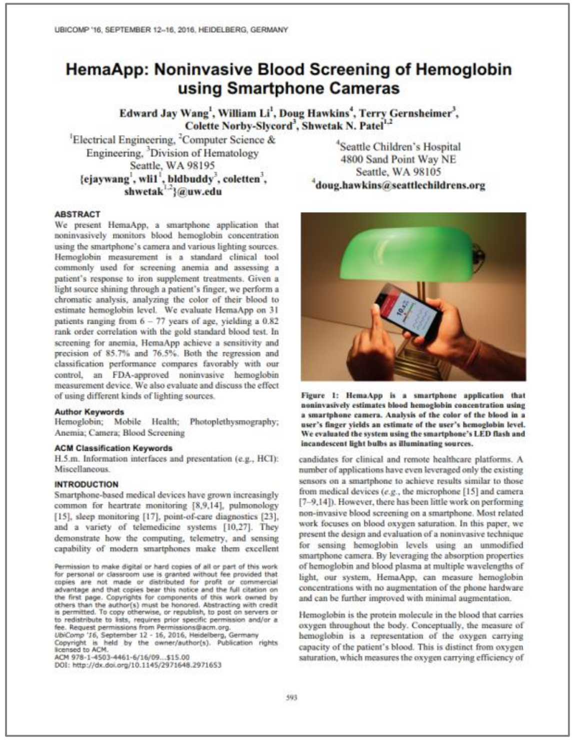
SpiroSmart: Using a Microphone to Measure Lung Function on a Mobile Phone
Larson *et al.*, UbiComp'12
87 citations



UBICOMP '14, SEPTEMBER 13 - 17, 2014, SEATTLE, WA, USA

BiliCam: Using Mobile Phones to Monitor Newborn Jaundice

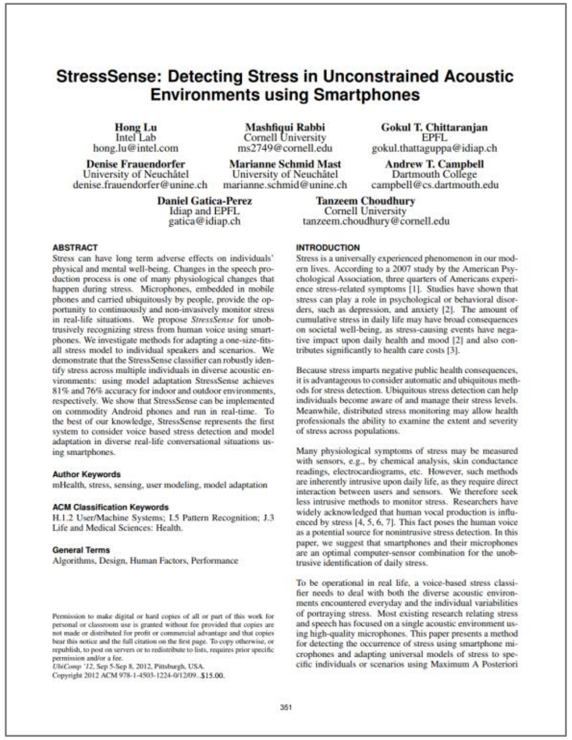
BiliCam: Using Mobile Phones to Monitor Newborn Jaundice
de Greef *et al.*, UbiComp'14
36 citations



UBICOMP '16, SEPTEMBER 12–16, 2016, HEIDELBERG, GERMANY

HemaApp: Noninvasive Blood Screening of Hemoglobin using Smartphone Cameras

HemaApp: Noninvasive Blood Screening of Hemoglobin using Smartphone Cameras
Wang *et al.*, UbiComp'16
12 citations

