

INTRO TO UBICOMP

CSE 590 Ubiquitous Computing | Lecture 1 | Mar 29

Jon Froehlich • Liang He (TA)

DOWNLOAD ANDROID STUDIO!

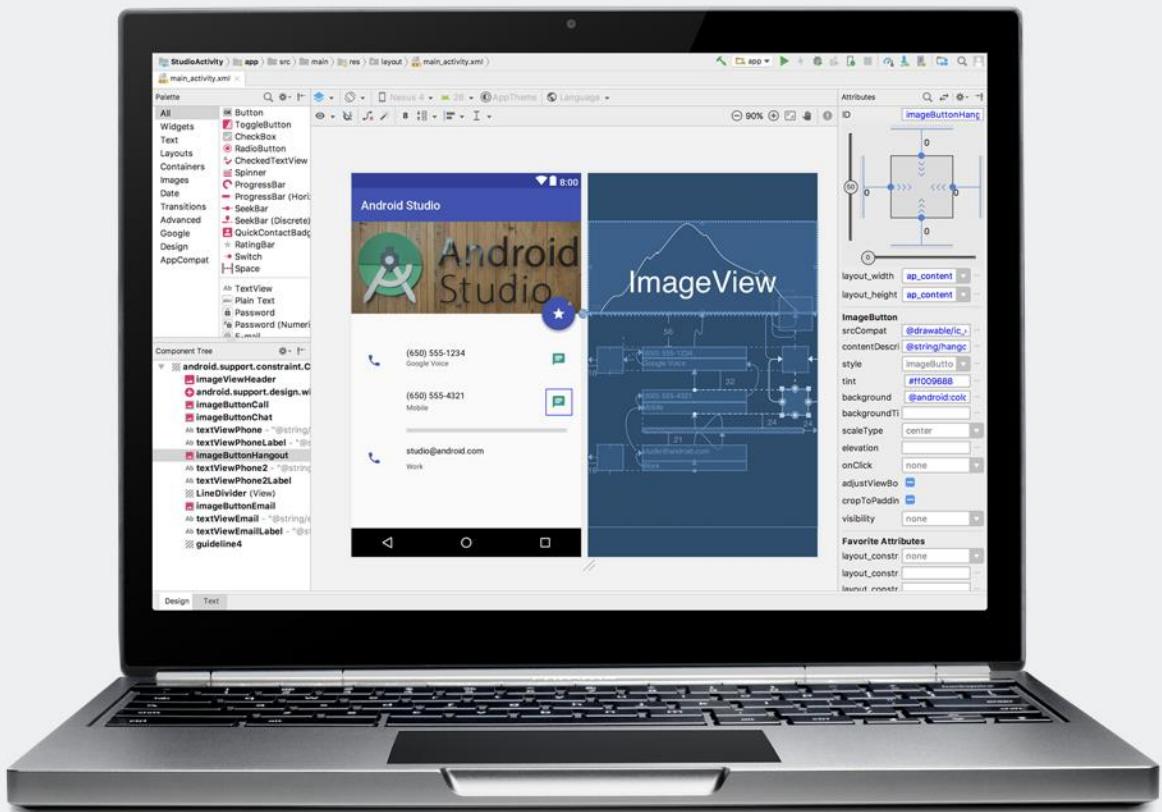
Android Studio

The Official IDE for Android

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.

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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



Name | website | Template Do Not Delete

Picture

Background:

Technical Interests:

Path:

Life:

Contact:

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



MAKEABILITY LAB



MAKEABILITY LAB

Our Mission

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

FOUR FOCUS AREAS



**ENVIRONMENTAL
SUSTAINABILITY**



**HEALTH
& WELLNESS**

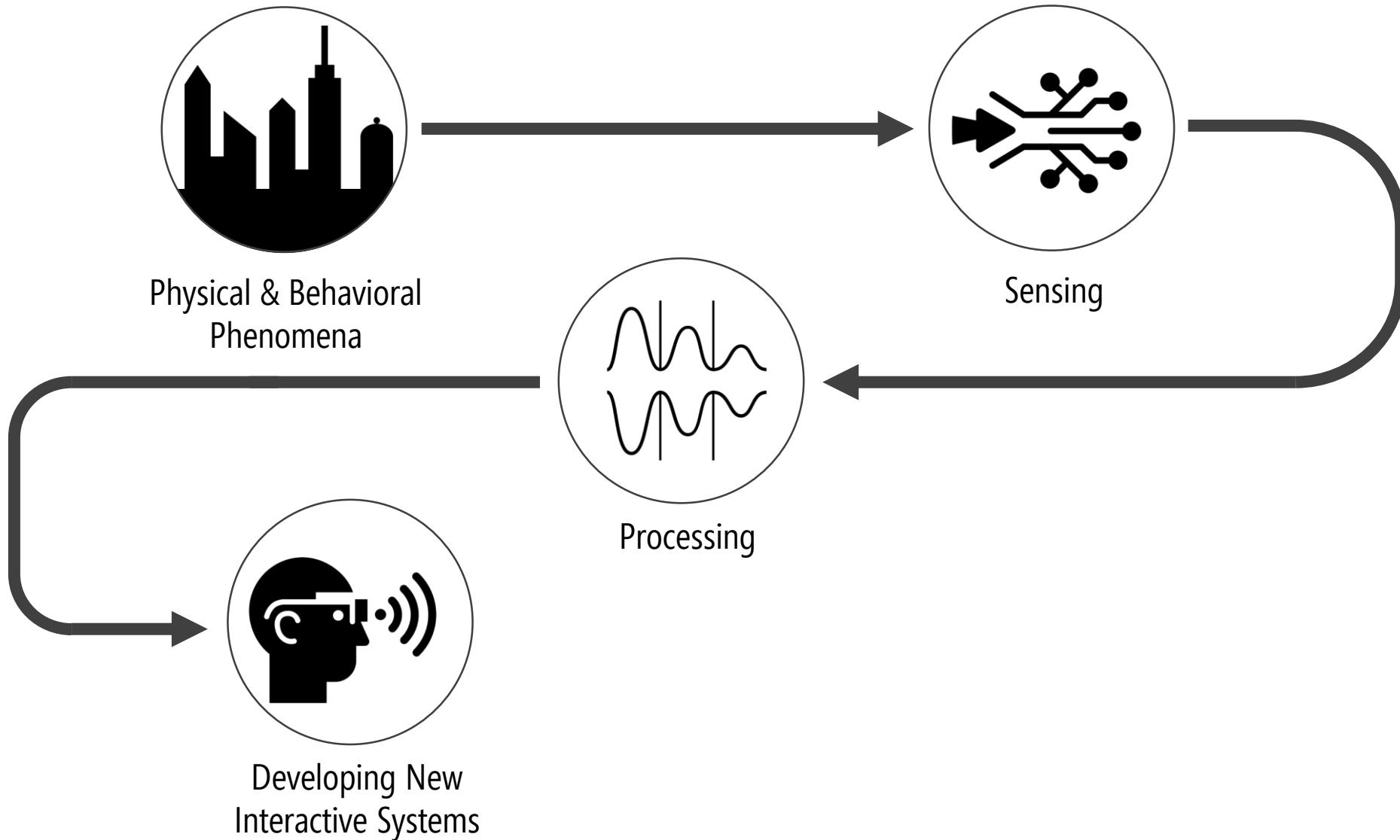


ACCESSIBILITY



**STEM
EDUCATION**

APPROACH



THREAD 1: ACCESSIBILITY

IMPROVING ACCESS TO THE PHYSICAL WORLD



PROJECT SIDEWALK

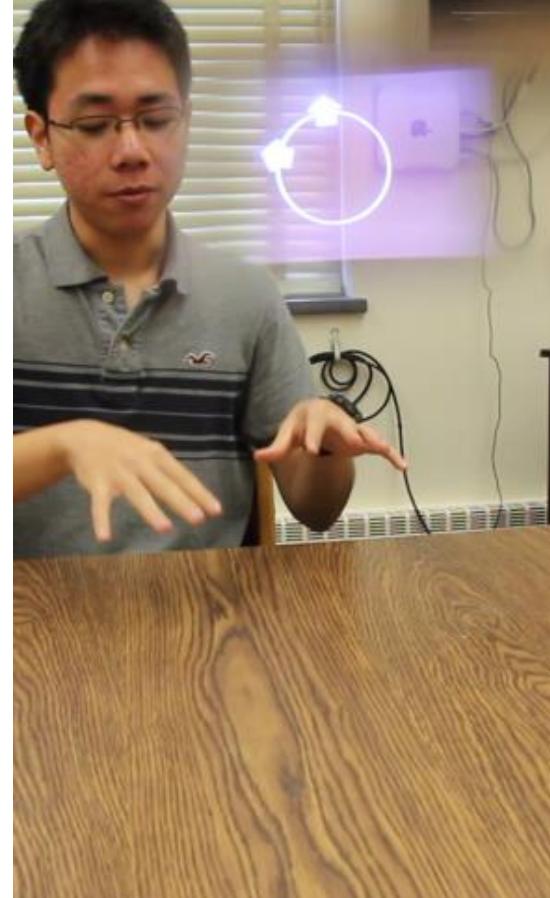
[ASSETS'12, CHI'13, HCOMP'13, ASSETS'13
Best Paper, UIST'14, TACCESS'15,
SIGACCESS'15, CHI'16, ASSETS'17]

age of patient data. I
and useful. Only the
e of end-users. Colla
d sp... tem
able to r
leralization of c

A close-up photograph of a person's hand wearing a translucent, fingerless glove. A small, bright light source is integrated into the tip of each finger, illuminating the surrounding area.

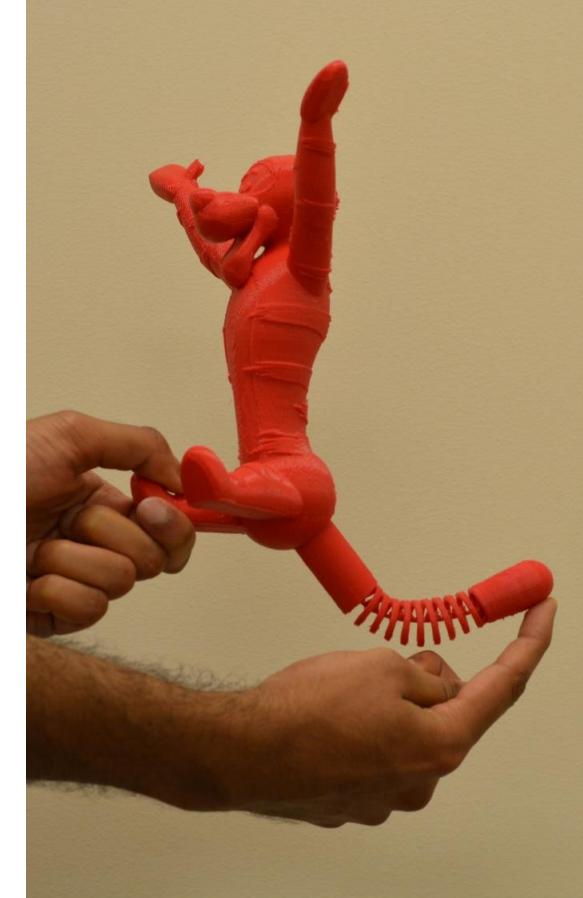
HANDSIGHT

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



GLASSEAR

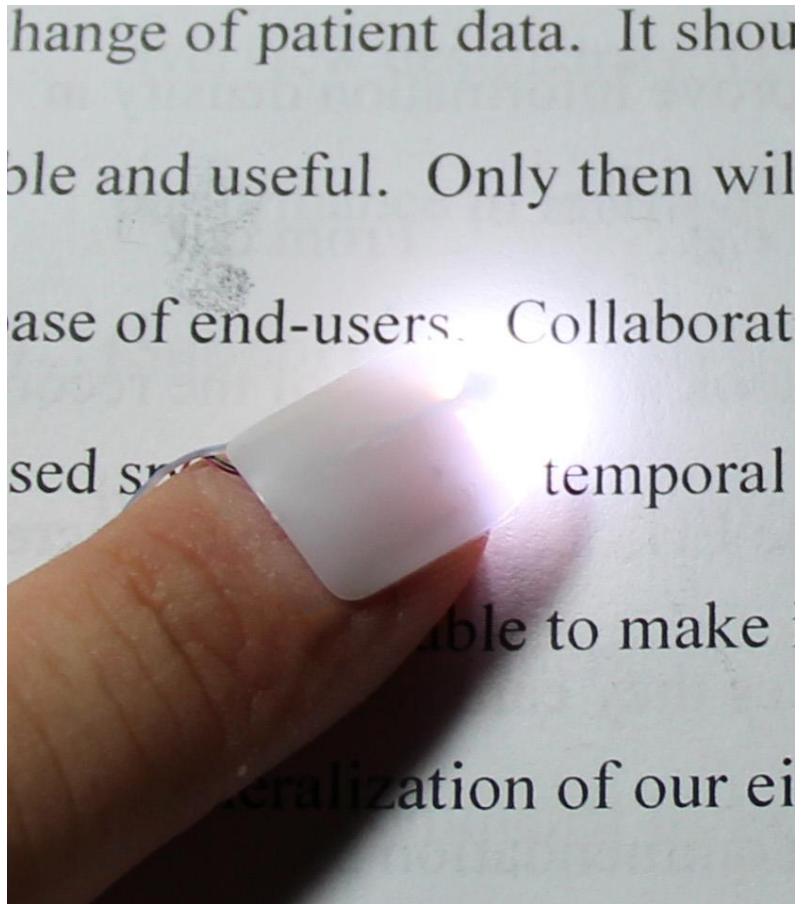
[CHI'15]



ONDULÉ

[CompFab'17, UIST'17 Poster]

IMPROVING ACCESS TO THE PHYSICAL WORLD

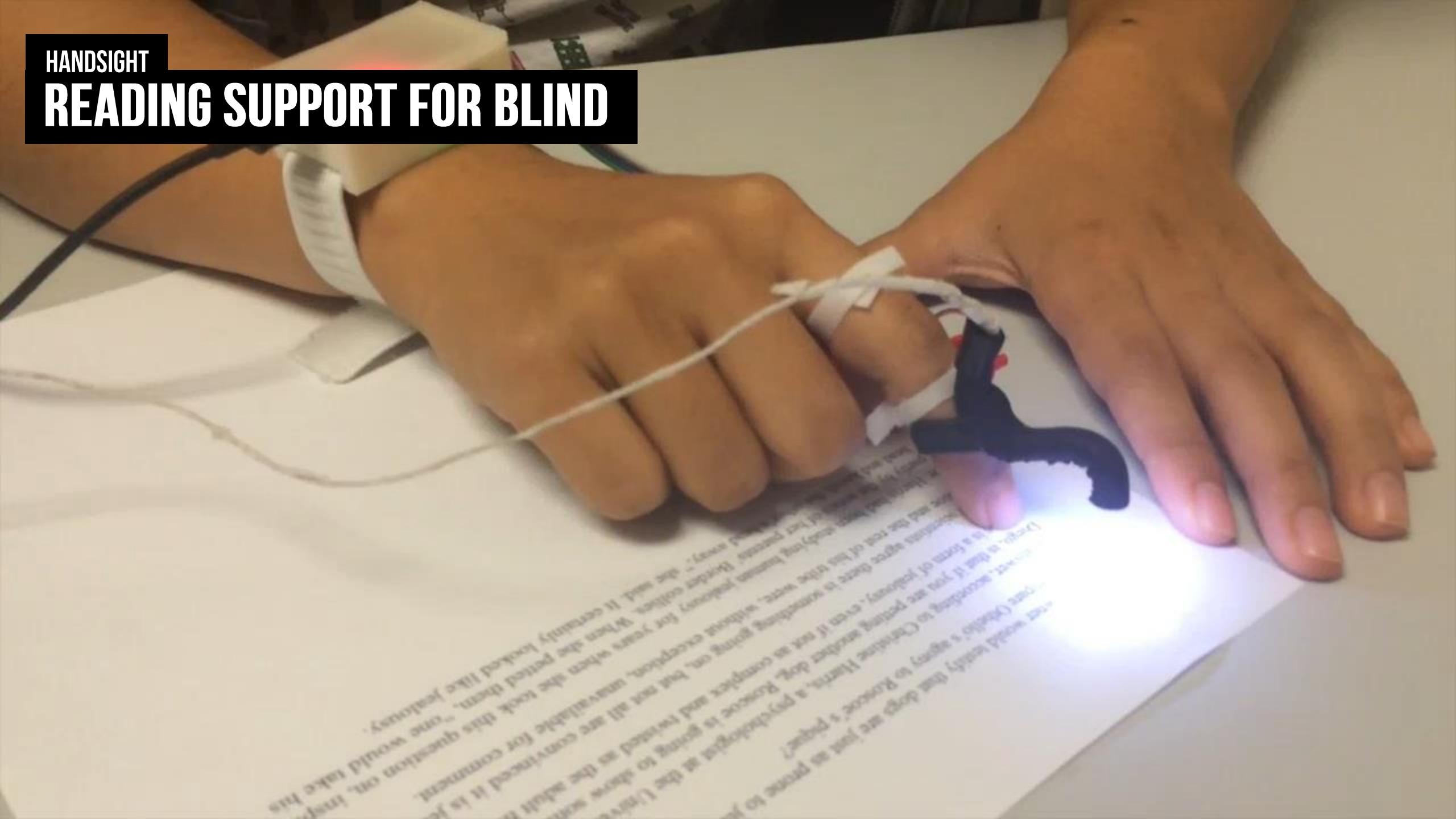


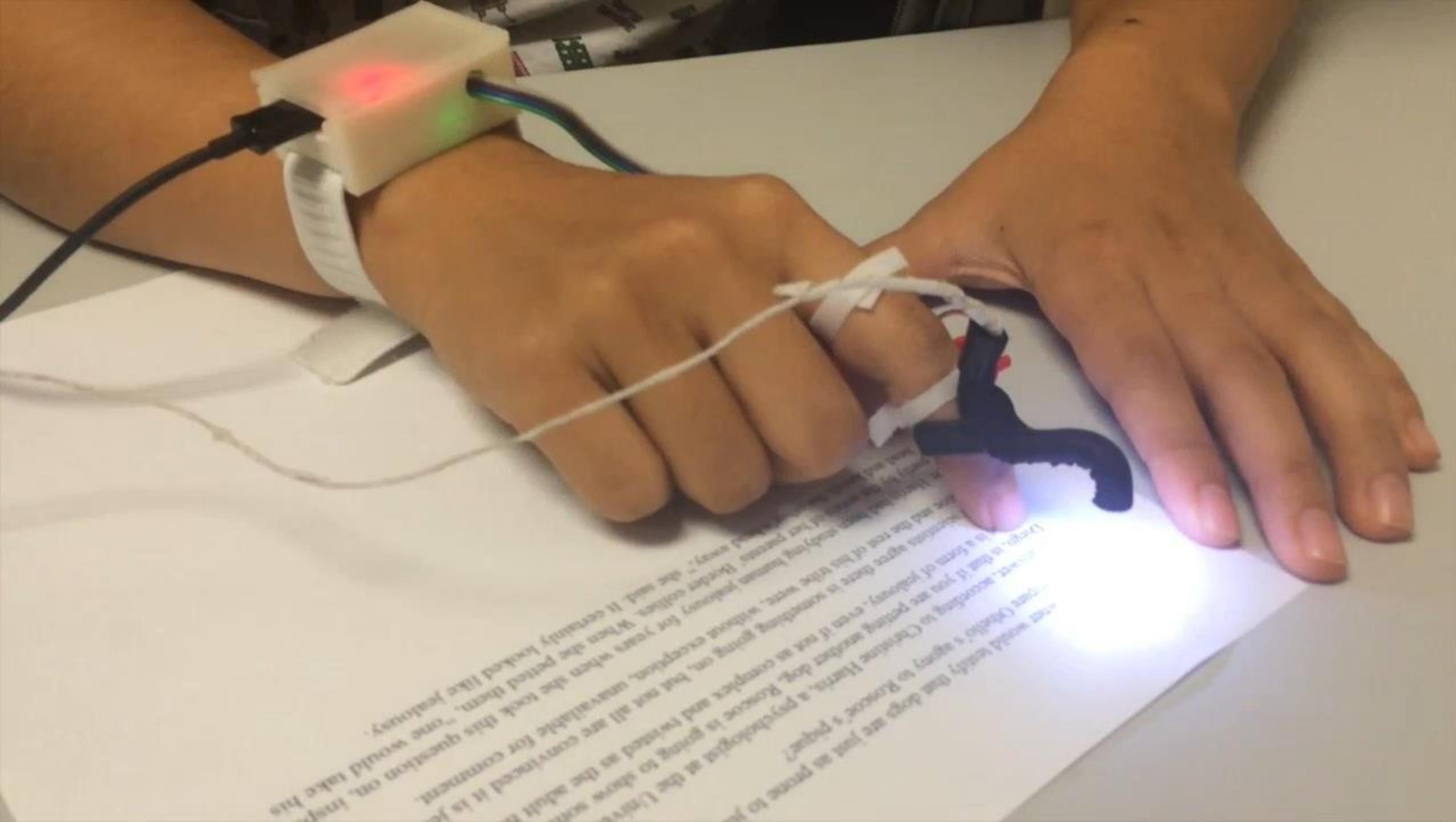
How can we...