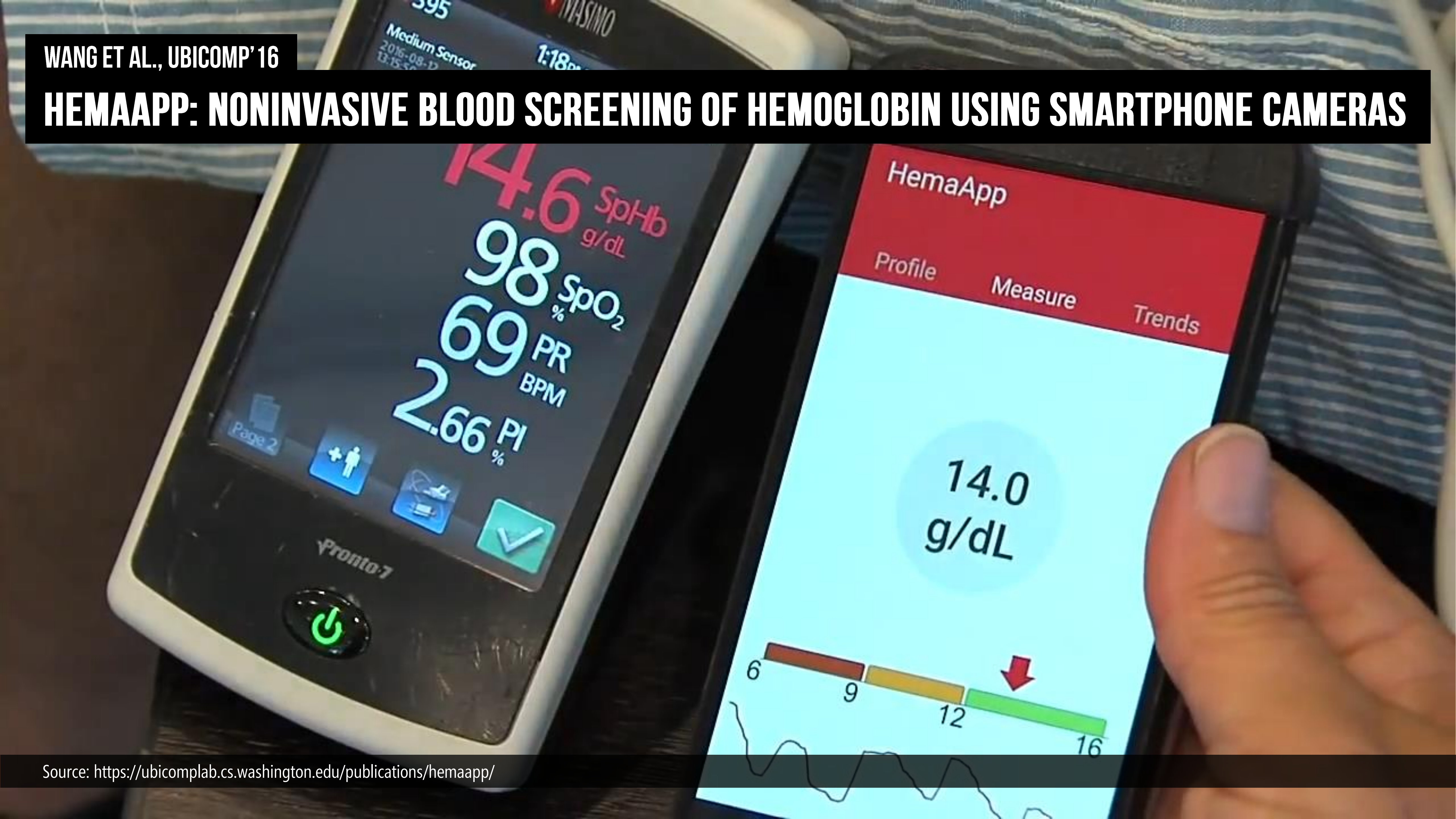


StressSense: Detecting Stress in Unconstrained Acoustic Environments using Smartphones

StressSense: Detecting Stress in Unconstrained Acoustic Environments using Smartphones
Wang *et al.*, UbiComp'16
12 citations

WANG ET AL., UBICOMP'16

HEMAAPP: NONINVASIVE BLOOD SCREENING OF HEMOGLOBIN USING SMARTPHONE CAMERAS



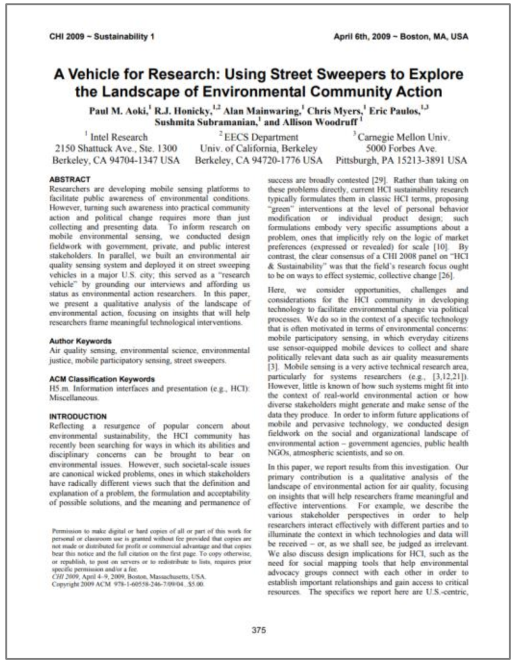
Source: https://ubicomplab.cs.washington.edu/publications/hemaapp/

Medium Sensor
2016-08-12
13:15:50
1:18PM
14.6 SpHb g/dL
98 SpO2 %
69 PR BPM
2.66 PI %
Page 2
Pronto-7
HemaApp
Profile
Measure
Trends
14.0
g/dL
6
9
12
16

ENVIRONMENTAL SUSTAINABILITY & POLLUTION

HydroSense, ElectriSense, GasSense
UbiComp'09, UbiComp'10, Pervasive'10
Shwetak Patel's UbiComp Lab

inAir: Measuring and Visualizing Indoor Air Quality
Kim & Paulos, UbiComp'09
53 citations



A Vehicle for Research: Using Street Sweepers to Explore the Landscape of Environmental Community Action
Aoki *et al.*, UbiComp'09
160 citations

Diagnosing New York City's Noises with Ubiquitous Data
Aoki *et al.*, UbiComp'14
111 citations

UBICOMP APPLICATION AREAS

ELDER CARE


CHI 2001 • 31 MARCH – 5 APRIL

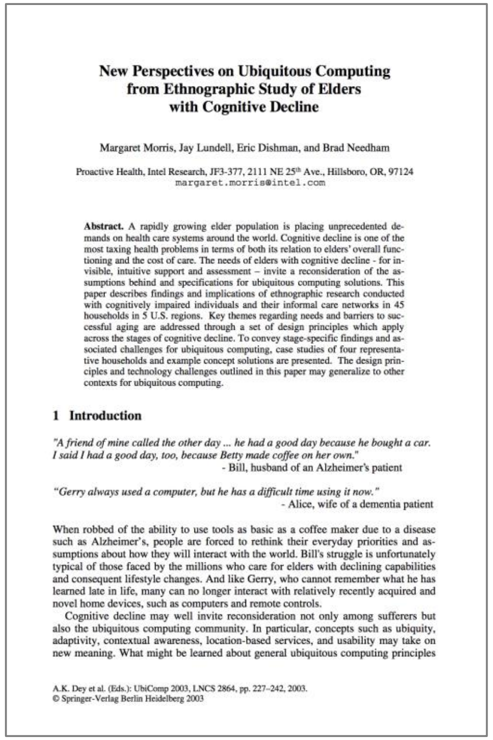
Digital Family Portraits: Supporting Peace of Mind for Extended Family Members

Elizabeth D. Mynatt, Jim Rowan, Annie Jacobs and Sarah Craighill

Digital Family Portraits: Supporting Peace of Mind for Extended Family Members

Mynatt *et al.*, CHI'01

708 citations


New Perspectives on Ubiquitous Computing from Ethnographic Study of Elders with Cognitive Decline