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

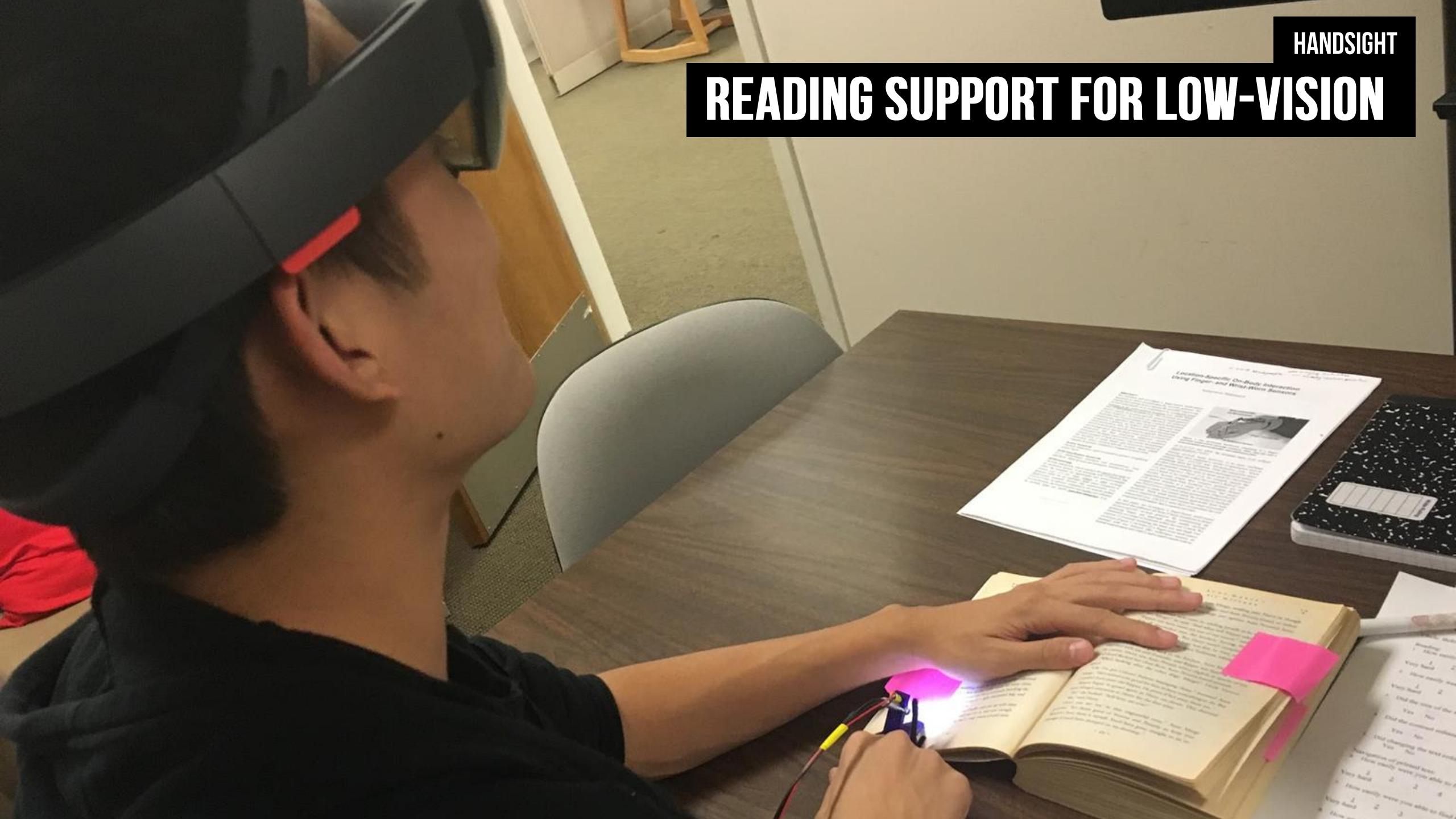
HANDSIGHT

READING SUPPORT FOR BLIND

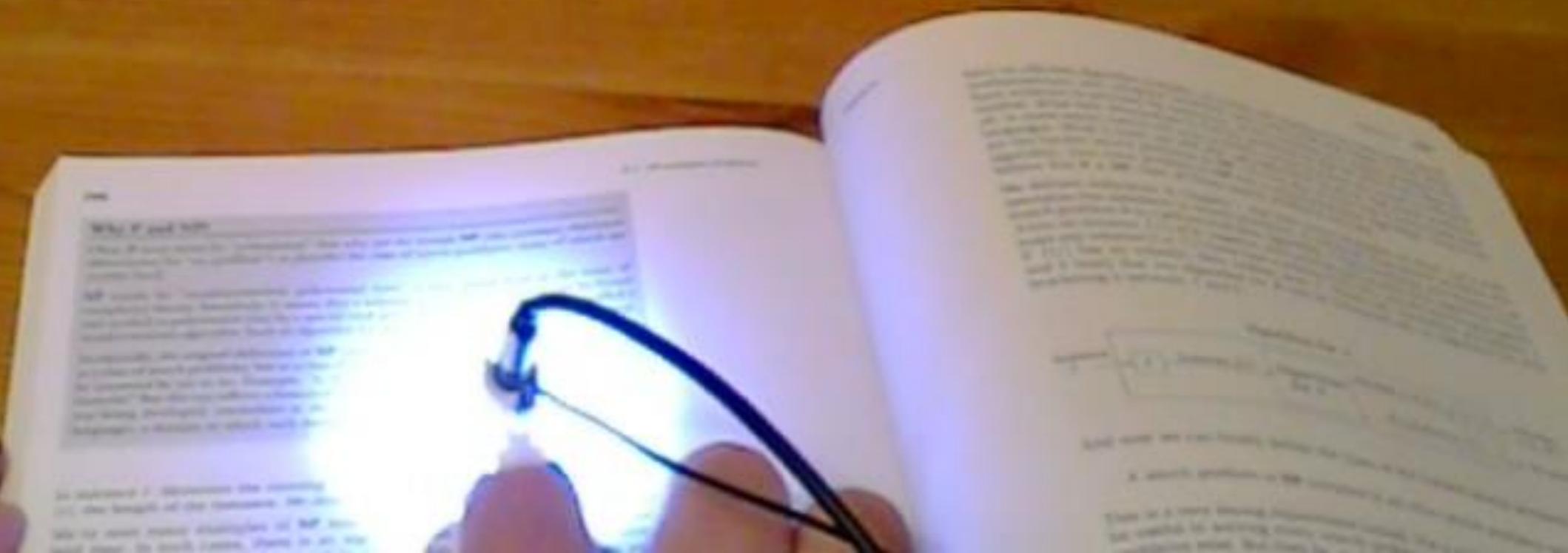




READING SUPPORT FOR LOW-VISION



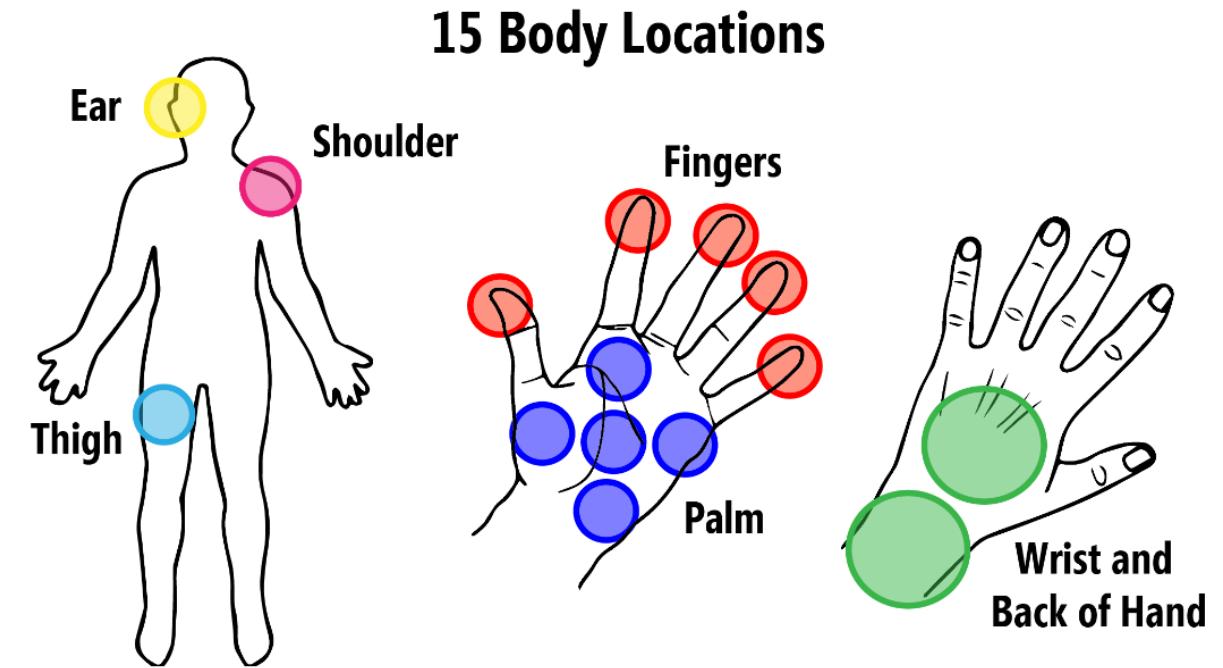
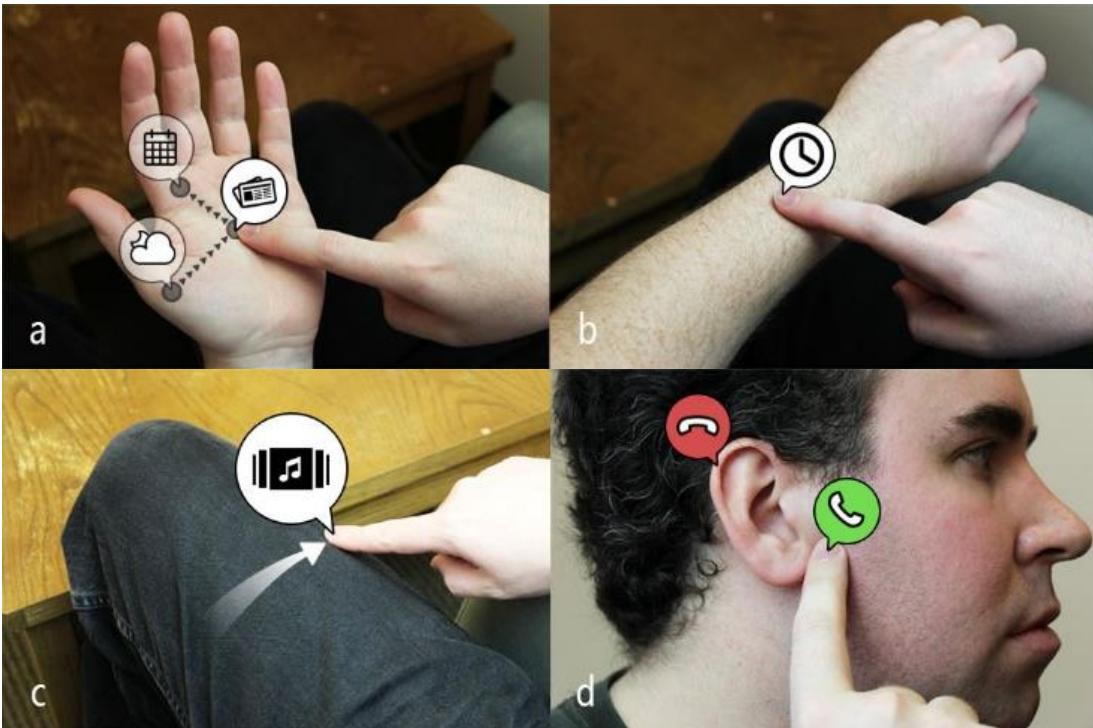
$(\mathcal{F}, \mathcal{S})$ is bounded
by the worst-case
loss of all search
implementations

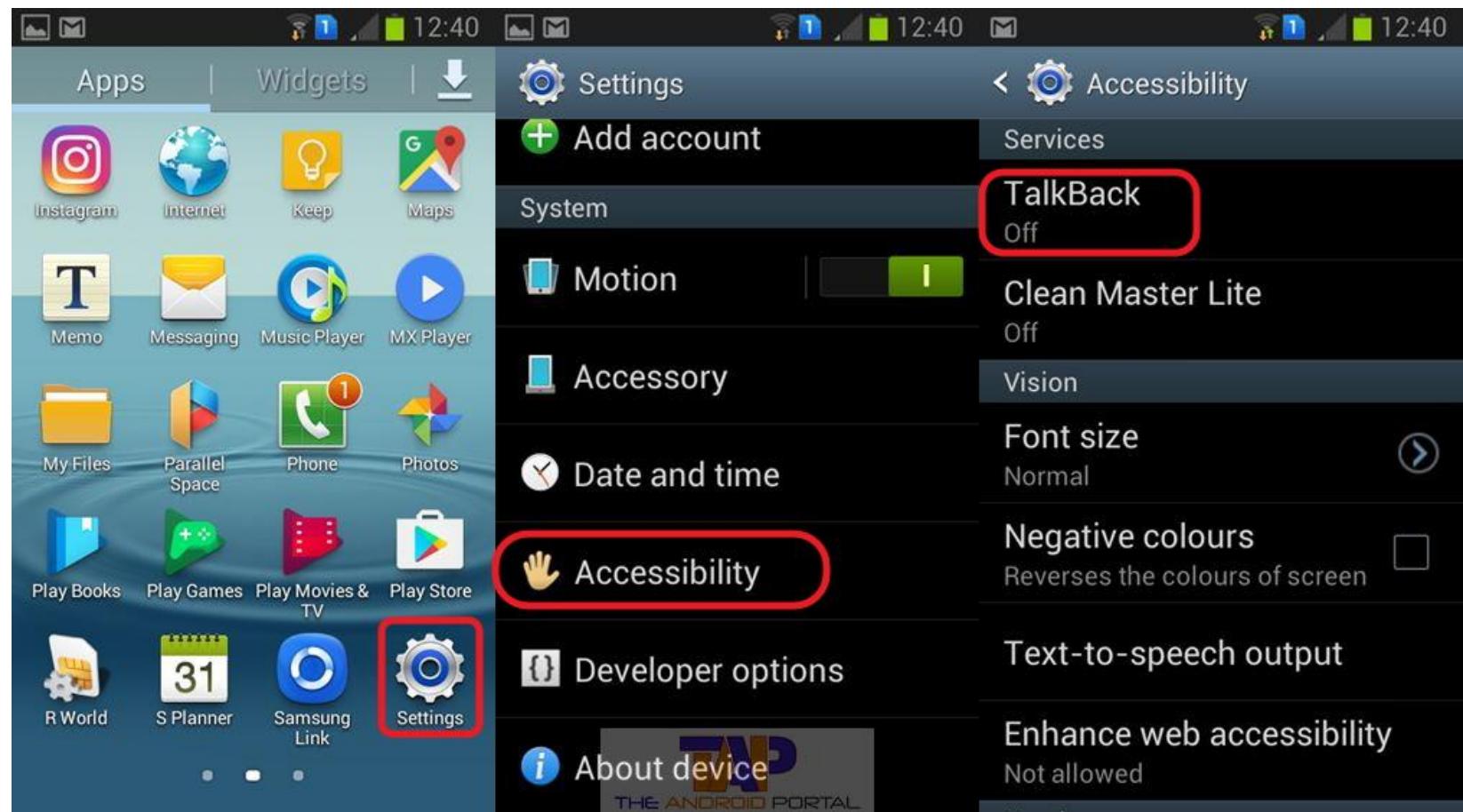
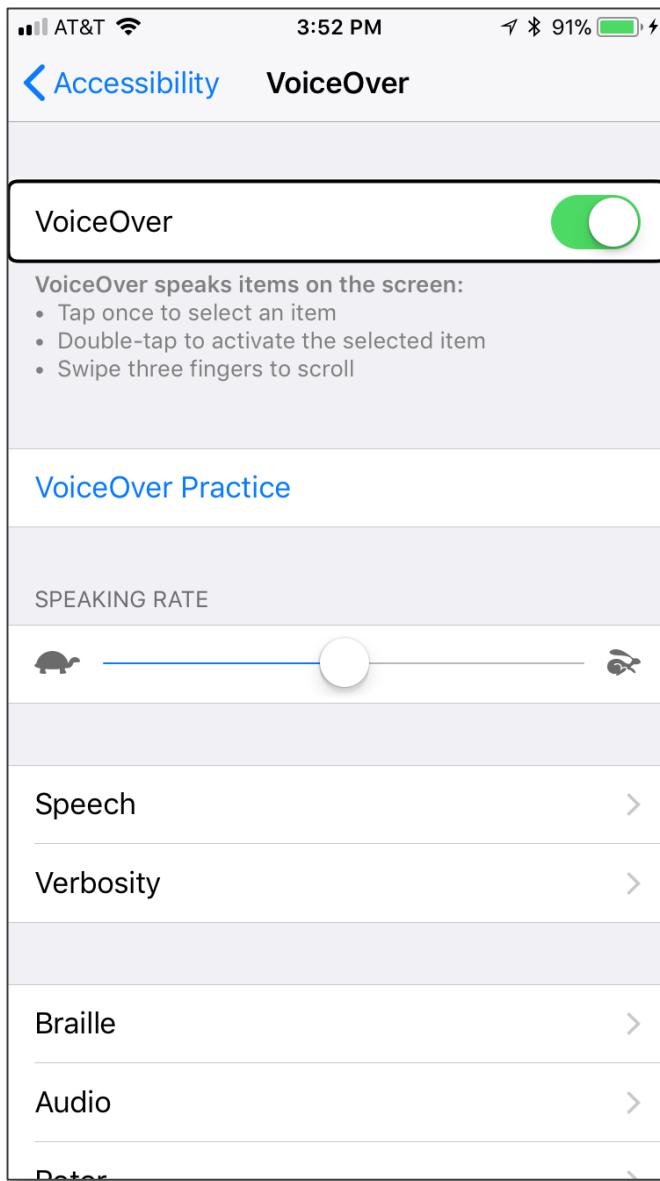


HANDSIGHT

ON-BODY INTERACTION FOR VISUALLY IMPAIRED

ICPR'16, ASSETS'17, IMWUT'17







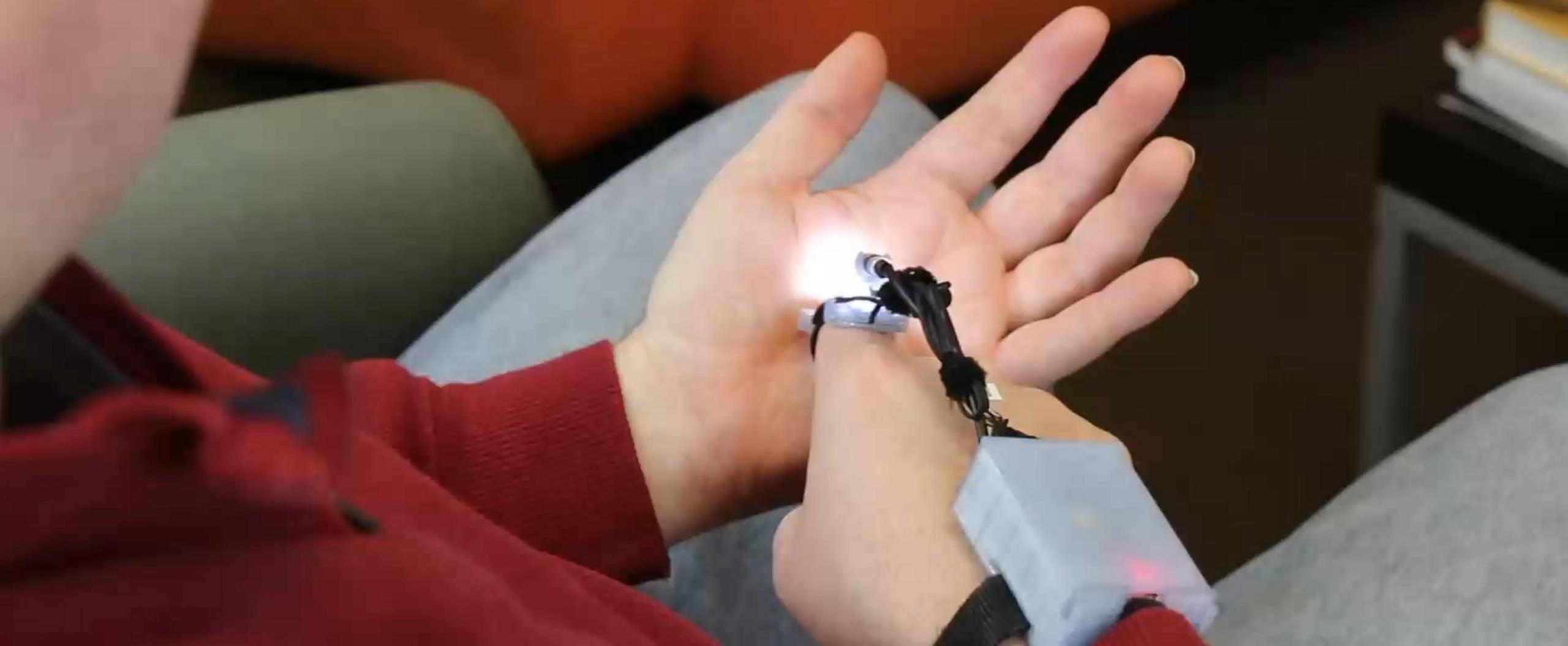
Daily Summary



Clock



Voice Input





Clock



Voice Input



Health & Activities

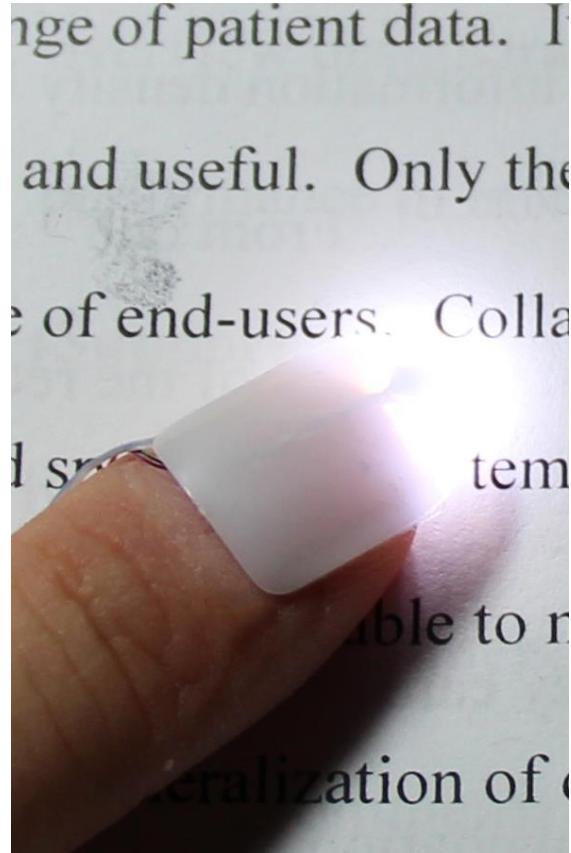
THREAD 1: ACCESSIBILITY

IMPROVING ACCESS TO THE PHYSICAL WORLD



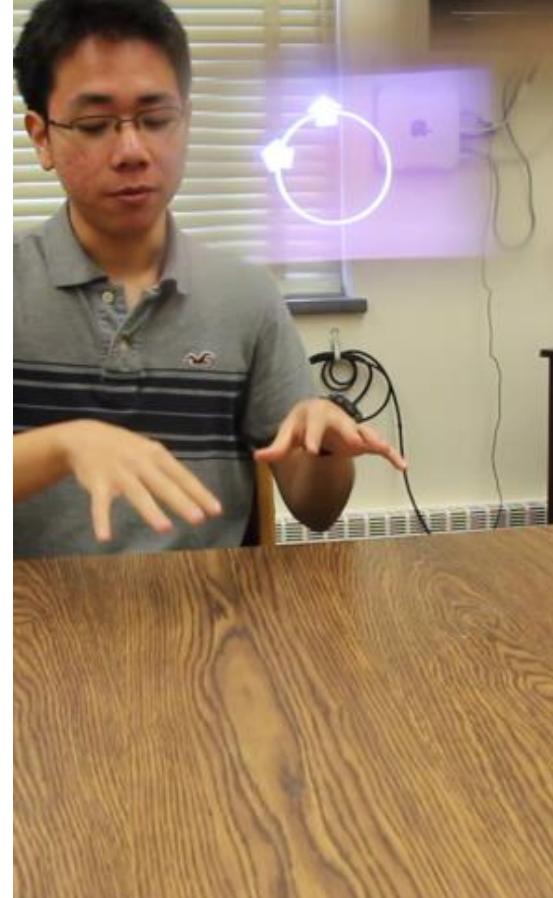
PROJECT SIDEWALK

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



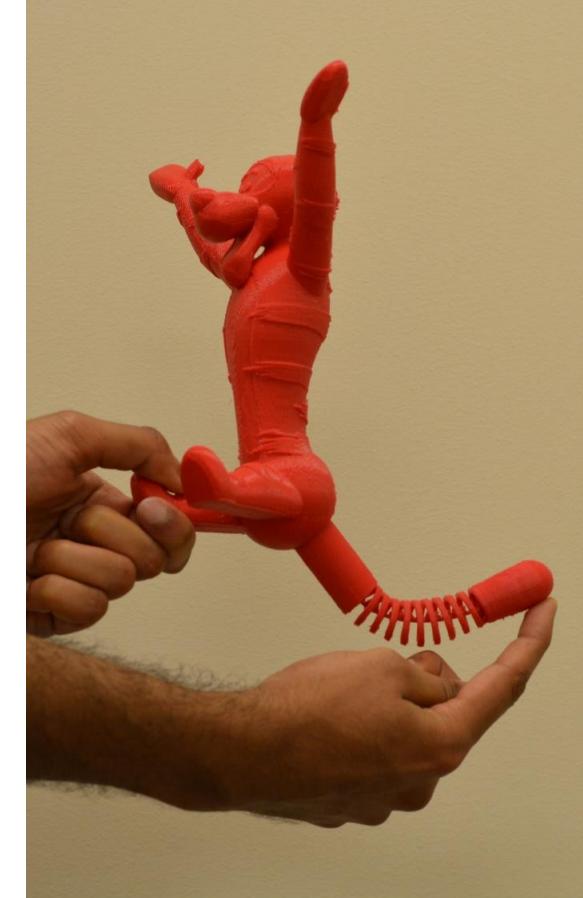
HANDSIGHT

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



GLASSEAR

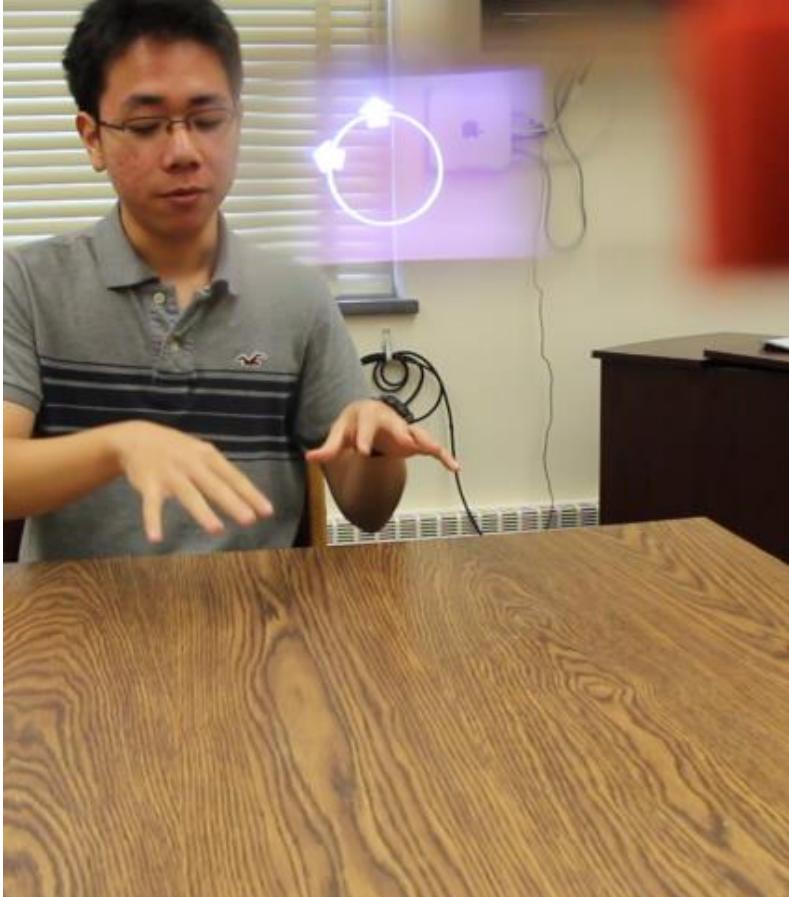
[CHI'15]



ONDULÉ

[CompFab'17, UIST'17 Poster]

IMPROVING ACCESS TO THE PHYSICAL WORLD



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

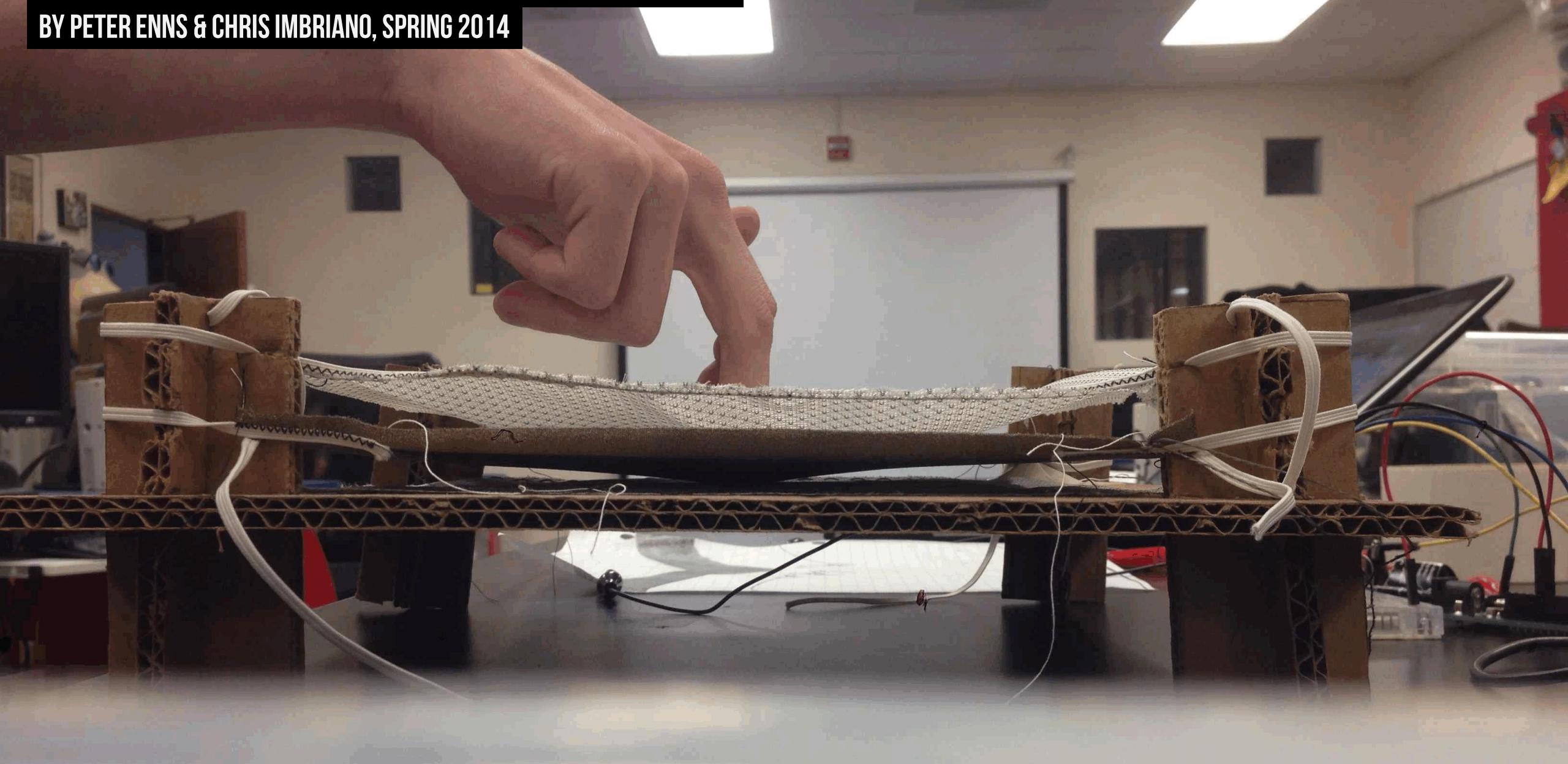
- [SPA01 Project Pitch](#)
- [SPA02 Project Presentation](#)
- [SPA03 Project Instructable](#)
- [SPA04 Project Video](#)
- [SPA05 Project Artifact](#)

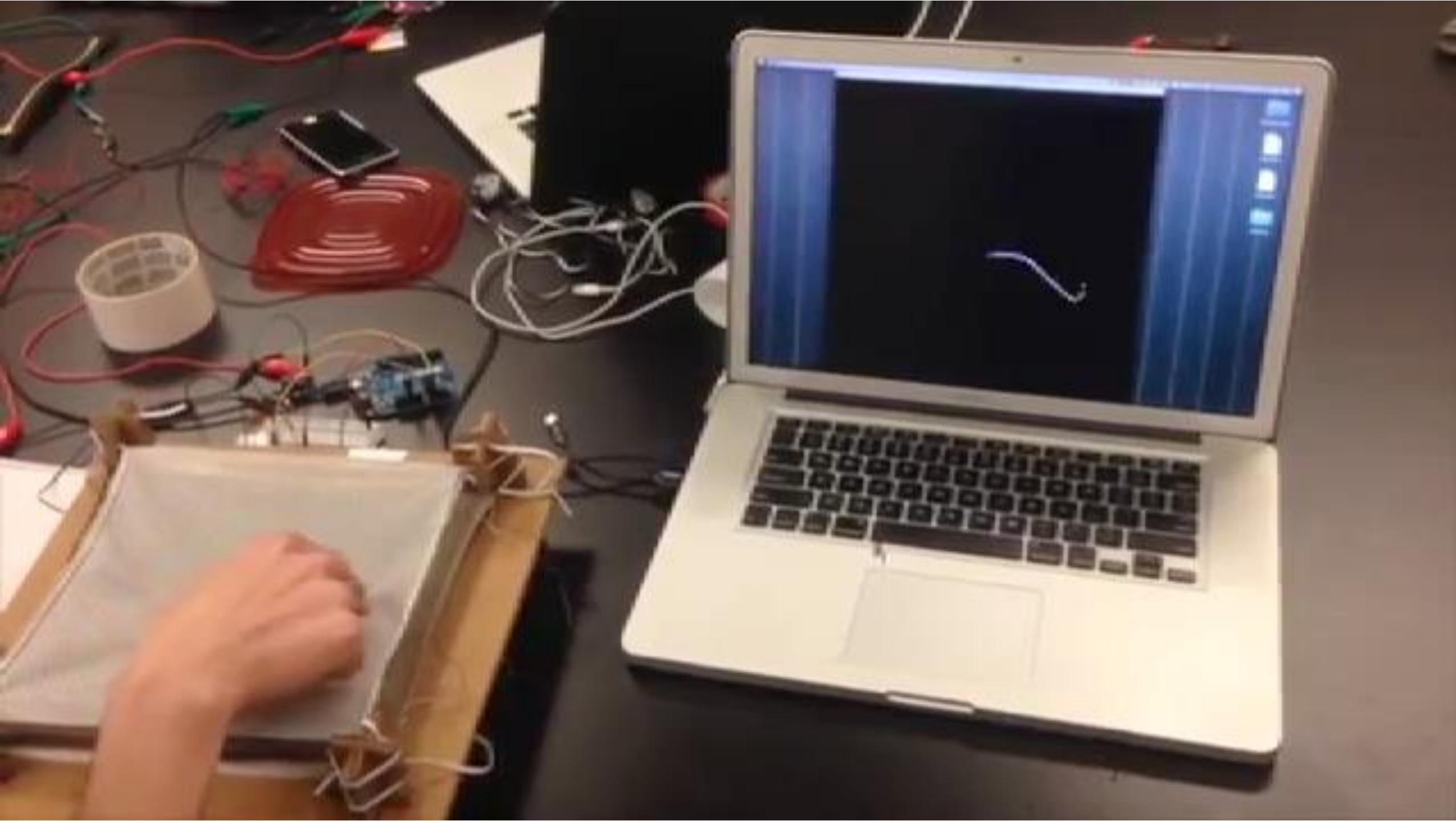
Reading Assignments

- [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

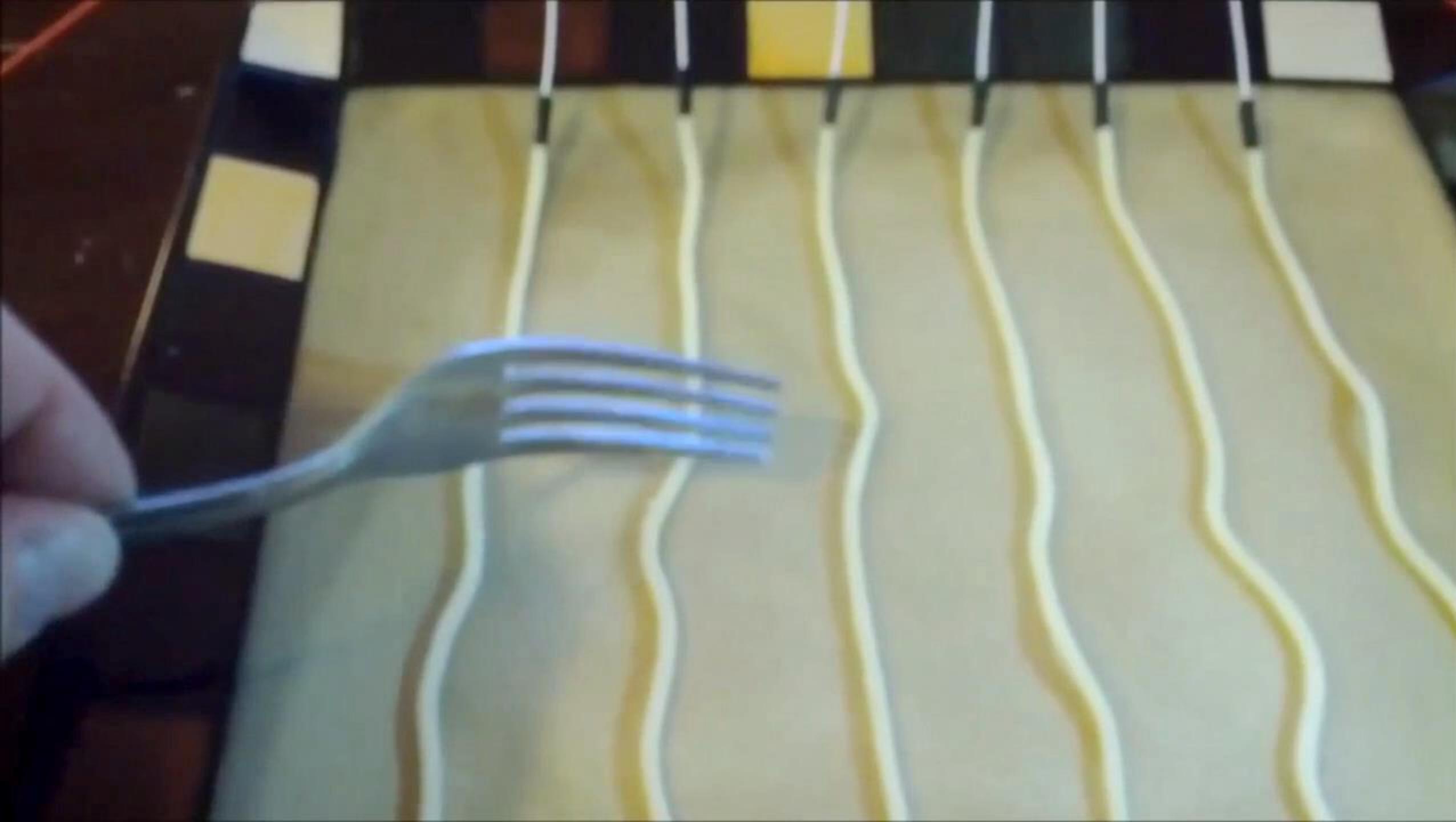




MUSICAL SPAGHETTI MADNESS

BY RICHARD JOHNSON, SPRING 2014





Introduction to Ubiquitous Computing: Some Background and Context

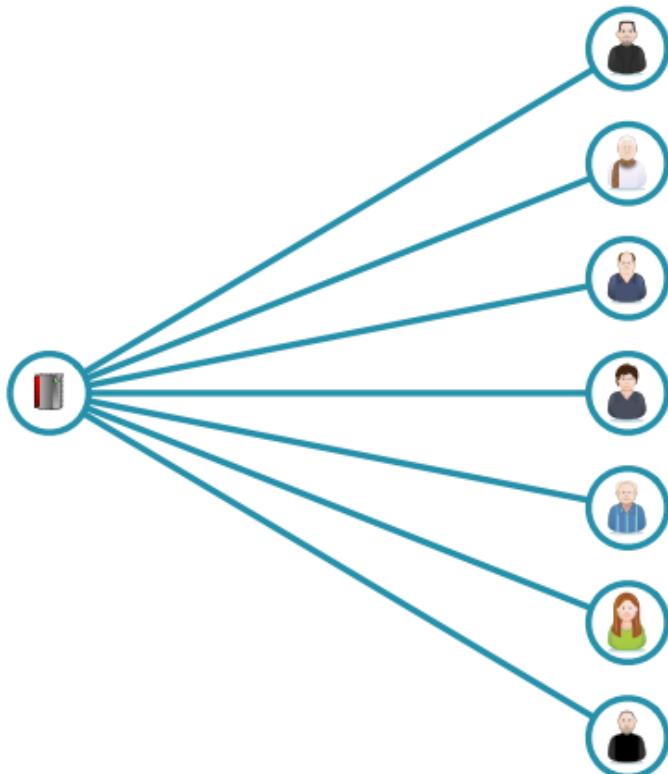
ORIGINS OF UBICOMP

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

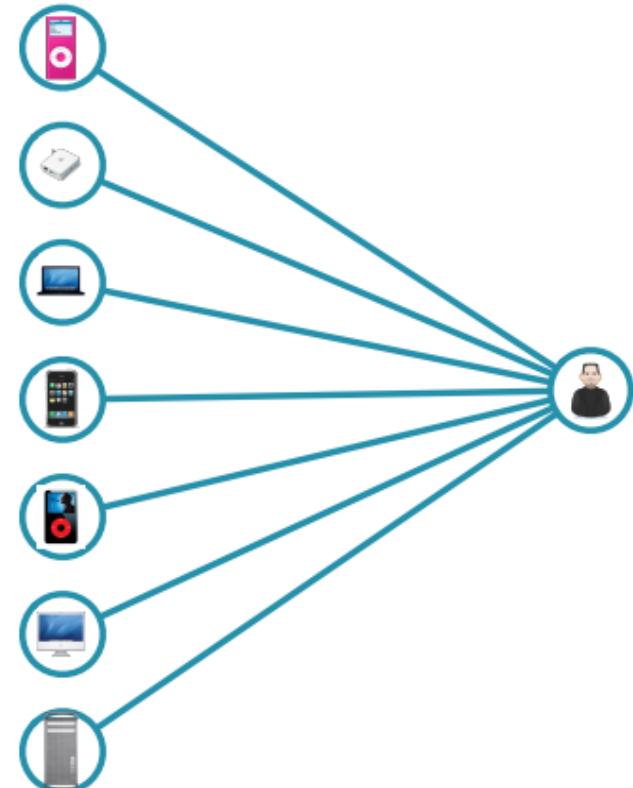


First Wave

1 Computer, Many People

Second Wave

1 Computer, 1 Person



Third Wave

Many Computers, 1+ Person

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.