Margaret Morris, Jay Lundell, Eric Dishman, and Brad Needham

New Perspectives on Ubiquitous Computing from Ethnographic Study of Elders

Morris *et al.*, UbiComp'03

96 citations

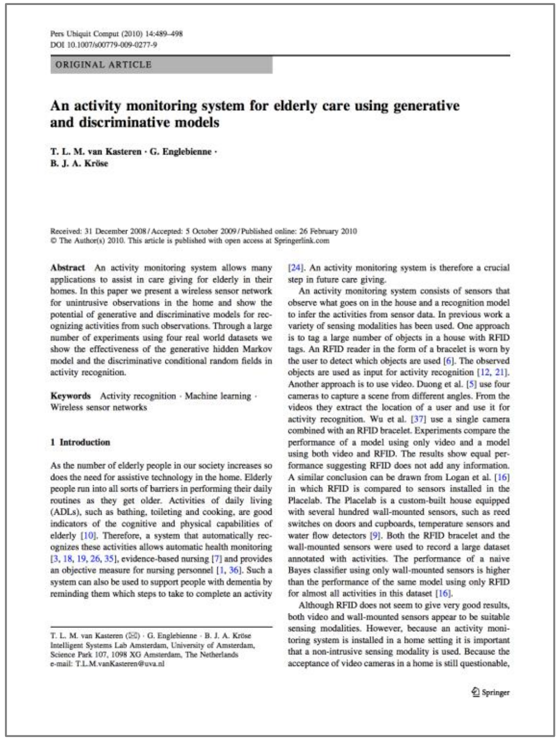

The CareNet Display: Lessons Learned from an In Home Evaluation of an Ambient Display

Sunny Consolvo, Peter Roessler, and Brett E. Shelton

The CareNet Display: Lessons Learned from an In-Home Evaluation of an Ambient Display

Consolvo *et al.*, UbiComp'04

274 citations


An activity monitoring system for elderly care using generative and discriminative models

T. L. M. van Kasteren · G. Englebienne · B. J. A. Kröse

An Activity Monitoring System for Elderly Care Using Generative and Discriminative Models

Van Kasteran *et al.*, Pers. & UbiComp'10

163 citations

ELDERCARE: THE CARENET DISPLAY

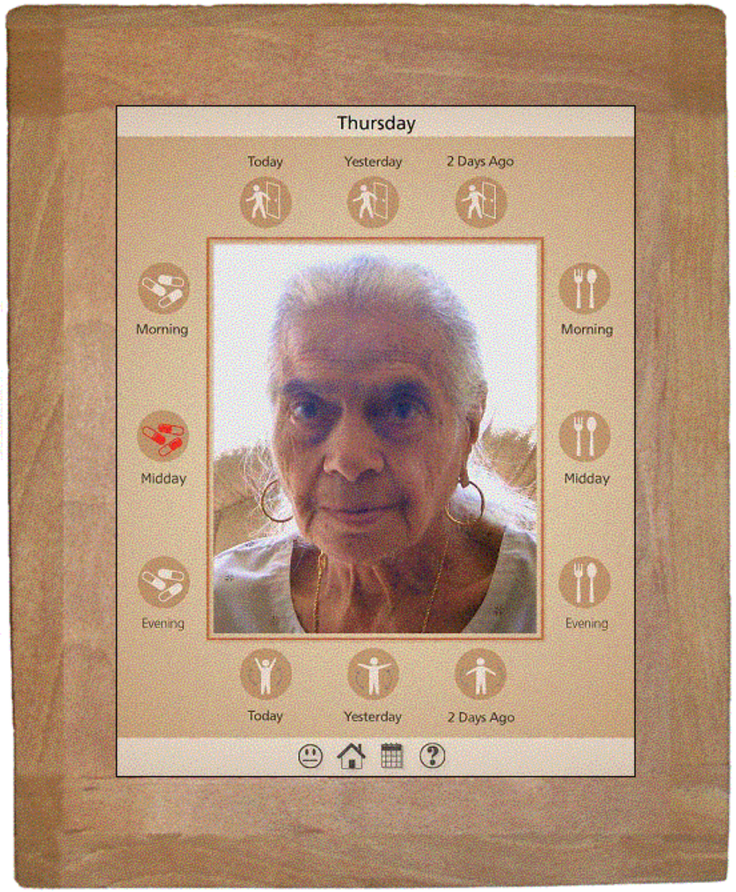


Figure 2. The CareNet Display prototype used in the deployments. The prototype uses a touch-screen tablet PC housed in a custom-built beech wood frame