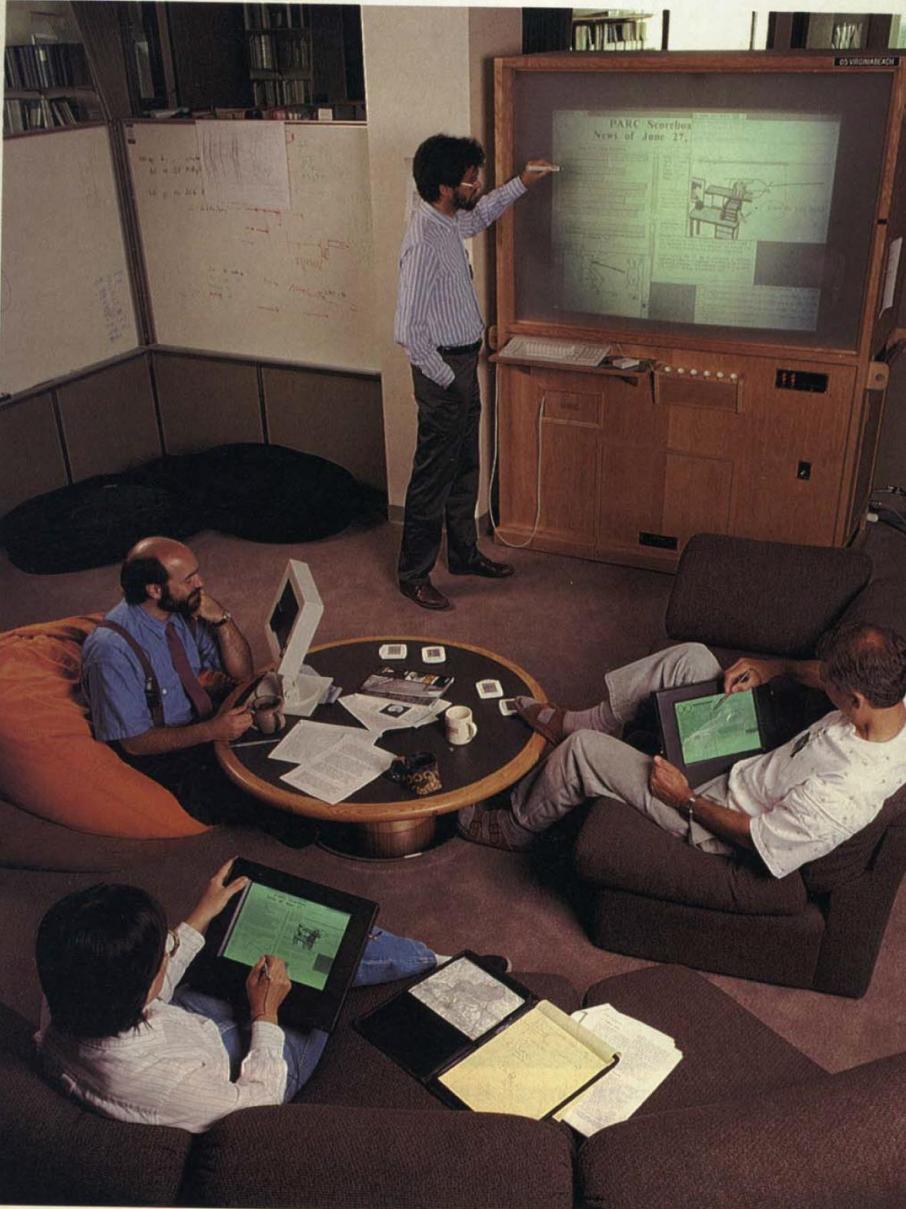
Such a disappearance is a fundamental consequence not of technology but of human psychology. Whenever people learn something sufficiently well, they cease to be aware of it. When you look at a street sign, for example, you absorb its information without consciously performing the act of reading. Computer 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.

Indeed, the opposition between 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 superlaptop 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.



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



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).

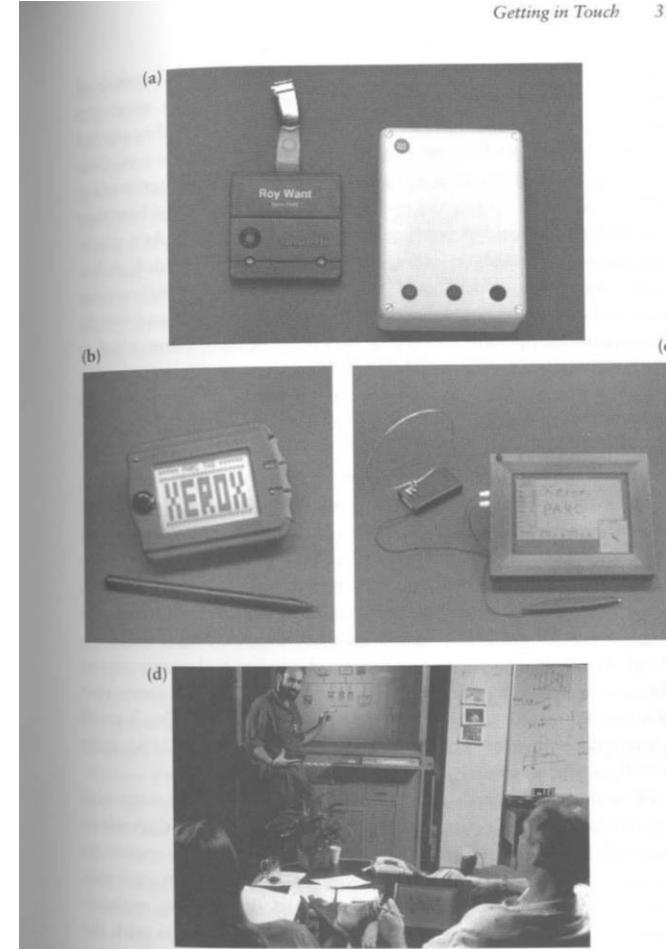


Figure 2.2
Computing by the inch, the foot, and the yard: (a) an active badge, (b) the PARC Tab, (c) the PARC Pad, and (d) a meeting at the Liveboard. Reprinted by permission of Xerox Palo Alto Research Center.

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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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



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?

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?

HARDER

What do we want to do but cannot?

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

Bill Schilit* Norman Adams Roy Want
Computer Science Dept Palo Alto Research Center Palo Alto Research Center
Columbia University Xerox Corporation Xerox Corporation
New York, NY 10025 Palo Alto, CA 94301 Palo Alto, CA 94304

Abstract
This paper describes a new class of 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. We believe that a limited amount of context-aware computing in a person's immediate environment is most important for this form of computing since the interesting part of the world around us is not necessarily the same as the person's environment. We define context-aware computing, and describe four categories of context-aware applications: proximate selection, ambient context-awareness, context-aware control, information and commands, and context-triggered actions. Instances of these application types have been prototyped on the PDA-Tab, a wireless, palm-sized computer.

1 Introduction
Our investigation focuses on an extended form of mobile computing in which users employ many different mobile, stationary and embedded computers over the course of the day. In this model computers do not just move from place to place, as in desktop computing, but rather spans a multitude of situations and locations covering the office, meeting room, hotel room, airport, subway station, bus, train, etc. Users might access their computing resources from wireless portable machines and also through stationary devices and computers connected to local area networks.

We call this collection of mobile and stationary computing devices that are communicating and coexisting with each other a distributed computing system. This form of computing is broader than mobile computing because it concerns mobile people not just mobile devices. These systems must provide ubiquitous access to information, communication, and computation.

One significant aspect of this emerging mode of computing is the constantly changing environment. The processors available for a task, the devices accessible for user input and display, the network connectivity, capacity, and costs may all change

*Visiting researcher Xerox Palo Alto Research Center.
†This work was supported by Xerox. Portions were also supported by AFIA under contract DAABT73-91-C-0067.

0-8186-6345/95 \$04.00 © 1995 IEEE

85

Context-Aware Computing Applications

Schilit *et al.*, WMCSA'94
4,707 citations

CHI 2000 • 1–6 APRIL 2000

Papers

Developing a Context-aware Electronic Tourist Guide: Some Issues and Experiences

Keith Cheverst, Nigel Davies, Keith Mitchell, Adrian Friday, Christos Estratiou

Distributed Multimedia Research Group
Department of Computing
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ABSTRACT

In this paper, we describe our experiences of developing and evaluating a context-aware electronic tourist guide. The GUIDE system has been built to overcome many of the limitations of the traditional information and navigation tools available to city visitors. For example, group-based tours are inherently inflexible with regard to start times and locations, and (like most guidebooks) are constrained by the need to satisfy the interests of the majority rather than the specific interests of individuals. Following a period of requirements capture, involving experts in the field, we developed and installed a system for visitors to Lancaster. The system combines mobile computing technologies with a wireless infrastructure to present city visitors with information tailored to both their personal and environmental contexts. In this paper we present an evaluation of GUIDE, focusing on the quality of the visitor's experience of using the system.

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 location of the user. Other factors of interest are also mobile and changing. Context includes lighting, noise level, network connectivity, communication facilities, and so on. In this paper we present an evaluation of GUIDE, focusing on the quality of the visitor's experience when using the system.

Keywords

Mobile computing, context-awareness, adaptive hypermedia, user interface design, evaluation.

INTRODUCTION

The rapidly maturing field of mobile computing has massive potential for providing dynamic multimedia information to people on the move. Indeed, it has been predicted that in a few years time a large proportion of web browsing will be carried out via mobile devices. However, restricting the use of mobile devices to such tasks greatly underestimates their potential.

GUIDE requires three main parts of the development of GUIDE, namely:

- The requirements for supporting the information and navigation needs of city visitors.
- The design of a customized web-browser application to meet these requirements.
- An evaluation of GUIDE focusing on the quality of the visitor's experience.

GUIDE REQUIREMENTS

General Approach
We gathered an initial set of requirements for GUIDE from a series of semi-structured, one-to-one interviews with members of staff at Lancaster's Tourist Information Centre (TIC). In addition, several days were spent at the TIC observing the information needs of visitors.

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CHI '00 The Hague, Amsterdam

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THE FUTURE IS HERE! CHI Letters volume 2 • issue 1

17

Developing a Context-Aware Electronic Tourist Guide: Some Issues and Experiences

Cheverst *et al.*, CHI'00
1,323 citations

Pers. Ubiquit. Comput. (2004) 8: 19–30
DOI 10.1007/s00790-003-0253-8

ORIGINAL ARTICLE

Paul Dourish
What we talk about when we talk about context

Understanding and Using Context

Anind K. Dey

College of Computing & GVU Center, Georgia Institute of Technology, Atlanta, GA, USA

Abstract Context is a proxy and source of information in our computing environments. As a result, we have an impeded understanding of what context is and how it can be used. In this paper, we provide an operational definition of context and discuss the different ways in which context can be used by context-aware applications. We also present the Context Toolkit, an architecture that enables the reuse of context-aware applications. We discuss the features and abstractions in the toolkit that makes the task of building applications easier. Finally, we introduce a new abstraction, a situation which we believe will provide additional support to application designers.

Keywords Application support; Context; Context-awareness; Situation-awareness

One area of research that is concerned with exploring the ways in which mobile devices can be used to provide more sophisticated services is that of context-aware computing [15]. Context-aware computing refers to the ability to extract information, such as location, display medium and user profile, in order to provide tailored functionality.

This paper describes some of the issues and experiences gained while developing and evaluating GUIDE, a prototype context-aware tourist guide.

The GUIDE system [4,6] makes use of the personal computing paradigm to support context-aware communications, context-awareness and adaptive hypermedia [2] in order to support the information and navigation needs of visitors to the city of Lancaster. In more detail, GUIDE utilizes a cell-based wireless communication infrastructure in order to broadcast dynamic information and positioning information to portable GUIDE units that run a customized web-browser.

This paper focuses on three main parts of the development of GUIDE, namely:

- The requirements for supporting the information and navigation needs of city visitors.
- The design of a customized web-browser application to meet these requirements.
- An evaluation of GUIDE focusing on the quality of the visitor's experience.

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CHI '00 The Hague, Amsterdam

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Personal and Ubiquitous Computing (2001) 5:4–7

Understanding and Using Context

Anind Dey, Pers. & UbiComp'01
5,690 citations

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Abstract The emergence of ubiquitous computing as a new design paradigm poses significant challenges for human-computer interaction (HCI). The HCI paradigm has largely remained static, even as the underlying technologies have changed. HCI has had to grow within a constrained and well-understood domain of experience—single users sitting at desks and interacting with conventionally-designed computers employing screens, keyboards and mice. However, the opportunities opened up by ubiquitous computing have engendered considerable interest in “context-aware computing”—computational systems that can sense and respond to aspects of the environment in which they are situated. However, considerable confusion surrounds the notion of “context”—what it means, what it includes and what role it plays in interactive systems. This paper suggests that the conventional stance implied by conventional interaction design—that “context” interprets the role of context in everyday human activity, and proposes an alternative model that suggests different directions for design.

Keywords Context-aware computing
Etimonethology

1 Introduction

One of the major research directions for human-computer interaction (HCI) over the past few years has been to explore the novel forms of interaction that can be achieved by integrating computer technology with the everyday physical world in which we live and work. This line of research goes by a number of names—ubiquitous computing (Weiser 1991), context-aware computing (Dey et al. 2001), pervasive computing (Arik and Sekler 1999), embodied interaction (Dourish 2001), and more.

Although the nomenclature varies, the central ideas are largely the same. Existing and frequent trends in design, particularly in low-cost, low-power mobile devices, ubiquitous computing proposes a digital future in which computation is embedded into the fabric of the world around us. In this view, the primary experience of computation is no longer with a traditional computer, but rather with a range of computationally-enhanced devices—pieces of paper, pens, walls, books, hammers, etc. The opportunity to capitalise on our familiarity with these objects and their affordances is clear. However, considerable confusion surrounds the notion of “context”—what it means, what it includes and what role it plays in interactive systems. This paper suggests that the conventional stance implied by conventional interaction design—that “context” interprets the role of context in everyday human activity, and proposes an alternative model that suggests different directions for design.

There are many significant research issues that this vision encompasses, but two have become particularly prominent in HCI. The first is the relationship between physical space and display, how we design computationally-enhanced devices and how their form as much as their interactive ability affects likely patterns of action and interaction. Researchers have looked towards other domains to explore this relationship and to improve the relationship between physical and digital systems (e.g., Strong and Gaver 1996; Brave and Dahley 1999). The second is the question of what will be the focus of the discussion here: is how computers are used sensitive and responsive to its setting? How can sensor technologies allow computational systems to be sensitive to changes in the physical world and act so that, as we move from one social or social setting to another, our computational devices can be attuned to these variations?

Whether we refer to it as context-aware computing or by one of its other names, the notion of “context” plays a crucial role in a new area of investigation. Context, in one form or another, has been a concern in many areas of design and computer science, but it is of central importance here. One reason is straightforward: when computation is moved “off the desktop,” then we

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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 centralised location service, through a network of sensors. The paper also examines alternative location technology, 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 and Protocols (e.g., voice, data, images); transmission; II.4.1 [Information Systems Applications]: Office Automation; Information Management (e.g., calendar, scheduler); II.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, PRX, 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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ACM Transactions on Information Systems, Vol. 10, No. 1, January 1992, Pages 91–102.

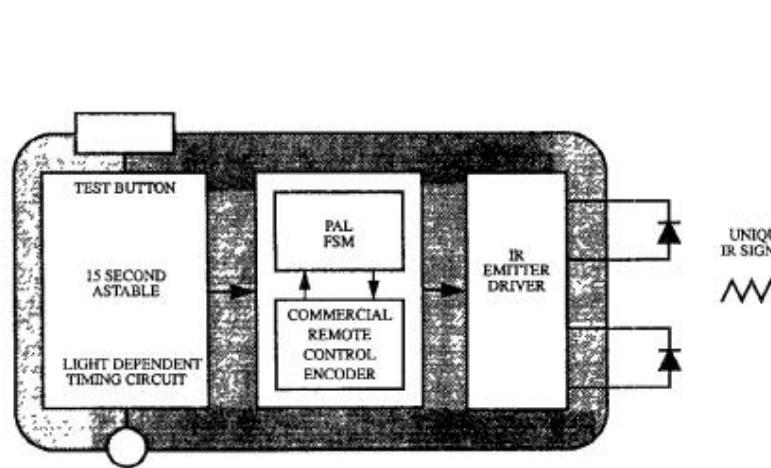
The Active Badge Location System
Want *et al.*, ACM Trans. InfoSys'92
5,252 citations

LOCATION INFERENCE: ACTIVE BADGE

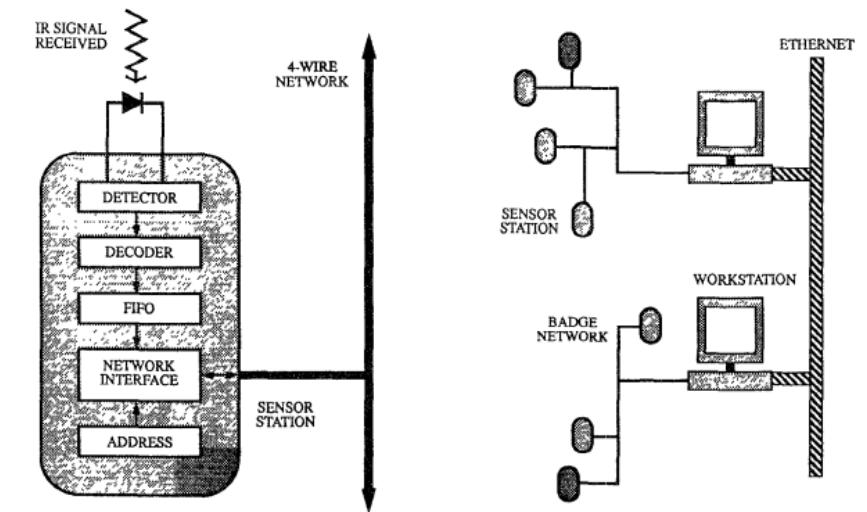
The *Active Badge* emits a unique IR code every 15 secs, which are picked up by a sensor network placed throughout a building, which communicates with a centralized server and provides a social location API. IR was chosen because ultrasonic too expensive.



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
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A novel system for the location of people in an office environment is described. Members of staff wear active badges, which broadcast their position to other badges. These badges can then provide a location service, through a network of sensors. The paper also examines alternative location technologies, 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]: Office Automation; H.4.2 [Information Systems Applications—Manufacturing]: Manufacturing, Quality Control, Reliability, Scheduling; H.4.3 [Information Systems Applications—Communications Applications]: Communications Applications; H.5.5 [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, tracking 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

be inefficient, unreliable, and expensive. In addition, they do not provide the kind of continuous monitoring that is required for emergency situations. The emergence of network-enabled devices and the promise of ubiquitous network connectivity has made the development of pervasive computing environments an attractive research goal. A compelling set of applications for such environments are location-aware, context-aware, location-dependent ones, which adapt their behavior and user interface to the current location in space, for which they need to know the physical location with some degree of accuracy. We have developed several location-aware services and applications in outdoor settings (e.g., Hertz's NeverLost navigator on

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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

The Cricket Location-Support System

The Cricket Location-Support System

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Abstract

This paper presents the design, implementation, and evaluation of Cricket, a location-support system for in-building, mobile, location-dependent applications. It allows applications running on mobile and static nodes to learn their physical location and that of listeners that have been placed in the environment. It also provides a way for we interact with our immediate environment, where computing elements will be "alive" [20] or "smart" [8, 4]. In particular, our system enables a mobile computer to learn its location, orientation, and user interactions in the context of Project Oxygen at MIT [16].

The design and deployment of a system for obtaining location and spatial information in an indoor environment is a challenging task for several reasons, including the preservation of user privacy, administration and management of the system, and the nature of the hardware and software infrastructure.

offered by the system is an important design consideration, since power usage is a valuable user privacy right.

The design must be able to manage the hardware and software infrastructure

must be minimal because of the potentially large number (possibly several thousands) in a building of devices and networked services

that would be required.

In-building environments often contain substantial amounts of metal and other materials that interfere with the propagation of radio frequency (RF) signals in ways that can cause severe multipath effects, dead-spots, noise, and interference.

1 Introduction

The proliferation of mobile computing devices and local-area wireless networks has fostered a growing interest in location-aware systems. One area of particular interest is in providing location-aware services to mobile users. A distinguishing feature of these systems is that they are application-oriented and interface presented to the user is, in general, a function of his or her physical location. The granularity of location-aware services can range from a city to a room. The needs must be able to scale to a high spatial density of devices. Finally, indoor environments often contain substantial amounts of metal and other materials that interfere with the propagation of radio frequency (RF) signals in ways that can cause severe multipath effects, dead-spots, noise, and interference.

Our goal is to develop a system that allows applications running on mobile devices and service nodes to learn their physical location. Once this information is obtained, it can be used by applications to a resource discovery service such as the MIT Intentional Naming System (INS) [2], IETF Service Location Protocol [18], Berkeley Service Discovery [7], or Sun's Network Discovery [14]. User applications do not need to understand where they were to be discovered by others; they learn about services in their vicinity via an application that runs on their mobile device and interacts with the system by communicating queries for services at a requested location. Through the processing of tracking services and obtaining location information, multiple resource discovery systems can be handled. By not tracking users and services, user privacy is maintained.

We have implemented the system in two ways: as an active map and device control can be developed with little effort or manual configuration.

1 Introduction

The emergence of network-enabled devices and the promise of ubiquitous network connectivity has made the development of pervasive computing environments an attractive research goal. A compelling set of applications for such environments are location-aware, context-aware, location-dependent ones, which adapt their behavior and user interface to the current location in space, for which they need to know the physical location with some degree of accuracy.

We have developed several location-aware services and applications in outdoor settings (e.g., Hertz's NeverLost navigator on

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Permission to make digital or hard copies of all or part of this work for personal or classroom use without prior permission or payment for photocopies or distribution for profit or commercial advantage is granted by copyright holder for the sole purpose of locating people and does not provide traditional data networking services. To avoid these limitations, we have developed a new system that we call RADAR. Our goal is a location-support system, rather than a conventional location-tracking system that tracks and stores location information for service providers.

Over the past many months, we have designed and implemented

Cricket, a location-support system for buildings-wide deployment in the context of Project Oxygen, and have conducted several experiments with it. We have integrated it with INS for resource discovery, and an active map application, which together enable location-

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

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

Bahl & Padmanabhan, INFOCOM'00

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

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Abstract

The proliferation of mobile computing devices and local-area wireless networks has fostered a growing interest in location-aware systems. One area of particular interest is in providing RADAR, a radio-frequency (RF) based system for locating and tracking users inside buildings. RADAR operates in multiple frequency bands to provide overlapping coverage in the area of interest. It combines energy detection and signal strength measurements to determine user location and thereby enable location-aware services and applications. We present experimental results that demonstrate RADAR to estimate user location with a high degree of accuracy.

Keywords: location-aware services, user location and tracking, wireless LAN, radio-frequency wireless network

1 Introduction

The proliferation of mobile computing devices and local-area wireless networks has fostered a growing interest in location-aware systems. One area of particular interest is in providing RADAR, a radio-frequency (RF) based system for locating and tracking users inside buildings. RADAR operates in multiple frequency bands to provide overlapping coverage in the area of interest. It combines energy detection and signal strength measurements to determine user location and thereby enable location-aware services and applications. We present experimental results that demonstrate RADAR to estimate user location with a high degree of accuracy.

2 Related Work

Related work in the area of user location and tracking falls into the following broad categories: (1) in-building RF networks, (2) wide-area cellular networks (based on RF), and (3) Global Positioning System (GPS).

The *in-building* systems [1, 2] have been an early and significant contribution to the field of location-aware systems. In these systems, a badge worn by a person emits a unique IR signal every second. Sensors placed at known locations pick up the unique signal and relay these to the location manager. While this system provides accurate location information, it suffers from several disadvantages: (a) it has a limited range of 10 m, (b) it incurs significant installation and maintenance costs, and (c) it performs poorly in the presence of windows, which is a problem in a building with a lot of windows.

While much research has focused on developing services architectures for location-aware systems (e.g., MobiNet [3]), little attention has been paid to the fundamental and challenging problem of location-aware tracking mobile users, especially in in-building environments. The few efforts made to solve this problem have focused on the context of mobile phones (e.g., [4]).

Another system based on RF technology is described in [10]. It uses multiple distance measurements between known points, or via *angulation*, which measures angles or bearing relative to points with known separations. The system suffers from the drawbacks of a large number of access points and high power consumption.

To make sense of this domain, we have developed a location system that helps developers of location-aware applications better evaluate their options when choosing a location-sensing system. The taxonomy may also aid researchers in identifying opportunities for new location-sensing techniques.

LOCATION SYSTEM PROPERTIES

A broad set of issues arises when we discuss classifying location-sensing systems. These issues are generally independent of the technological details of a system, as described in the "Location-Sensing Techniques" sidebar. Although certainly not all orthogonal,

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IEEE INFOCOM 2000

Location Systems for Ubiquitous Computing

Location Systems for Ubiquitous Computing

Hightower & Boriello, IEEE Computer'01

4,284 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
Washington

To serve as well, emerging mobile computing applications will need to know the physical location of things that they can record and report to them. What kind of location information is needed? What kind of location system is perhaps the most suitable? What kinds of location-aware services can be built on top of location systems? How can location systems be used to help mobile computing applications? GPS provides an excellent location framework for determining geographic position. The worldwide satellite constellation has reliable and ubiquitous coverage, and a differential reference or use of the Wide Area Augmentation System allows receivers to com-

Location-Sensing Techniques

When attempting to determine a given location, we can choose from three major techniques:

- *Trilateration*: This technique makes use of distance measurements between known points, or via *angulation*, which measures angles or bearing relative to points with known separations.
- *Proximity*: measures nearness to a known set of points.
- *Scene analysis*: examines a view from a particular vantage point.

Location sensing techniques can be used to implement one or more of these techniques to locate objects, people, or both. A paper describing these techniques in detail can be found at www.cs.washington.edu/research/portfolios/papers/UW-CSE-01-07-01.pdf.

August 2001

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LOCATION INFERENCE: PIGGYBACKING ON INFRASTRUCTURE

FM Radio

**1 Introduction**

One of the promises of ubiquitous computing is to connect users to important information as they move around the world. Our research organization has created a small, low-power device called a Smart Personal Object Technology (SPOT). The first manufactured SPOT device will be a commercially available wristwatch, a prototype of which is shown in Figure 1. The SPOT device is designed to listen for digitally encoded data such as news stories, weather forecasts, personal messages, traffic updates, and retail directory information, and frequently select data from commercial FM radio stations. The device holds programs for selecting millions of items to receive notifications and alerts.

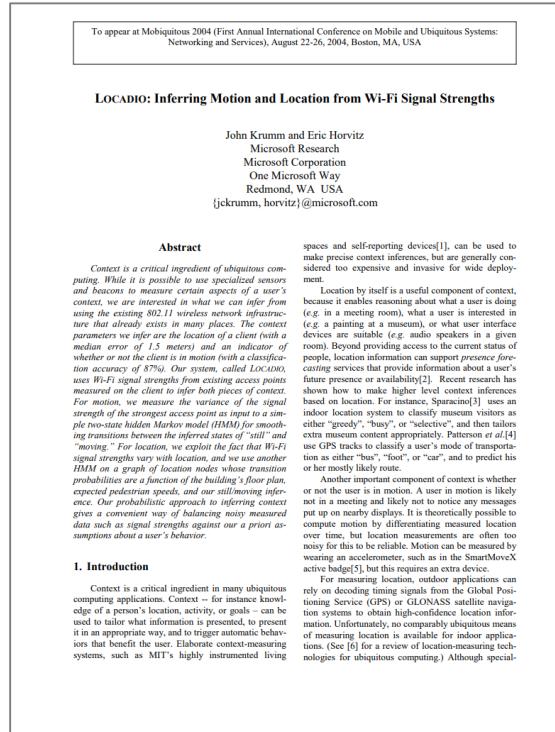
The location method for localizing data is particular to SPOT. It needs to depend on the limited range of FM radio signals, so that only devices within range of a particular radio tower will get data relevant to that tower's coverage area. Unfortunately, for certain messages, this coarse location resolution is inadequate. Traffic updates, limited time discounts, offers, and lists of nearby attractions need finer location filtering than that provided by FM radio station coverage areas. One alternative is

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

Krumm *et al.*, UbiComp'03

173 citations

WiFi (& Bluetooth)

**1. Introduction**

Context is a critical ingredient in many ubiquitous computing applications. Context – for instance knowledge of a person's location, activity, or goals – can be used to tailor what information is presented, to present it in an appropriate way, and to trigger automatic behaviors that benefit the user. Elaborate context-measuring systems, such as MIT's highly instrumented living

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 LaMarca¹, Yatin Chawathe¹, Sunny Consolvo¹, Jeffrey Hightower¹, Ian Smith¹, James Scott², Timothy Sohn¹, James Howard¹, Jeff Hughes³, Fred Potter⁴, Jason Tabert⁵, Pauline Powledge¹, Gaetano Borriello⁴, and Bill Schilit¹

¹Intel Research Seattle²Intel Research Cambridge³Department of Computer Science, UC San Diego⁴Department of Computer Science & Engineering, University of Washington⁵Information School, University of Washington

Abstract. Location awareness is an important capability for mobile computing. Yet inexpensive, pervasive positioning—a requirement for wide-scale adoption of location-aware computing—has been elusive. We demonstrate a radio beacon-based approach to location, called Place Lab, that can overcome the lack of ubiquity and high cost of existing sensing approaches. Using Place Lab, we compare laptop Wi-Fi and cell phone beacons as alternatives to people, location information can support presence, forewarning, and navigation. Beyond passive access to the current status of people, location information can support presence, forewarning, and navigation. Recent research has shown how to use level context to infer location based on position. For instance, Specified[3] uses an indoor location system to classify museum visitors as either "greedy", "busy", or "selective", and then tailors exhibits and content appropriately. Patterson *et al.*[4] used GPS track data to characterize a user's mode of transportation as either "bus", "foot", or "car", and to predict his or her most likely route.

Another important consideration is whether or not a user is in motion. A user in motion is likely not in a room and likely not to notice any messages put up on nearby displays. It is theoretically possible to compute motion by detecting measured location over time, but location measurements are often too noisy for this to be practical. Motion can be detected by using an accelerometer, such as in the SmartMoteX active badge[5], but this requires an extra device.

For measuring location, outdoor applications can rely on GPS, receiving signals from Global Positioning System (GPS) or Global Positioning System (GPS) satellite navigation systems to obtain high-confidence location information. Unfortunately, no consistently ubiquitous means of measuring location is available for indoor applications. (See [6] for a review of location-measuring technologies for ubiquitous computing.) Although special-

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Place Lab: Device Positioning Using Radio Beacons in the Wild

LaMarca *et al.*, Pervasive Comp'05

1,337 citations

GSM Cells

Accurate GSM Indoor LocalizationVeljo Otsason¹, Alex Vanharanta², Anthony LaMarca³, and Eyal de Leon⁴¹Tutte University, www.tutte.tut.fi/~otsason/²University of Toronto, www.cs.toronto.edu/~valer/³Intel Research Seattle, [anthony.iamarc@intel.com](http://www.iamarc@intel.com)⁴141

Abstract. Accurate indoor localization has long been an objective of the ubiquitous computing research community, and numerous indoor localization solutions based on 802.11, Bluetooth, ultrasound and infrared technologies have been proposed. This paper presents the first accurate GSM-based localization system that provides median accuracy of 3 meters in large-scale buildings. The key idea is making possible GSM-based indoor localization possible is the use of wide-signal-strength fingerprinting. In addition to the 6 strongest cells traditionally used in the GSM-based localization, we also use 10 additional cells that are strong enough to be detected, but too weak to be used for efficient communication. Experiments conducted on three multi-story buildings show that the proposed solution is comparable to an 802.11-based implementation, and can accurately differentiate between floors in both wooden and steel-reinforced concrete structures.

1 Introduction

The accurate localization of objects and people in indoor environments has long been considered an important building block for ubiquitous computing applications [7,8]. Most research on indoor localization systems has been based on the use of short-range signals, such as WiFi [3,5,11], Bluetooth [1], ultra sound [15], or infrared [16]. These signals are popular due to popular belief in indoor localization systems based wide-area GSM fingerprints can achieve high accuracy, and is in fact comparable to an 802.11-based implementation.

GSM-based indoor localization has several benefits: (i) GSM signals are all last permanent signal, including the 11 ms idle period; (ii) the wide acceptance of cellular phones makes them ideal candidate for the delivery of ubiquitous computing applications. A localization system based on cellular signals, such as GSM, leverages the phone's existing hardware and removes the need for additional radio interface [10], because cellular towers are deployed across the entire globe; (iii) cellular towers are located in urban areas where a building's electrical infrastructure has failed. Moreover, cellular systems are designed to tolerate power failures. For example, the cellular network kept working during the massive power outage that left most of the Northeastern United States and Canada in the dark in the Summer of 2003; (iv) GSM, unlike 802.11 networks, operates in a licensed band, and therefore does not suffer

M. Bouj et al. (Eds.): UbiComp 2003, LNCS 3060, pp. 141–158, 2003.
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Accurate GSM Indoor Localization

Otsason *et al.*, UbiComp'05

542 citations

BEACON-BASED POSITIONING

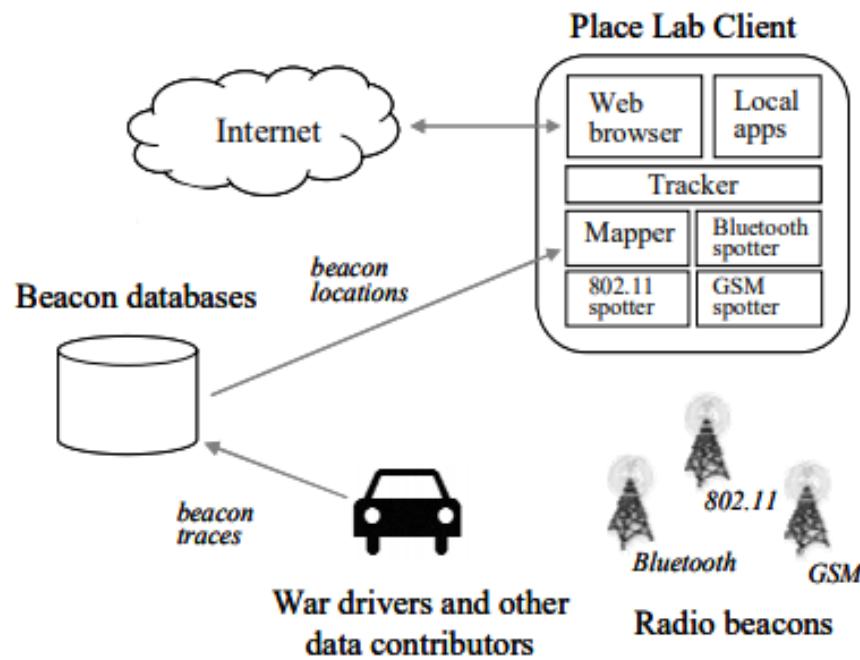


Fig.1. Key components in the Place Lab architecture

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.

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).

HUMAN TRAJECTORY PREDICTION

Research Track Paper

Trajectory Pattern Mining

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ABSTRACT

The increasing pervasiveness of location-acquisition technologies (GPS, GSM networks, etc.) is leading to the collection of large spatio-temporal datasets and to the opportunity of discovering new knowledge about movement, which fosters novel applications and services. In this paper, we move towards this direction and develop an extension of the sequential pattern mining paradigm that analyzes the trajectories of moving objects. We introduce *Trajectory pattern mining*, a descriptive framework that views record their latitude-longitude position at each moment they are exposed to a GPS satellite, and transmit their trajectories to a collecting server. Thus, we can analyze patterns of ubiquitous objects (i.e., the regions of space visited during movements) and time (i.e., the duration of movement). In this setting, we provide a general formal statement of the model and its properties, and we propose two different instantiations of different complexity. The various approaches are then empirically evaluated over real data and synthetic benchmarks, comparing their strengths and weaknesses.

Categories and Subject Descriptors

H.2.8 [Database Applications]: Data mining

General Terms

Algorithms

Keywords

Trajectory patterns, Spatio-temporal data mining

1. INTRODUCTION

Spatio-temporal patterns that succinctly allow the comparative behaviour of a population of moving objects are useful abstractions to understand mobility-related phenomena. In particular, a form of pattern, which represents an aggregated abstraction of many individual trajectories of moving objects within an observed population, would be extremely useful in the domain of sustainable mobility and traffic management in metropolitan areas, where the discovery of traffic

flows among sequences of different places in a town (origin-destination flows) is a key issue [2].

Nowadays, the movement of people or vehicles within a population can be observed from their GPS traces left behind by the wireless network infrastructures. For instance, mobile phones leave positioning logs, which specify their location (e.g., cell, at each moment they are exposed to the GPS network). Moreover, GPS-enabled portable devices can record their latitude-longitude position at each moment they are exposed to a GPS satellite, and transmit their trajectories to a collecting server. Thus, we can analyze patterns of ubiquitous objects (i.e., the regions of space visited during movements) and time (i.e., the duration of movement).

In this setting, we provide a general formal statement of the model and its properties, and we propose two different instantiations of different complexity. The various approaches are then empirically evaluated over real data and synthetic benchmarks, comparing their strengths and weaknesses.

In this paper, we precisely address this problem, and introduce a novel form of spatio-temporal pattern, which formalizes the concept of aggregate movement behaviour.

The new pattern, that we call *Trajectory pattern*, represents a set of individual trajectories that share the property of visiting the same sequence of places within similar times.

There are two types of trajectory patterns: (i) the *spatial pattern* in the given space, and (ii) the *typical travel time* of moving objects from region to region. In fact, in our approach a trajectory pattern is a sequence of spatial regions that, on the basis of their position, encounter frequently visited in the order specified by the route; in addition, the transition between two consecutive regions in such a sequence is associated with a typical travel time that, again, comes from the input trajectories. For instance, consider the following two trajectory patterns over regions of interest in the centre of a town:

Railway Station $\xrightarrow{\text{train}}_{\text{bus}}^{\text{bus}} \text{Castle Square} \xrightarrow{\text{bus}}^{\text{bus}} \text{Museum}$ (a)
 Railway Station $\xrightarrow{\text{train}}_{\text{bus}}^{\text{bus}} \text{Middle Bridge} \xrightarrow{\text{bus}}^{\text{bus}} \text{Campus}$ (b)

Here, pattern (a) may be interpreted as a typical behaviour of tourists that rapidly reach a major attraction from the railway station and spend there about two hours before heading to the castle square. Pattern (b), instead, may highlight the pedestrian flow of students that reach the university campus from the station; the central bridge over the river is a compulsory passage. It should be observed that a trajectory pattern does not specify any particular route among two consecutive regions; instead, a

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 KDD'07, August 12-15, 2007, San Jose, California, USA.
 Copyright 2007 ACM 978-1-59593-609-7/07/08 ...\$5.00.

330

Trajectory Pattern Mining

Giannotti *et al.*, KDD'07
 965 citations

Predestination: Inferring Destinations from Partial Trajectories

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 (jckrumm, horvitz@microsoft.com)

Abstract. We describe a method called *Predestination* that uses a history of a driver's trips, along with data about driving behavior, to predict where a driver is going as a trip progresses. Driving behaviors include types of navigation, driving efficiency, and trip times. Beyond considering previously visited destinations, Predestination leverages an open-world modeling methodology that considers the likelihood of users visiting previously unobserved locations based on trends in the data and on the background properties of locations. This allows our algorithm to smoothly transition between "out of the box" with no training data to more fully trained with increasing numbers of observations. Multiple components of the analysis are fused via Bayesian inference to produce a probabilistic map of destinations. Our algorithm was trained and tested on hold-out data drawn from a database of GPS driving data gathered from 169 different subjects who drove 7,335 different trips.

1 Introduction

Location has played a central role in ubicomp research. Information about the location of users can enable numerous compelling location-based services. For example, location can be used to fetch relevant information such as nearby points of interest and available services. Beyond current location, services can be developed around predictions about future locations. For example, a driver may want to know about restaurants or traffic problems before encountering them to give time to prepare and make decisions. Location-based services could present their availability in anticipation of a user's arrival. In another application, a prediction of a person's destination can be helpful in deciding if the person is deviating from an intended route [2]. Cheng *et al.*[3] even speculate that destination prediction could be used to catch automobile thieves in the city.

We present a methodology named *Predestination* that is aimed at predicting a driver's destination as a trip progresses. The probabilistic prediction is based on several sources of data, including the driver's history of destinations and an ensemble of trips from a group of drivers. We demonstrate how to combine these data sources in a

P. Dourish and A. Friday (Eds.): Ubicomp 2006, LNCS 4206, pp. 243–260, 2006.
 © Springer-Verlag Berlin Heidelberg 2006

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

Route Prediction from Trip Observations

Jon Froehlich
 University of Washington
 John Krumm
 Microsoft Research

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2008-01-0201

ABSTRACT

This paper develops and tests algorithms for predicting the end-to-end route of a vehicle based on GPS observations of the vehicle's past trips. We show that a large portion of a typical driver's trips are repeated. Our algorithm exploits this fact by predicting by matching the first part of a driver's trip with the last part of a sequence of previously observed trips. We find that, in some cases, route prediction is accurate within the first two miles of the trip. Our accuracy is lower in other cases, and our results give details on how often our algorithm achieves various levels of prediction accuracy.

We trained and tested our algorithms on GPS data from 252 drivers. The next few sections describe how we cleaned our typically noisy GPS data, extracted distinct trips, and found drivers' regular routes. We then go on to describe two algorithms for route prediction and give details on how well they perform. First, we highlight some related work.