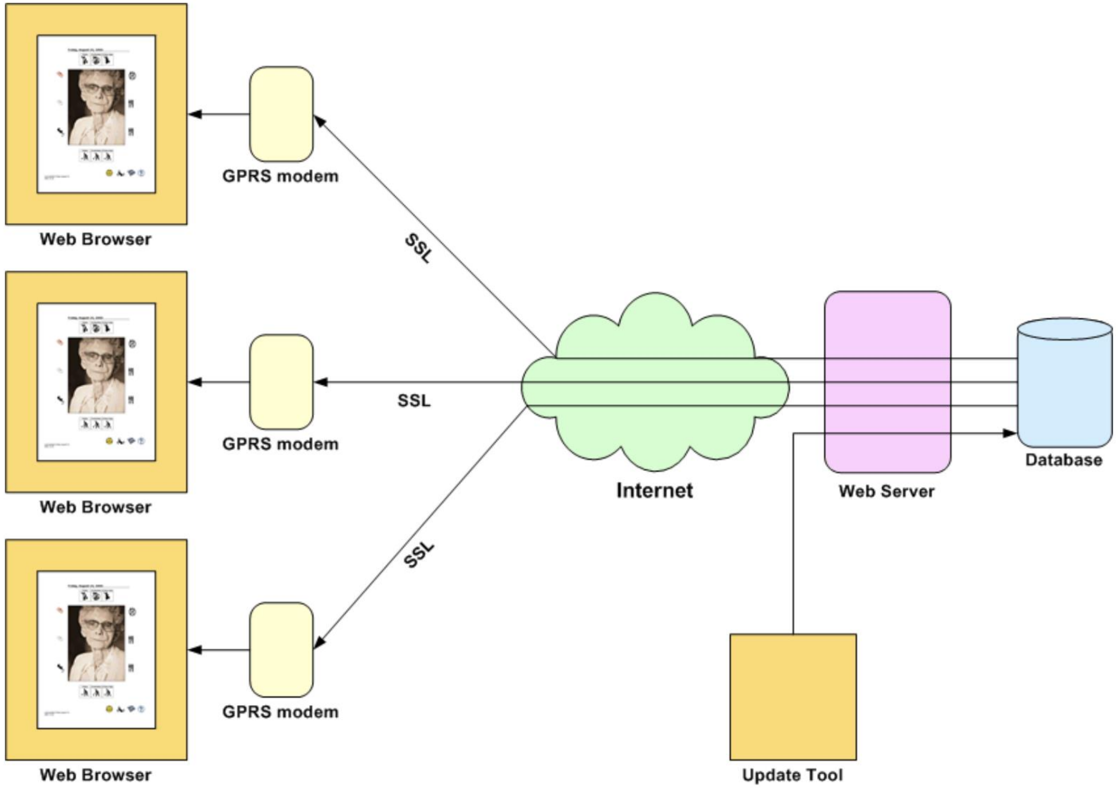
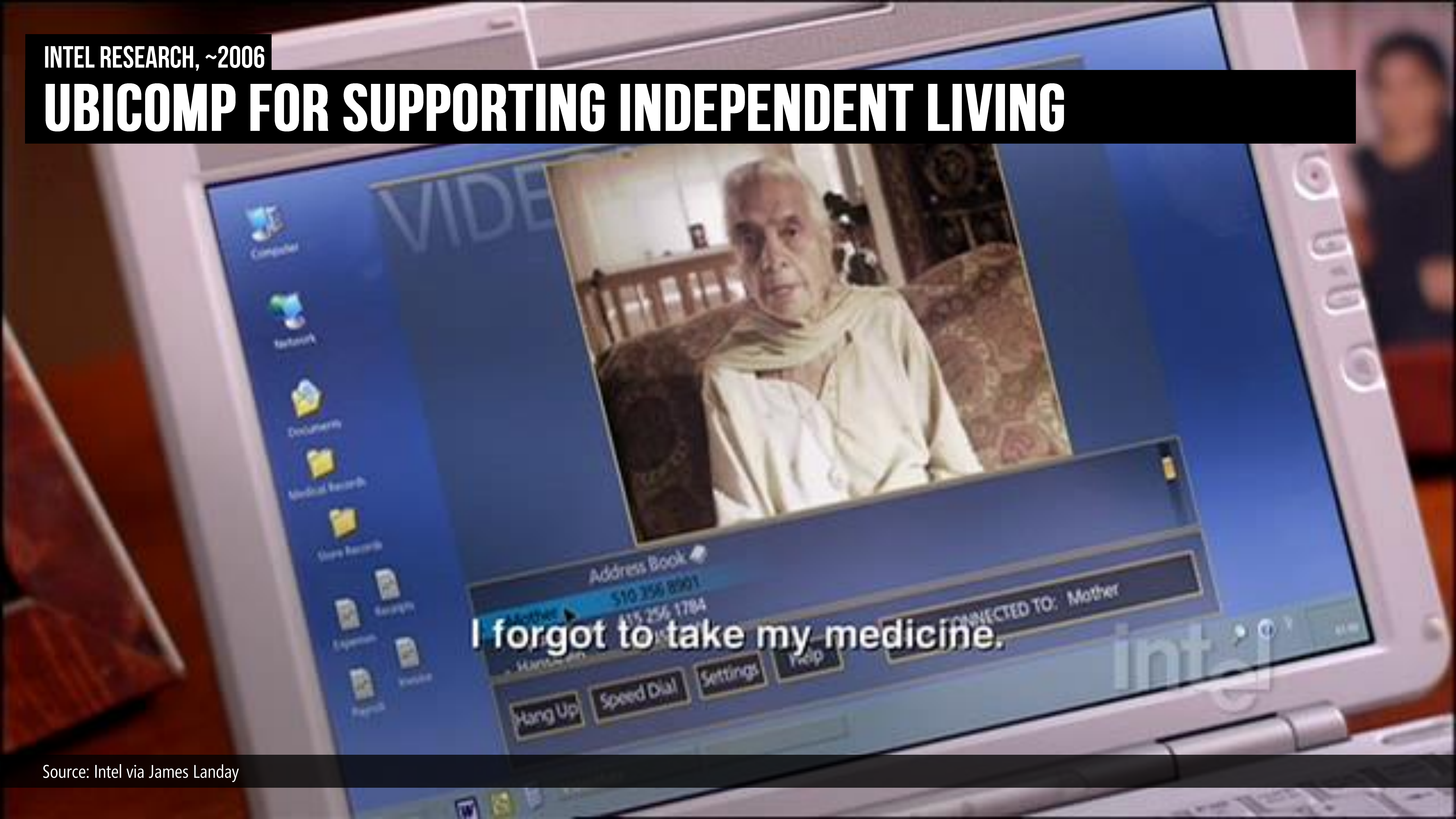