INTRODUCTION

Route prediction is the missing piece in several proposed ideas for intelligent vehicles. In this paper, we present algorithms that predict a vehicle's entire route as it is driven. Such predictions are useful for giving the driver warnings about upcoming traffic hazards or informing about upcoming segments of interest, including the transition to the most interesting segments or of end-to-end route prediction is for improving the efficiency of hybrid vehicles. Given knowledge of future changes in elevation and speed, a hybrid control system can optimize the vehicle's charge/discharge schedule. For example, if a hybrid vehicle knows about an upcoming opportunity to recharge energy from regenerative braking (e.g., stop-and-go traffic, sharp curves, or a steep hill), it can use up part of its battery power prior to the opportunity to make room for the expected incoming charge. Researchers from Nissan showed that it is possible to improve fuel economy by up to 10% if the route is known in advance [1]. This paper also explores the optimal control scheme for a hybrid assuming the route is already known [2].

While the driver could be asked for his or her route before every drive, we suspect that most drivers would tire of this quickly. This is especially true for a driver's

regular route, which is where we concentrate our efforts. We found that, for drivers observed for at least 40 days, nearly 60% of their trips were duplicated in our six-month period. We find that, in contrast with the random trajectories predicted by the preceding Levy flight random walk model, most drivers show a clear pattern of time and spatial regularity, each individual being characterized by a time-independent characteristic distance and a significant probability to return to a few highly frequent locations. After correctly identifying the locations and the time and space anisotropy of each trajectory, the individual travel patterns collapse into a single spatial probability distribution, indicating that, despite the diversity of their travel history, most drivers could impact all phenomena driven by human mobility, from epidemic prediction to emergency response, urban planning and agent-based modelling.

Given the above factors that influence a population's mobility patterns, ranging from means of transportation to job and family-imposed restrictions and priorities, human trajectories are often approximated with various random walks. Indeed, one can approximate a trajectory with a random walk, followed by recent data on monkeys and marine predators¹⁰, suggested that animal trajectories are approximated by a Levy flight¹¹ random walk for which step size Δt follows a power law distribution $P(\Delta t) \propto -\Delta t^{-\beta}$, where the slope $\beta = 1.75 \pm 0.15$ (mean \pm standard deviation), and cutoff value $\Delta t_c = 2.5$ km. Although the trajectory is not far from a straight line in the Δt -log(Δs) plot, the distance travelled by animals, requiring further study¹², this finding has been generalized to humans, documenting that the distribution of distances between consecutive sightings of nearly half-a-million bus notes is fat-tailed. Given that most of us move in a similar way, suggesting that human movement, suggesting that human trajectories are best modelled as a continuous-time random walk with fat-tailed distance and waiting-time distributions. A particle following a Levy flight has a tendency to visit the same place again during a single step^{13,14}, which seems to be consistent with human travel patterns. Most of the time we travel only over short distances, while home work, whereas occasionally we take longer journeys.

Each consecutive step of a trajectory is the composite motion of two or more individuals who own the two reported sightings. Thus, it is not clear whether the observed distance travelled reflects the sum of individual distances previously unknown, or the sum between individual-based home and individual human trajectories. Counter to bank notes, mobile phone calls are carried by the same individual during his/her daily routine, offering the chance to track the same person over time. Thus, we can calculate the radius of gravity for each user (see Supplementary Information), interpreted as the characteristic distance travelled by user when observed up to time t (Fig. 1). Next, we can calculate the mean of gravity distances for each user, for all users included in the D_3 data, finding that they also can be approximated with a truncated power-law.

We used two data sets to explore the mobility pattern of individuals. The first (D_1) consisted of the mobility patterns recorded over a six-month period for 100,000 individuals selected randomly from a sample of more than 6 million anonymized mobile phone users. Each time a user initiated or received a call or a text message, the location of the tower routing the communication was recorded, allowing us to determine the user's position at a specific time. The time between consecutive calls followed a "bursty" pattern¹⁵ (see Supplementary Fig. 1), indicating that although most consecutive calls are placed shortly after a previous occasion, the occasions that are long are much more rare and irregular. To make sure that the user's position was not affected by the irregular call pattern, we also studied a data set (D_2) that captured the location of 206 mobile phone users, recorded every two hours for an entire week. In both data sets, the average distance travelled by the location of the user over time is less than 10³ mobile towers, registering movement only when the user moved between areas serviced by different towers. The average service area each tower covers is approximately 3 km², and over 30% of the users cover an area of 1 km² or less.

To explore the statistical properties of the population's mobility patterns, we measured the distance of user's positions at consecutive calls, capturing 16,264,508 displacements for the D_3 and 10,407 displacements for the D_3 data set. We found that the distribution of displacements over all users is well approximated by a truncated power-law:

$$P(Ar) = (\Lambda_r + \Lambda_0)^{-\alpha} \exp(-Ar/\kappa) \quad (1)$$

with exponent $\beta = 1.75 \pm 0.15$ (mean \pm standard deviation), $\Lambda_0 = 1.5$ km and cutoff values $\kappa|_{D_3} = 400$ km and $\kappa|_{D_3} = 80$ km for the D_3 and D_3 data sets, respectively.

Given the above factors that influence a population's mobility patterns, ranging from means of transportation to job and family-imposed restrictions and priorities, human trajectories are often approximated with various random walks. Indeed, one can approximate a trajectory with a random walk, followed by recent data on monkeys and marine predators¹⁰, suggested that animal trajectories are approximated by a Levy flight¹¹ random walk for which step size Δt follows a power law distribution $P(\Delta t) \propto -\Delta t^{-\beta}$, where the slope $\beta = 1.75 \pm 0.15$ (mean \pm standard deviation), and cutoff value $\Delta t_c = 2.5$ km. Although the trajectory is not far from a straight line in the Δt -log(Δs) plot, the distance travelled by animals, requiring further study¹², this finding has been generalized to humans, documenting that the distribution of distances between consecutive sightings of nearly half-a-million bus notes is fat-tailed. Given that most of us move in a similar way, suggesting that human movement, suggesting that human trajectories are best modelled as a continuous-time random walk with fat-tailed distance and waiting-time distributions. A particle following a Levy flight has a tendency to visit the same place again during a single step^{13,14}, which seems to be consistent with human travel patterns. Most of the time we travel only over short distances, while home work, whereas occasionally we take longer journeys.

Each consecutive step of a trajectory is the composite motion of two or more individuals who own the two reported sightings. Thus, it is not clear whether the observed distance travelled reflects the sum of individual distances previously unknown, or the sum between individual-based home and individual human trajectories. Counter to bank notes, mobile phone calls are carried by the same individual during his/her daily routine, offering the chance to track the same person over time. Thus, we can calculate the radius of gravity for each user (see Supplementary Information), interpreted as the characteristic distance travelled by user when observed up to time t (Fig. 1). Next, we can calculate the mean of gravity distances for each user, for all users included in the D_3 data, finding that they also can be approximated with a truncated power-law.

We used two data sets to explore the mobility pattern of individuals. The first (D_1) consisted of the mobility patterns recorded over

$$P(t_q) = (t_q + t_q^0)^{-\beta} \exp(-t_q/\kappa) \quad (2)$$

with exponent $\beta = 1.59 \pm 0.05$ (mean \pm standard deviation), $t_q^0 = 1.59$ hours and $\kappa = 1.59$ hours for the D_3 data set.

Given the above factors that influence a population's mobility patterns, ranging from means of transportation to job and family-imposed restrictions and priorities, human trajectories are often approximated with various random walks. Indeed, one can approximate a trajectory with a random walk, followed by recent data on monkeys and marine predators¹⁰, suggested that animal

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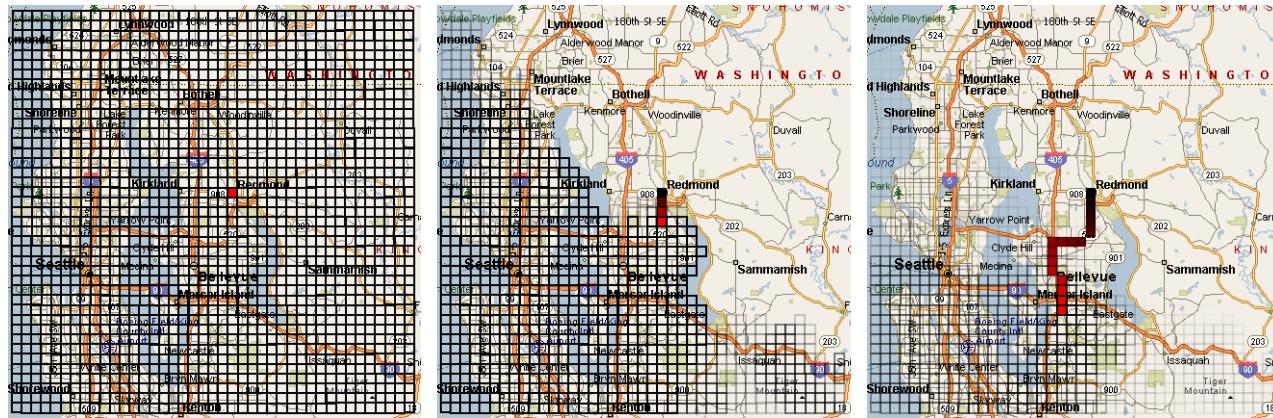
LETTERS

Understanding individual human mobility patterns

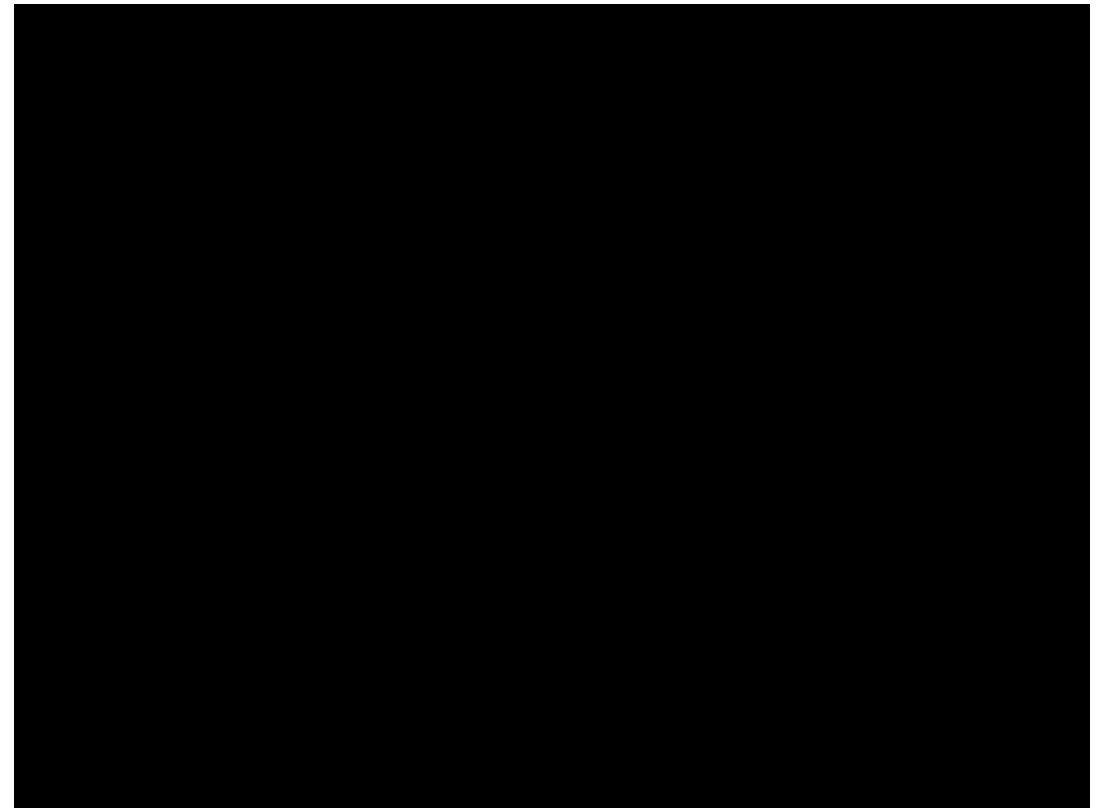
Marta C. González¹, César A. Hidalgo^{1,2} & Albert-László Barabási^{1,2,3}¹Center for Complex Networks Research and Department of Physics, Biology and Computer Science, Northeastern University, Boston, Massachusetts 02135, USA; ²Center for Complex Networks Research and Department of Physics and Computer Science, University of Notre Dame, Notre Dame, Indiana 46556, USA; ³Center for Cancer Systems Biology, Dana Farber Cancer Institute, Boston, Massachusetts 02115, USA

779

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

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Abstract. In this work, algorithms are developed and evaluated to detect physical activities from data acquired using five small biaxial accelerometers worn simultaneously on different parts of the body. Acceleration data was collected from 20 subjects without researcher supervision or observation. Subjects were asked to perform a sequence of everyday tasks but not told specifically where or how to do them. Mean, energy, frequency-domain entropy, and correlation of acceleration data was calculated and several classifiers using these features were tested. Decision tree classifiers showed the best performance recognizing everyday activities with an accuracy rate of 84%. The results show that although most activities are recognized well with subject-independent training data, others appear to require subject-specific training data. The results suggest that multiple accelerometers aid in recognition because conjunctions in acceleration feature values can effectively discriminate many activities. With just two biaxial accelerometers – thigh and wrist – the recognition performance dropped only slightly. This is the first work to investigate performance of recognition algorithms with multiple, wire-free accelerometers on 20 activities using datasets annotated by the subjects themselves.

1 Introduction

One of the key difficulties in creating useful and robust ubiquitous, context-aware computer applications is developing the algorithms that can detect context from noisy and often ambiguous sensor data. One facet of the user's context is his physical activity. Although prior work discusses physical activity recognition using acceleration (e.g. [17,5,23]) or a fusion of acceleration and other data modalities (e.g. [18]), it is unclear how most prior systems will perform under real-world conditions. Most of these works compute recognition results with data collected from subjects under artificially constrained laboratory settings. Some also evaluate recognition performance on data collected in natural, out-of-lab settings but only use limited data sets collected from one individual (e.g. [22]). A number of works use naturalistic data but do not quantify recognition accuracy. Lastly, research using naturalistic data collected from multiple subjects has focused on

A. Ferscha and F. Mattern (Eds.): PERVERSIVE 2004, LNCS 3001, pp. 1–17, 2004.
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Activity Recognition from User-Annotated Acceleration Data

Bao & Intille, Pervasive'04
 2,795 citations

Inferring Activities from Interactions with Objects

Recognizing and recording activities of daily living is a significant problem in elder care. A new paradigm for ADL inferring leverages radio-frequency-identification technology, data mining, and a probabilistic inference engine to recognize ADLs, based on the objects people use.

A key aspect of pervasive computing is using computers and sensor networks to effectively and unobtrusively infer users' behavior in their environment. This includes inferring which activity users are performing and where they're performing it, and its current stage. The elder care field is a prime, yet difficult application area for inferring whether and how people with early-stage cognitive decline are performing *activities of daily living*. (For most older ADLs, see the "Activities of Daily Living" sidebar.)

Recognizing ADLs, particularly in the home, is a challenging problem for several reasons. First, we can perform ADLs in various ways, models of activities and recognition software must adapt to this variety. Second, the underlying sensors must report the features of the environment in various sensing contexts (such as light levels, sounds, and locations). Third, given the large number of ADLs—20 to 30 classes (such as making a meal) with thousands of instances—a system should model each activity with minimum human effort. Addressing these challenges simultaneously has been a key barrier to success for ADL-recognition systems.

We propose an approach that addresses these challenges and shows promise in automating some types of ADL monitoring. Our key observation is that the sequence of objects a person uses while performing an ADL robustly characterizes both the ADL's identity and the quality of its execution. So, our Proactive Activity Toolkit (Proact) project • Represents activities as a probabilistic sequence of objects used
 • Adapts a cheap, durable, easy-to-use sensing technology to robustly sense the objects being used across various sensing and use contexts
 • Minimizes probabilistic models of activity use from plain English descriptions of activities, such as recipes

Project

Our system has three components: specialized sensors to detect object interactions, a probabilistic engine that infers activities given observations from sensors, and a model creator that lets us easily create probabilistic models of activities. (The Related Work in ADL Inferring sidebar describes related research.)

Sensors

We tag objects of interest using radio-frequency-identification (RFID) tags, which we can attach unobtrusively onto objects such as a potato fork. These tags are postage stamp-sized, durable, battery free, and inexpensive (US\$0.40 each and falling). When interrogated by a reader,

Inferring Activities from Interactions with Objects

Philipose *et al.*, Pervasive Comp'04
 987 citations



Learning and Inferring Transportation Routines

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Abstract

This paper introduces a hierarchical Markov model that can learn and infer a user's daily movements through an urban community. The model leverages the location of GPS data logs to help infer a user's daily movement patterns, and high-level information such as a user's destination and mode of transportation. To achieve efficient inference, we apply Rao-Blackwellized particle filters at multiple levels of the model hierarchy. Locations such as bus stops and parking lots, where the user frequently changes mode of transportation, are learned from GPS data logs without manual labeling of training data. We experimentally demonstrate how to accurately detect novel behavior or user errors (e.g. taking a wrong bus) by explicitly modeling activities in the context of the user's historical data. Finally, we discuss an application called "Opportunity Knocks" that employs our techniques to help cognitively-impaired people use public transportation safely.

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Keywords: Activity recognition, Hierarchical Markov model; Location tracking; Novelty detection; Rao-Blackwellized particle filters

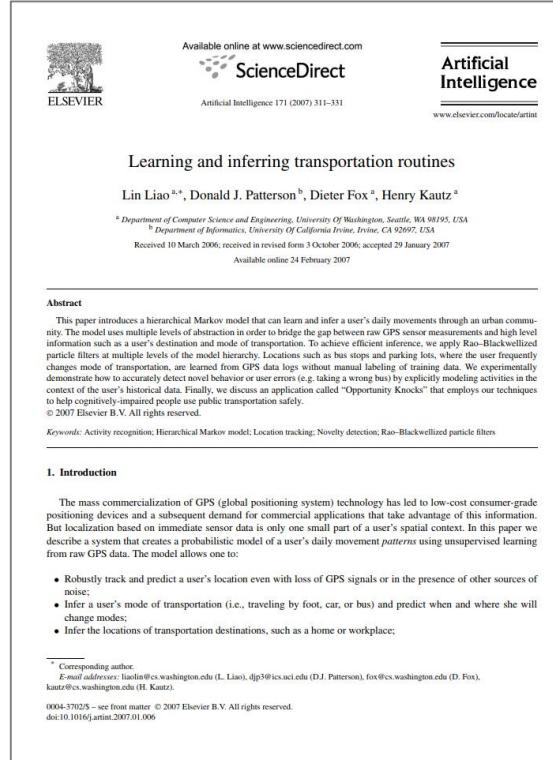
1. Introduction

The mass commercialization of GPS (global positioning system) technology has led to low-cost consumer-grade positioning devices and a subsequent demand for commercial applications that take advantage of this information. But localization based on imprecise sensor data is only one small part of a user's spatial context. In this paper we describe a system that creates a probabilistic model of a user's daily movement patterns using unsupervised learning from raw GPS data. The model allows one to:

- Robustly track and predict a user's location even with loss of GPS signals or in the presence of other sources of noise;
- Infer a user's mode of transportation (i.e., traveling by foot, car, or bus) and predict when and where she will change modes;
- Infer the locations of transportation destinations, such as a home or workplace;

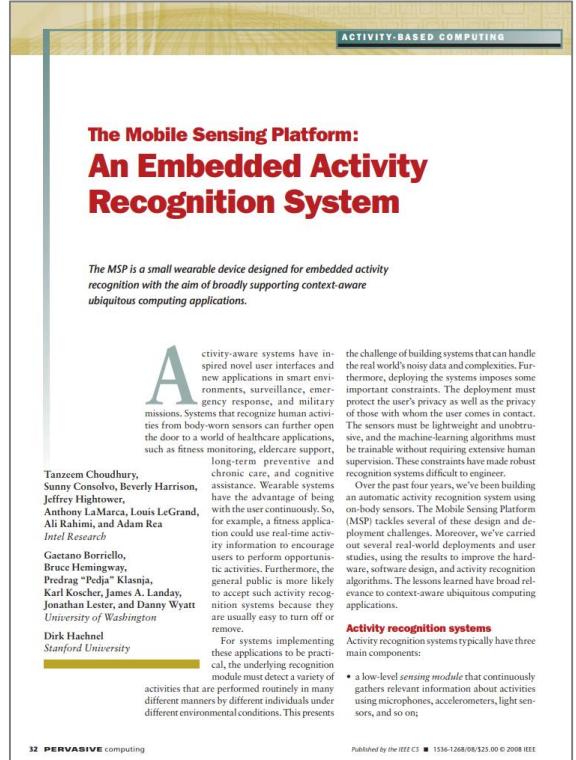
*Corresponding author.
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 doi:10.1016/j.artint.2007.01.006



Learning and Inferring Transportation Routines

Liao *et al.*, Artificial Intelligence'07
 987 citations



The Mobile Sensing Platform: An Embedded Activity Recognition System

The MSP is a small wearable device designed for embedded activity recognition with the aim of broadly supporting context-aware ubiquitous computing applications.

Activity-aware systems have inspired new user interfaces and new applications in smart environments, mobile healthcare, emergency response, and military missions. Systems that recognize human activities from body-worn sensors can further open the door to a world of healthcare applications, such as fitness monitoring, eldercare supports, long-term care, and cognitive assistance. Wearable systems have the advantage of being with the user continuously. So, for example, a fitness application could use real-time activity information to encourage users to engage in more active physical activities. Furthermore, the general public is more likely to accept such activity recognition systems because they are usually easy to turn off or remove.