Figure 3. CareNet Display Prototype Architecture. Updates were made by evaluators through a web-based tool. Data was pushed to the displays through an always-on connection from a GPRS modem

Source: Consolvo *et al.*, UbiComp'04

INTEL RESEARCH, ~2006

UBICOMP FOR SUPPORTING INDEPENDENT LIVING



Source: Intel via James Landay

Address Book
CONNECTED TO: Mother
I forgot to take my medicine.
Hang Up
Speed Dial
Settings
Help

ACCESSIBILITY

How to ensure that emerging ubicomp systems are accessible to all?

How to leverage ubicomp technologies to make the world more accessible?

UBICOMP APPLICATION AREAS

ACCESSIBILITY

Using Handhelds to Help People with Motor Impairments

Using Handhelds to Help People with Motor Impairments

Myers *et al.*, ASSETS'02

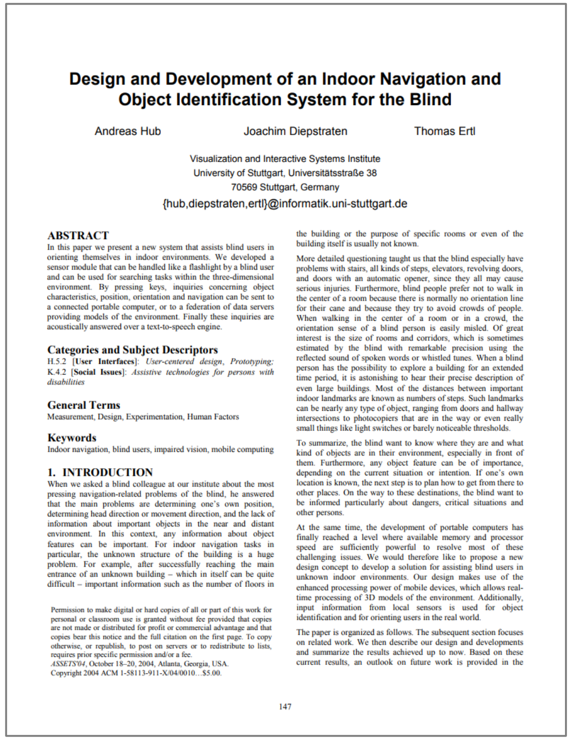
47 citations

Opportunity Knocks: a System to Provide Cognitive Assistance with Transportation Services

Opportunity Knocks: A System to Provide Cognitive Assistance with Transportation Services

Patterson *et al.*, UbiComp'04

233 citations

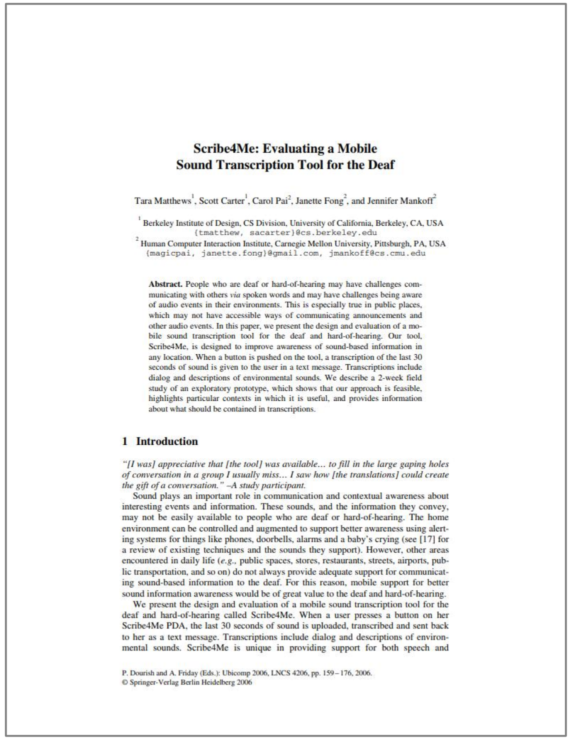


Design and Development of an Indoor Navigation and Object Identification System for the Blind

Design and Development of an Indoor Navigation and Object Identification System for the Blind

Hub *et al.*, ASSETS'04

202 citations



Scribe4Me: Evaluating a Mobile Sound Transcription Tool for the Deaf

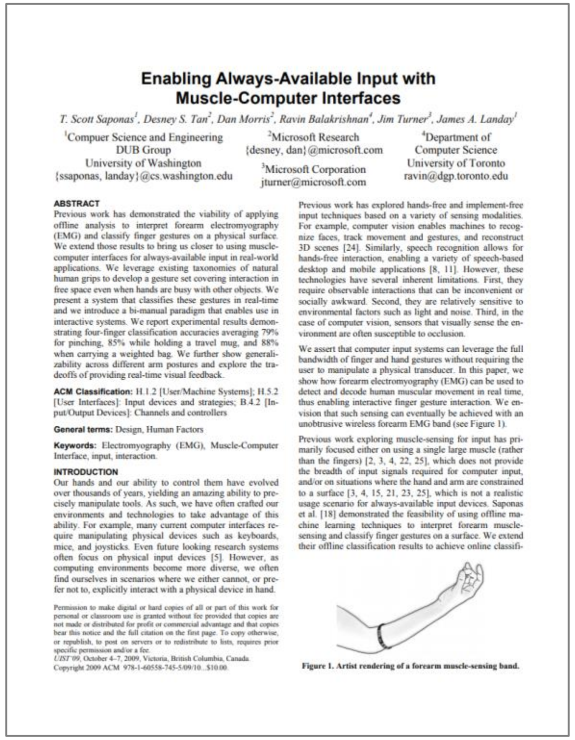
Scribe4Me: Evaluating a Mobile Sound Transcription Tool for the Deaf