For systems implementing these applications to be practical, the underlying recognition module must detect a variety of activities that are performed routinely in many different manners by different individuals under different environmental conditions. This presents the challenge of building systems that can handle the real world's noisy data and complexities. Furthermore, deploying the systems imposes some constraints on the design. The system must protect the user's privacy as well as the privacy of those with whom the user comes in contact. The sensors must be lightweight and unobtrusive, and the machine-learning algorithms must be trainable without requiring extensive human supervision. The sensors must have made robust recognition systems difficult to build.

Over the past four years, we've been building an automatic activity recognition system using on-body sensors. The Mobile Sensing Platform (MSP) tackles several of these design and deployment challenges. Moreover, we've carried out several real-world deployments and user studies, including evaluations of sensor hardware, software design, and activity recognition algorithms. The lessons learned have broad relevance to context-aware ubiquitous computing applications.

Activity recognition systems
 Activity recognition systems typically have three main components:

• a low-level sensing module that continuously gathers relevant information about activities using microphones, accelerometers, light sensors, and so on;

The Mobile Sensing Platform: An Embedded Activity Recognition System

Choudhury *et al.*, Pervasive Computing'08
 562 citations

MOBILE SENSING PLATFORM (~2005-2009)

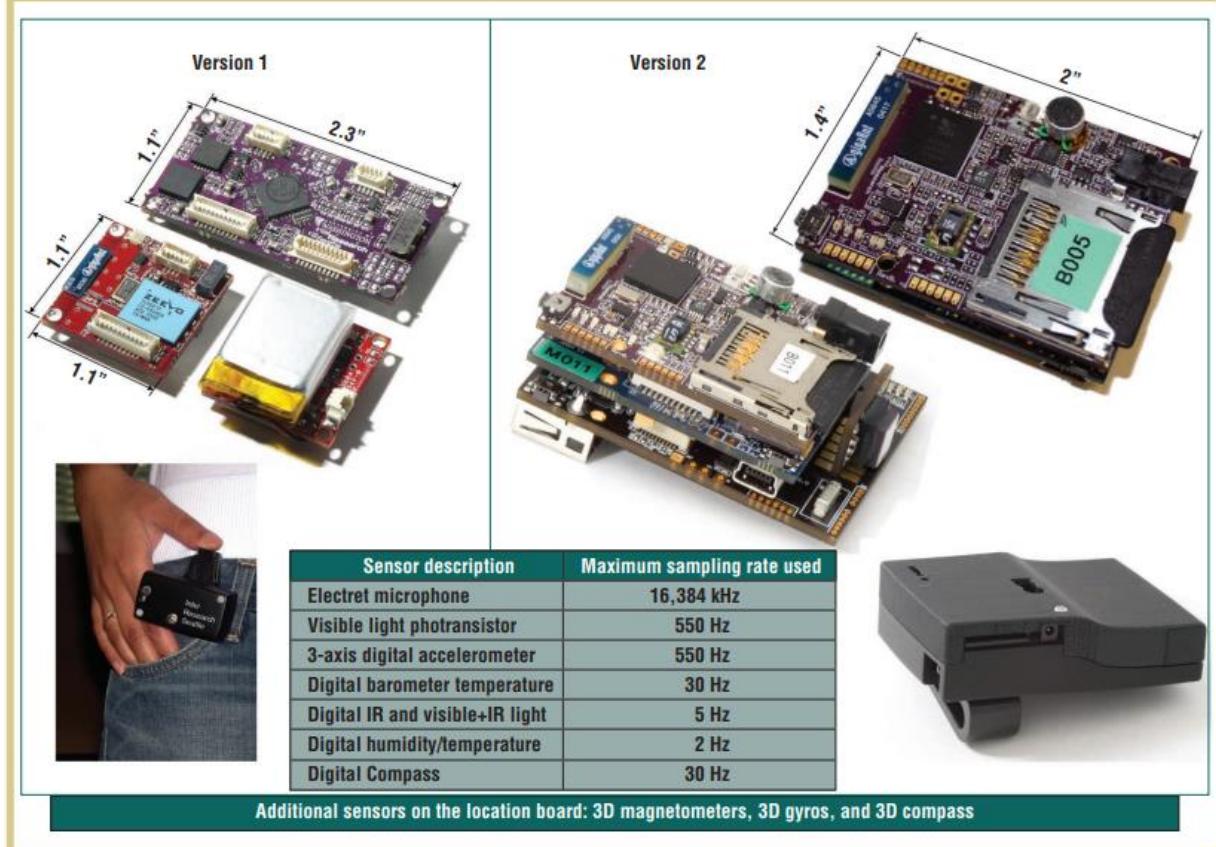


Figure 1. The Mobile Sensing Platform hardware, versions 1.0 and 2.0., with and without cases. Both MSP versions support seven sensors. In addition, version 2.0 offers a location daughterboard that includes additional 3D sensors. The MSP can communicate wirelessly with other devices in real time or store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

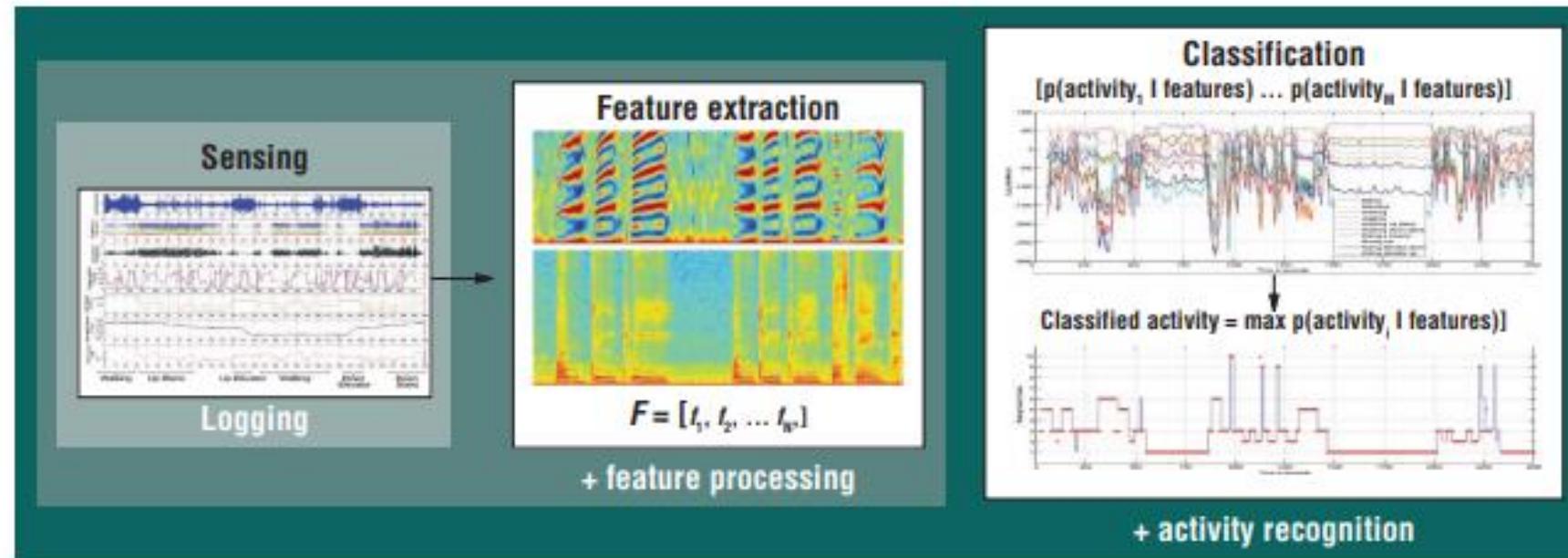
The beginning of “activity recognition” as a service.

Hardware/software platform for activity recognition.

Multi-sensor, belt-worn device.

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

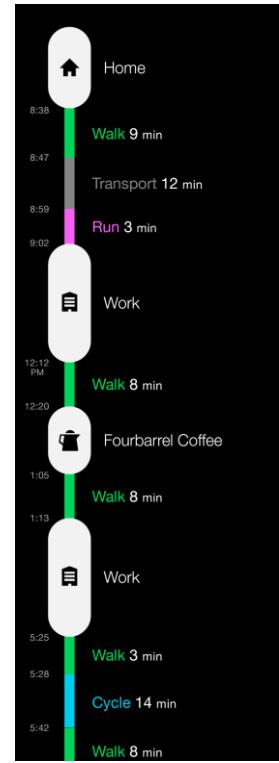
MOBILE SENSING PLATFORM (~2005-2009)



Activities modeled during various deployments: walking, running taking stairs up/down, taking elevator up/down, cooking, working on computer, eating, watching TV, talking, cycling, using an elliptical trainer, and using a stair machine.

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.

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



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 fitbit ionic™

ACTIVITY RECOGNITION APIs: COMMERCIAL EXAMPLE

The screenshot shows the Apple Developer website interface. At the top, there's a navigation bar with links for Developer, Discover, Design, Develop, Distribute, Support, Account, and a search icon. Below the navigation bar, the URL is shown as Documentation > Core Motion > CMMotionActivity. To the right of the URL are Language: Swift and API Changes: Show dropdown menus. The main content area has a dark background with white text. It starts with the word "Class" and then the title "CMMotionActivity". Below the title, it says "The data for a single motion update event." On the left side, there's a sidebar with sections for SDKs (iOS 7.0+, watchOS 2.0+), Framework (Core Motion), and links for "On This Page" (Overview, Topics, Relationships, See Also). On the right side, there are two main sections: "Getting the Type of Motion" and "Getting Metadata for the Motion", each with a list of properties and their descriptions.

Class

CMMotionActivity

The data for a single motion update event.

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 [CMMotionActivity Manager](#).

SDKs

iOS 7.0+

watchOS 2.0+

Framework

Core Motion

On This Page

[Overview](#)[Topics](#)[Relationships](#)[See Also](#)

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

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(emunguis,intille,kll)@mit.edu

Abstract. In this work, a system for recognizing activities in the home setting using a set of small, easy-to-install, and low-cost sensing sensors is introduced. We show early results that suggest 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.

Our system works when 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 for the user and advice that can help the user know what his/her behavior can do 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

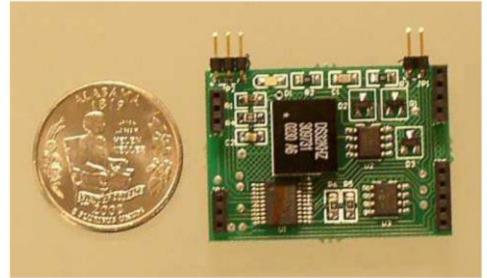
¹This work was supported, in part, by National Science Foundation ITR grant #0112900 and the Changing Places/House.n Consortium.

Activity Recognition in the Home Using Simple and Ubiquitous Sensors

Tapia *et al.*, Pervasive'04

1,406 citations

ACTIVITY RECOGNITION IN THE HOME (2004)



(a)



(b)

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.

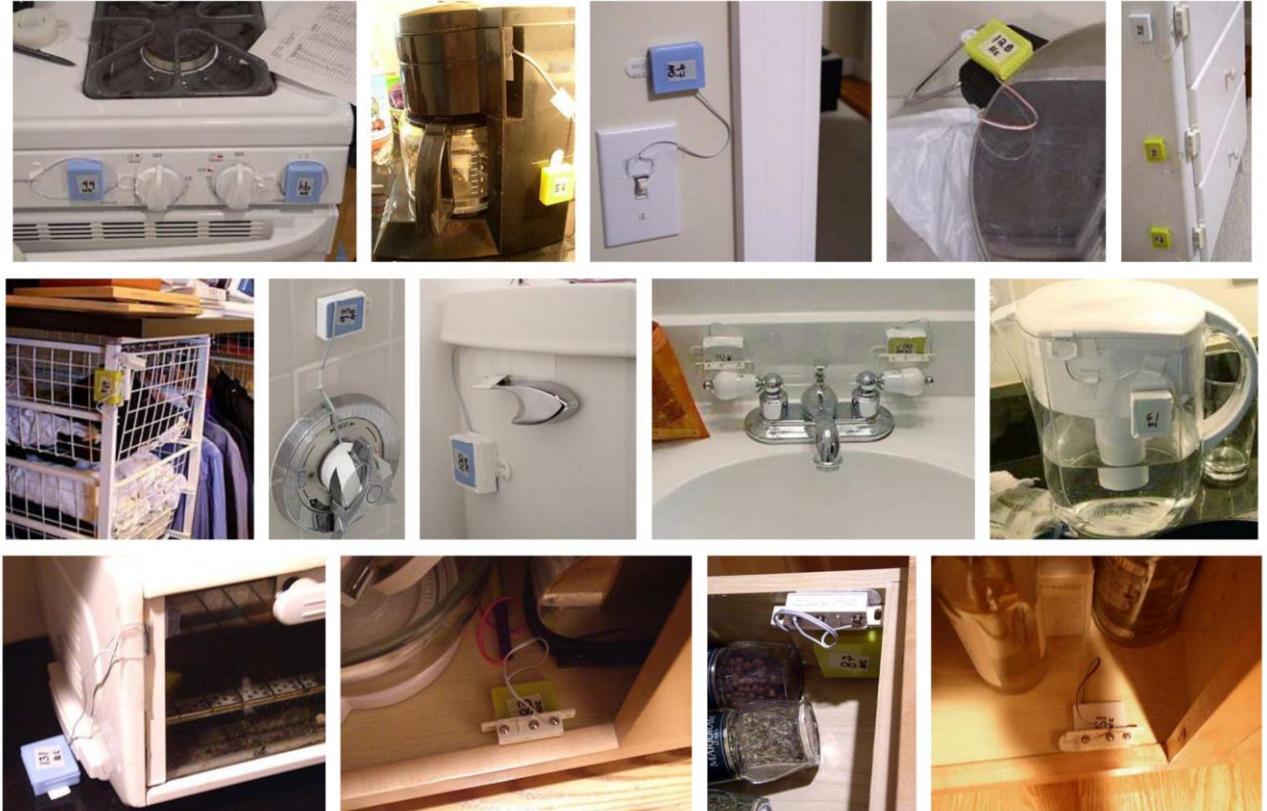


Fig. 2. Examples of some of the 77 sensors that were installed in the home of the first subject. The sensors and data collection boards were literally taped to objects and surfaces for the duration of the data collection period.

ACTIVITY RECOGNITION VIA INSTRUMENTED SPACES

Activity Recognition in the Home Using Simple and Ubiquitous Sensors

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Abstract. In this work, 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. These sensors are designed to be “tucked” on mobile devices that can be quickly and easily deployed in the environment. The proposed sensing system presents an alternative to sensors that are sometimes perceived as invasive, such as cameras and microphones. Unlike prior work, the proposed system is designed to be deployed in the home setting with non-research 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 and show promise. They are not yet complete because the sensor system and recognition pipeline 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, “tuck-and-forget” sensors are easily tagged onto 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 falls is to monitor movement patterns before they become critical. It is also important in the activities of daily living (ADLs), instrumental ADLs (IADLs) [17], and enhanced ADLs (EADLs) [24]. These activities include eating, getting

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Activity recognition using the velocity histories of tracked keypoints

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Abstract

We present an activity recognition feature inspired by human psychophysical performance. This feature is based on the velocity history of tracked keypoints. We present a generative mixture model for video sequences using this feature, and show that it performs competitively to local spatio-temporal features on the KTH activity recognition dataset. In addition, we introduce a new activity recognition dataset, focusing on activities of daily living, with high resolution video sequences of complex actions. We demonstrate the superior performance of history features on high-resolution video sequences of complex activities. Further, we show how the velocity history feature can be extended, both with a more sophisticated latent velocity model, and by combining the velocity history feature with other useful information like appearance, pose, and motion level.

Our approach compares favorably to established and state-of-the-art methods on the KTH dataset, and significantly outperforms all other methods on our challenging new dataset.

1 Introduction

Activity recognition is an important area of active computer vision research. Recent focus has been on bag-of-spatiotemporal-features approaches that have proven effective on established datasets. These features have very strong limits in the sense that they cannot offer general models of the information in video sequences.

Recent work in activity recognition has been largely based on local spatio-temporal features. Many of these features seem to be inspired by the success of statistical models of local features in object recognition. In both domains, the features are typically extracted over short time intervals, running over all locations at multiple scales. Local maxima of the detector are taken to be the center of a local spatial or spatio-temporal patch, which is extracted and summarized by some descriptor. Most of the time, these features are then clustered and assigned to words in a codebook, allowing the use of bag-of-words models from statistical natural language processing.

Our work is motivated an important application of activity recognition, assisted cognition health monitoring systems designed to unobtrusively monitor users. These systems are intended to ensure the mental and physical health of patients either at home or in an extended care facility.

1

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)

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Abstract. Activity sensing in the home has a variety of important applications, including fall detection, energy management, energy monitoring and post-retirement research studies. Many existing systems for detecting occupant activity require large numbers of sensors, invasive vision systems, or extensive installation procedures. We present an approach that uses a single plug-in sensor to detect a variety of electrical events throughout the home. This sensor detects the electrical noise on residential power lines created by the abrupt switching of electrical devices and the noise created by certain devices while in operation. We use machine learning techniques to recognize electrically noisy events, such as turning on or off a incandescent light switch, a television set, or an electric kettle. We test our system in one home for several weeks and in five homes for one week each to evaluate the system performance over time and in different types of houses. Results indicate that we can learn and classify various electrical events with accuracies ranging from 85-90%.

1 Introduction and Motivation

A common research interest in ubiquitous computing has been the development of inexpensive and easy-to-deploy sensing systems to support activity detection and context-aware applications in the home. For example, many researchers have explored the application of low-cost sensors to detect human motion and body switches [15, 16, 18]. Although these solutions are cost-effective on an individual sensor basis, they are not without some drawbacks. For example, having to install and maintain many sensors may be a time-consuming task, and the appearance of many sensors may detract from the aesthetics of the home [3, 7]. In addition, the large number of sensors required for coverage of an entire home may increase the number of potential failure points. To address these concerns, recent work has focused on sensing through existing infrastructure in a home. For example, researchers have looked at monitoring plumbing infrastructure in the home to infer basic activities [6] or using the residential power line to provide indoor localization [13]. Inspired by the theme of leveraging existing infrastructure to support activity detection, we present an approach that uses the home's electrical system as an information source to

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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

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ABSTRACT
 We present a first study of using RGB-D (Kinect-style) cameras for fine-grained recognition of kitchen activities. Our prototype system combines depth (shape) and color (appearance) to solve a number of perception challenges for smart kitchens: location, identifying objects and their functionalities, recognizing actions and tracking object states through actions. Our RGB-D camera is robustly track and accurately recognize detailed steps through cooking activities, for instance, how many spoons of sugar are in a cake mix. We also demonstrate how a RGB-D based solution for fine-grained activity recognition in real-world conditions will bring the intelligence of pervasive and interactive systems to the next level.

Author Keywords
 Smart Spaces, Kitchen, Activity Tracking, Object Recognition, Action Recognition, RGB-D

ACM Classification Keywords
 H.5.2 Information interfaces and presentation (e.g., HCI): Miscellaneous

INTRODUCTION
 Future pervasive systems, if they are to be seamlessly monitor and assist people in their daily activities, must have the capability to understand the environment in great detail. For example, during cooking, a kitchen assistant system would want to know what actions a person is doing, and which step in the recipe he/she is at (see Figure 1). In addition, the system needs to keep track of how many spoons of sugar have been added. We believe that using RGB-D cameras, such as the Kinect, has great potential in realizing fully automatic fine-grained activity recognition without instrumentation such as RFID tags or markers.

leads to more robust solutions [11]. Computer vision, however, is computationally demanding and often brittle; despite a lot of recent progress in vision-based object recognition [7, 1] and action recognition [5], fine-grained understanding of complex activities, such as cooking [9] and cleaning [12], is still an open challenge in unconstrained conditions.

RGB-D cameras, affordable Kinect-style cameras that provide both color and depth, are changing the landscapes of vision research and applications. Using infrared projection, these cameras provide real-time 3D data that is largely independent of the lighting condition, making them potentially much more robust (and efficient) than previously possible. RGB-D perception has greatly advanced to the art of many vision problems, including body pose [8], hand tracking [6], object recognition [3] and user interfaces [12].

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However, there are still many challenges that RGB-D perception has great potentials for fully automatic recognition of activities at a very fine granularity. We will examine objects that transition, such as flour to be mixed or vegetables to be chopped, which are often the most difficult to recognize. Recognizing interactions between hands and objects, such as grease/lemon and touch/touch, which would be hard to detect if using a color-only camera. We build a prototype system where

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ACTIVITY RECOGNITION VIA INSTRUMENTED SPACES

Activity recognition using the velocity histories of tracked keypoints

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Abstract

We present an activity recognition feature inspired by human psychophysical performance. This feature is based on the velocity history of tracked keypoints. We present general features for activity recognition, validate this feature, and show that it performs comparably to local spatio-temporal features on the KTH activity recognition dataset. In addition, we contribute a new activity recognition dataset, featuring velocity histories for more than 100 high-resolution video sequences of daily living. We demonstrate the superiority of our velocity history feature on high resolution video sequences of complicated activities. Further, we show how the velocity history feature can be extended both with a more sophisticated latent velocity model, and by combining velocity histories for features with other useful information, like appearance, position, and high level semantic information. Our approach performs comparably to established and state-of-the-art methods on the KTH dataset, and significantly outperforms all other methods on our challenging new dataset.