Matthews *et al.*, UbiComp'06

40 citations

UBICOMP APPLICATION AREAS

NOVEL INTERACTIONS


Enabling Always-Available Input with Muscle-Computer Interfaces

T. Scott Saponas, Desney S. Tan, Dan Morris, Ravin Balakrishnan, Jim Turner, James A. Landay

Enabling Always-Available Input with Muscle-Computer Interfaces

Saponas *et al.*, UIST'09

228 citations

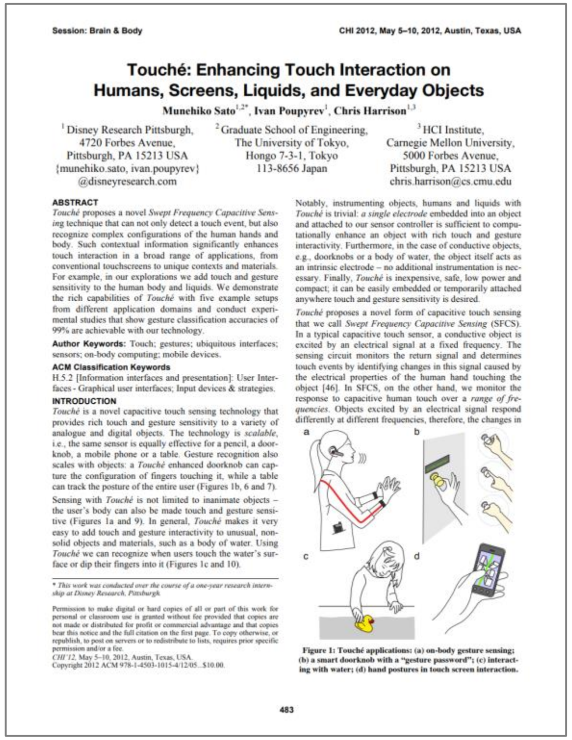

Optically Sensing Tongue Gestures for Computer Input

T. Scott Saponas, Daniel Kelly, Babak A. Parviz, and Desney S. Tan

Optically Sensing Tongue Gestures for Computer Input

Saponas *et al.*, UIST'09

59 citations

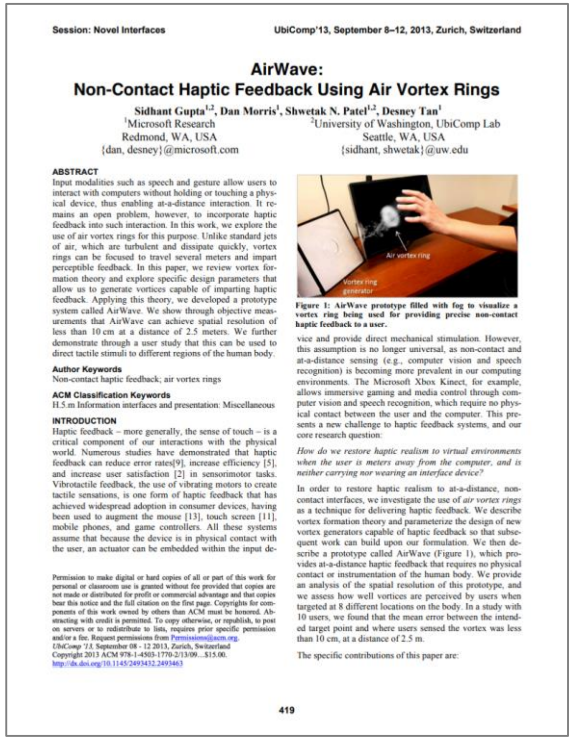

Touché: Enhancing Touch Interaction on Humans, Screens, Liquids, and Everyday Objects

Munehiko Sato, Ivan Poupyrev, Chris Harrison

Touché: Enhancing Touch Interaction on Humans, Screens, Liquids, and Everyday Objects

Harrison *et al.*, CHI'12

219 citations


AirWave: Non-Contact Haptic Feedback Using Air Vortex Rings

Sidhant Gupta, Dan Morris, Shwetak N. Patel, Desney Tan

AirWave: Non-Contact Haptic Feedback Using Air Vortex Rings

Harrison *et al.*, CHI'12

219 citations

Enabling Always-Available Input With Muscle-Computer Interfaces

T. Scott Saponas[1,2], Desney S. Tan[1], Dan Morris[1], Ravin Balakrishnan[1,3], Jim Turner[4], James A. Landay[2]

[1]Microsoft Research
[2]University of Washington
[3]University of Toronto
[4]Microsoft Corporation

ACM UIST 2009

</end tour>

SCHEDULE TODAY: 6:30-9:20

06:30-06:45: Ice breaker

06:45-07:45: Intro to UbiComp

07:45-07:55: Short break

07:55-08:05: This class

08:05-09:20: Intro to Android