1. Introduction

Activity recognition is an important area of active computer vision research. Recent work has focused on bag-of-spatio-temporal-features approaches that have put very strong limits on the amount of space and time that they can describe. Human performance suggests that more global spatial and temporal information could be necessary and sufficient for activity recognition. Some recent work has attempted to capture global information by learning the relationships between local space-time features. We instead propose a feature, directly inspired by studies of human performance, with a much less limited spatio-temporal range.

Our work is intended for medical applications of activity recognition, assisted cognition monitoring systems designed to ubiquitously monitor patients. These systems are intended to ensure the mental and physical health of patients either at home or in an extended care facility.

1

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

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Abstract. Activity sensing in the home has a variety of important applications, including healthcare, entertainment, home automation, energy monitoring and post-occupancy research studies. Many existing systems for detecting occupant activity require large numbers of sensors, invasive vision systems, or extensive installation procedures. We present an approach that uses a single plug-in sensor to detect a variety of electrical events throughout the home. This sensor detects the electrical noise on residential power lines created by the abrupt switching of electrical devices such as light switches, televisions, and small home appliances. We use machine learning techniques to recognize electrically noisy events such as turning on or off a particular light switch, a television set, or an electric stove. We tested our system in one home for several weeks and in five homes for one week each to evaluate the system performance over time and in different types of houses. Results indicate that we can learn and classify various electrical events with accuracies ranging from 85-90%.

1. Introduction and Motivation

A common research interest in ubiquitous computing has been the development of inexpensive and easy-to-deploy sensing systems to support activity detection and context-aware applications in the home. For example, several researchers have explored using arrays of low-cost sensors, such as motion detectors or simple contact switches [15, 16, 18]. Although these solutions are cost-effective on an individual sensor basis, they are not without some drawbacks. For example, having to install and maintain many sensors may be a time-consuming task, and the appearance of many sensors detract from the aesthetics of the home [3, 7]. In addition, the large number of sensors required for accurate sensing increases the number of potential failure points. To address these concerns, recent work has focused on sensing through existing infrastructure in a home. For example, researchers have looked at monitoring the plumbing infrastructure in the home to infer basic activities [6] or using the residential power line to provide indoor localization [13]. Inspired by the theme of leveraging existing infrastructure to support activity detection, we present an approach that uses the home's electrical system as an information source to

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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

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ABSTRACT

We present a first study of using RGB-D (Kinect-style) cameras for fine-grained activity sensing in smart spaces. Our proposed system combines depth (shape) and color (appearance) to solve a number of perception problems crucial for smart space applications: detecting hands, identifying objects and their affordances, recognizing actions, and tracking object state changes through actions. Our proposed concept results demonstrate great potentials of RGB-D perception: without need for instrumentation, our system can robustly track and accurately recognize detailed steps through cooking activities, for example, when a person is stirring a cake mix, or how long it has been mixing. A robust RGB-D based solution to fine-grained activity recognition in real-world conditions will bring the intelligence of pervasive and interactive systems to the next level.

Author Keywords
Smart Spaces, Kitchen, Activity Tracking, Object Recognition, Action Recognition, RGB-D

ACM Classification Keywords
H.5.2. Information interfaces and presentation (e.g., HCI); Miscellaneous.

INTRODUCTION
Future pervasive systems, if they are to seamlessly monitor and assist people in their daily activities, must have the capabilities to understand human activities in *fine-grain* details. For example, during cooking, a kitchen assistant system would want to know where the ingredients are and what states they are, what a person is doing, and which step in the recipe he/she is at (see Figure 1).

How could a system automatically acquire such a large variety of information? Our approach is to employ instrumentation, such as using RFID tags or markers, to simplify the perception problem [2]. In comparison, a camera-based approach would attempt to directly analyze the scene for many vision problems, including body pose [8], hand tracking [6], object recognition [3] and user interfaces [12].

In this work we demonstrate that RGB-D perception has great potentials for fully automatic recognition of activities at a very fine granularity. We use cooking in smart kitchens as the testbed for our experiments. In a typical kitchen environment, such as flour to be mixed or vegetables to be chopped, which would be hard to instrument, we will also examine interactions between hands and objects, such as grasp/release and touch/contact, which would be hard to detect if using a color-only camera. We build a prototype system where

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Fine-Grained Kitchen Activity Recognition using RGB-D

Lei *et al.*, UbiComp'12

99 citations

Synthetic Sensors: Towards General-Purpose Sensing

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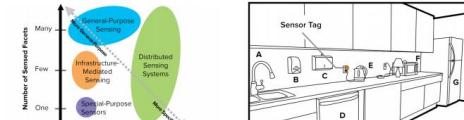


Figure 1. This high-level taxonomy demands canonical approaches in environmental sensing.

ABSTRACT
A series of structured environments and the Internet of Things (IoT) relies on robust sensing of diverse environmental facets. Traditional approaches rely on direct or distributed sensing, often by measuring physical properties or interacting with specialized sensors. In this work, we explore the notion of “synthetic sensors” which simultaneously mitigate immediate privacy issues. We use a series of structured, formative studies to inform the design of new synthetic sensors and associated information archetypes. We deployed our system across many months and environments, the results of which show the versatility, accuracy and potential of this approach.

Author Keywords
Internet-of-Things; IoT; Smart Home; Universal Sensor
ACM Classification Keywords
H.5.2. [User interfaces]: Input devices and strategies.

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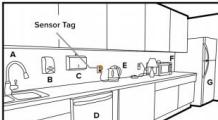


Figure 2. This kitchen-scale example typifies the ethos of general-purpose sensing, where one sensor (the orange tag) enables the detection of many environmental facets, including rich operational states of a faucet (A), soap dispenser (B), paper towel dispenser (C), dishwasher (D), oven (E), and refrigerator (F).

Figure 3. A real-world demonstration of this scene.

INTRODUCTION
Smart, sensing environments have long been studied and sought after. Today, such efforts might fall under catch-phrases like the “smart home” or “internet of things”. In this work, we explore the notion of “general-purpose sensing”, wherein a single, highly capable sensor can indirectly monitor a large context, without direct instrumentation of objects. From this thought, we call “synthetic sensors” to simultaneously mitigate immediate privacy issues while simultaneously enabling the detection of many environmental facets.

One option is for users to upgrade their environments with newly released “smart” devices (e.g., light switches, kitchen appliances), many of which contain sensing functionality. However, there is growing interest in “universal” sensing approaches, where a single sensor can be applied to almost anything (e.g., a smart light switch because it is on or off) or when it serves its core function (e.g., a thermostat sensing occupancy). Likewise, few smart devices are interoperable, thus forming silos of sensed data that thwarts a holistic experience. In this work, we argue that the future lies in the sensors that can hope for—at least in the foreseeable future—small islands of smartness. This approach also carries a significant upgrade cost, which so far has proven unpopular with consumers, who generally upgrade appliances individually, articulated, though none have reached widespread use to date.

One option is for users to upgrade their environments with newly released “smart” devices (e.g., light switches, kitchen appliances), many of which contain sensing functionality. However, there is growing interest in “universal” sensing approaches, where a single sensor can be applied to almost anything (e.g., a smart light switch because it is on or off) or when it serves its core function (e.g., a thermostat sensing occupancy). Likewise, few smart devices are interoperable, thus forming silos of sensed data that thwarts a holistic experience. In this work, we argue that the future lies in the sensors that can hope for—at least in the foreseeable future—small islands of smartness. This approach also carries a significant upgrade cost, which so far has proven unpopular with consumers, who generally upgrade appliances individually, articulated, though none have reached widespread use to date.

To address this issue, we are developing artificial products (e.g., [39, 41, 56]) and research systems (e.g., [30, 45, 54]) that allow users to distribute sensors around their environments to capture a variety of events and states. For ex-

Synthetic Sensors: Towards General-Purpose Sensing

Laput *et al.*, CHI'17

9 citations

SYNTHETIC SENSORS: TOWARDS GENERAL-PURPOSE SENSING





SOCIAL INTERACTION INFERENCE

Sensing and Modeling Human Networks using the Sociometer

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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 structure that arises within human groups 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 sensors can be used to automatically sense interactions and 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 proximity, detect 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 presence of others around us. Who are the people near? 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 [1].

Can we identify the individuals who talk to a large fraction of the group or community members? Such individuals, often referred to as *connectors*, have an important role in information diffusion [1]. Thus, learning the connection structure and nature of communications 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 of information is mostly exchanged through face-to-face interactions [2]. The strengths of collaboration in 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. Finally, the probability that two people communicate declines rapidly with the distance between their work locations [2, 4].

We believe the best way to learn about networks is through observation. We 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 to build a system that observes the interactions and plays the role of a musical "familiar" that sits perched on a user's shoulder, seeing what he sees, with the opportunity to learn what he learns (i) build an algorithmic pipeline that can take these sensors data and process it to find the interactions 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 contexts interact. This will help us understand how information propagates through 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

As far as we know, there has been no previous work on modeling face-to-face interactions within a community. This absence is probably due to the difficulty in obtaining reliable measurements from real-world interactions. One has to overcome the uncertainty in sensor measurements, this is in contrast to modeling virtual communities where we can get unambiguous measurements about how people interact - the duration and frequency (available from chat

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

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Keywords

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

1. Introduction

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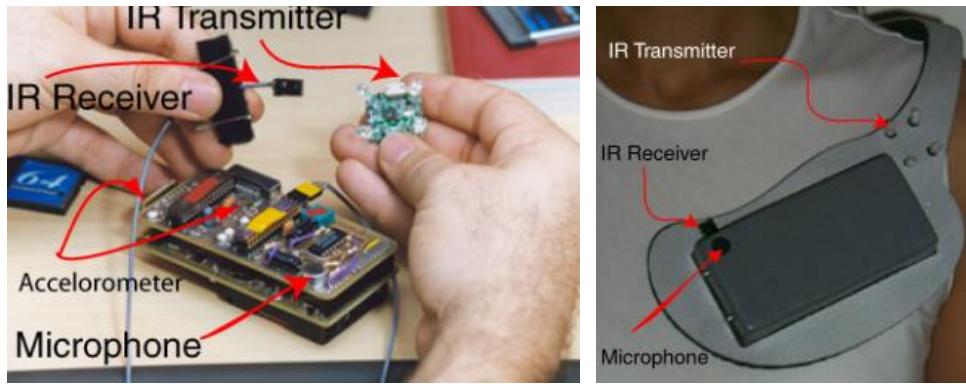
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Sensing and Modeling Human Networks using the Sociometer

Choudury *et al.*, Wearable Comp'03

197 citations



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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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 structure that arises within human groups and work settings. At present surveys or diaries 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 sensors can be used to collect data on interactions and 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 close 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 know? 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 individuals who are most active in interactions? Can we identify the individuals who talk to a large fraction of the group or community members? Such individuals, often referred to as the *connectors*, have an important role in information diffusion [1]. Thus, learning the connector structure and nature of communications 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 of information is mostly exchanged through face-to-face interactions [2]. These exchanges of collective intelligence that occur 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. Results that establish that two people communicate decline rapidly with the distance between their work locations [2, 4].

We believe the best way to learn about networks is through observation. We do not need to have a meeting 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 to build systems that can observe the world and see what plays the role of a musical "familiar" that sits perched on a user's shoulder, seeing what he sees, with the opportunity to learn what he learns (i) build an algorithmic pipeline that can take these sensors off the market and build a system that can collect data from different players in the community. We hope to lay the groundwork for being able to automatically study how different groups within social or business contexts interact. This will help us understand 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

As far as we know, there has been no previous work on modeling face-to-face interactions within a community. This absence is problematic to directly obtain measurements from real-world interactions. One has to overcome the uncertainty in sensor measurements, this is in contrast to modeling virtual communities where we can get unambiguous measurements about how people interact - the duration and frequency (available from chat

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ORIGINAL ARTICLE

Nathan Eagle · Alex (Sandy) Pentland
Reality mining: sensing complex social systems

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Abstract We introduce a system for sensing complex social systems with a collection of mobile phones placed over the course of a month. We demonstrate the ability to standardize 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 exponential growth 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, rule-like structures in the interactions of 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 mobile devices for sensing social systems and lower-level individual and organizational interactions. 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.

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 basic, continuous data that also hinders machine learning and data-based modeling communities from creating more comprehensive predictive models of human dynamics. Over the last decade, there has been a significant amount of research attempting to address this issue by building location-aware devices capable of collecting rich behavioral data [1, 6, 11, 16, 22, 24].

Although these projects were moderately successful, by depending on a limited subset 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 of human behavior [10, 18]. The very nature of mobile phones makes them a valuable 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 demonstrate how mobile phones can provide 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

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

SOCIAL INTERACTION INFERENCE: “REALITY MINING”

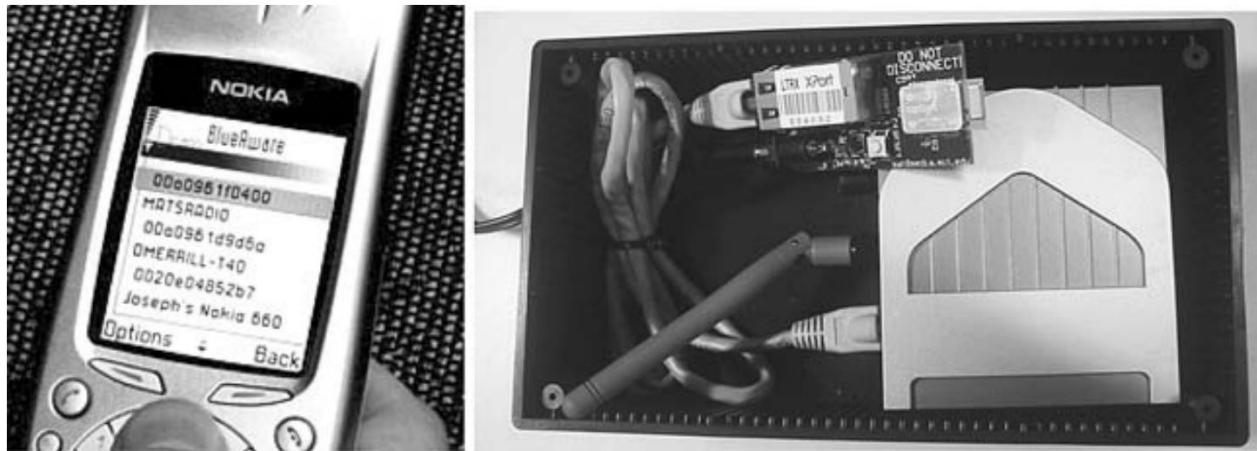


Fig. 1 Methods of detecting Bluetooth devices—BlueAware and Bluedar. BlueAware (*left*) is running in the foreground on a Nokia 3650. BlueAware is an application that runs on Symbian Series 60 phones. It runs in the background and performs repeated

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

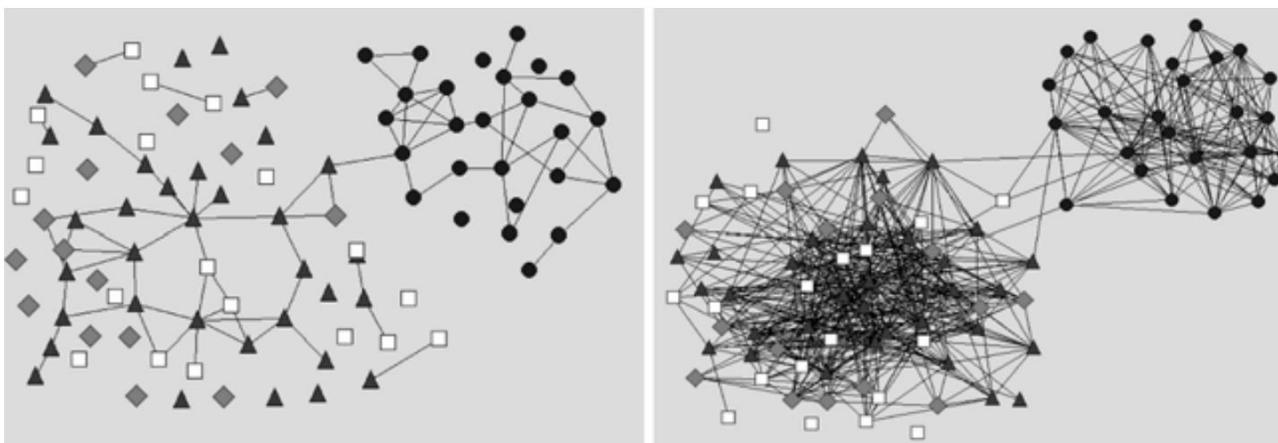


Fig. 11 Friendship (*left*) and daily proximity (*right*) networks. Circles represent incoming Sloan business school students. Triangles, diamonds and squares represent senior students, incoming students, and faculty/staff/freshman at the Media Lab. While the two networks share similar structure, inferring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

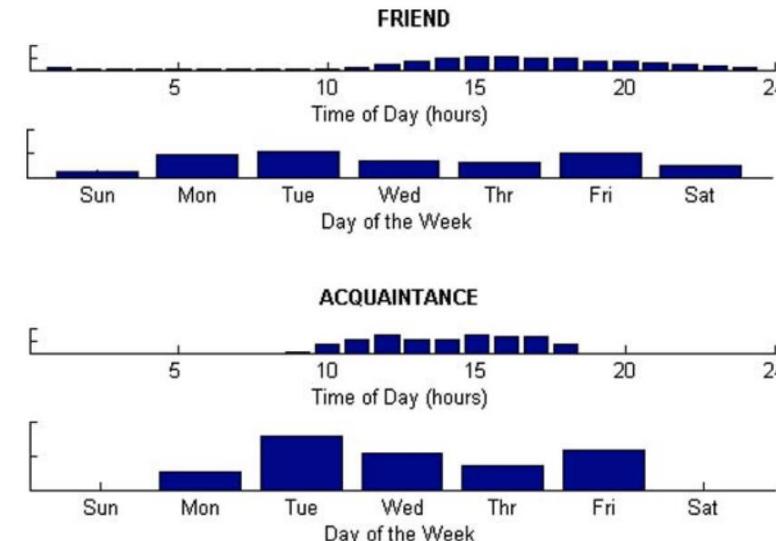


Fig. 12 Proximity frequency data for a friend and a workplace acquaintance. The top two plots are the times (time of day and day of the week, respectively) when this particular subject encounters another subject he has labeled as a “friend.” Similarly, the subsequent two plots show the same information 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

UBICOMP INFERENCE SYSTEMS SOCIAL INTERACTION INFERENCE

Sensing and Modeling Human Networks using the Sociometer

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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 structure that arises within human groups and organizations. 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 sensors and mobile devices can be used to automatically 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 close 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 people around us. Who are the people? How often do we see them? 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. How do people interact with each other in these interactions? Can we identify the individuals who talk to a large fraction of the group or community members? Such individuals, often referred to as *connectors*, have an important role in information diffusion [1]. Thus, learning the connection structure and status of interactions 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 of information is mostly exchanged through face-to-face interactions [2] and exchanges of formal communication over the course of a month. 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

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introduced as a useful metric for quantifying organizational behavior.

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 thus a challenge of social computing to develop more continuous, context-aware, and data-based modeling communities from collecting more comprehensive and fine-grained models of human dynamics. Over the two decades there has been a significant amount of research attempting to address this issue by building location-aware devices capable of collecting rich behavioral data [6, 11, 16, 22, 24].

We believe the best way to learn about networks is to let the observers be part of the network. We need 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 to build systems and sensors that can play the role of a musical "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 and analyze the data collected to learn what is happening in the mobile phone. In 2004, over 600 million handsets were sold, dwarfing the number of personal computers sold that year [27]. The rapid growth of mobile phones and 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, rule-governed, and the emergent behaviors of this mobile communication system. This paper is to be followed 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 mobile individuals tracking their own behavior and velocity, and discovered Bluetooth IDs. Turning our attention away from individuals and towards dyads, in Sect. 4 we extract salient features indicative of the relationships between individuals and between dyads, calling them as a "mobile phone proximity logs". Finally, with the nodes and edges of this social network identified, the concept of organizational rhythms is

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

and a long-range cellular network to provide coverage to the entire globe. This feature is critical to the success of our approach.

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Reality Mining: Sensing Complex Social Systems
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Using the Influence Model to Recognize Functional Roles in Meetings

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during the meeting makes it possible to explore the possibility of providing various kinds of support to dysfunctional teams, from facilitation to training sessions addressing both the individuals and the group as a whole. A necessary step in this direction is of naturally capturing and understanding group dynamics.

In order to improve performance in meetings, external interventions by experts such as facilitators and trainers are commonly employed. Facilitators participate in the meetings as external elements of the group and their role is to help participants to achieve their goals. Trainers are external experts assigned to set the pace of the discussion. Training experiences aim at increasing the relational skills of individual participants by providing them (and with respect to meetings) guidance—or even coaching—and the participant will be able to overcome its dysfunctionalities.

In [17], the absence of any detectable difference in the acceptability of reports about recent relational behaviour according to whether the reports were made by self-report or by an automatic system was reported. Clearly, crucial to any such an automatic system is that it be capable of understanding people's social behaviour, e.g., by abstracting over low-level (visual, auditory, etc.) features. In this paper we propose to extend one about the social roles members play in the group.

The latter is the kind of information that coaches and managers value most. The first is the kind of information that friends value most. In this paper we propose to extend one about the social roles members play in the group.

In [21][18], sliding windows multiclass SVMs with radial kernels were used to recognize functional relational roles in meetings.

The results were very positive, with the macro F-measure for the three roles being 0.75, 0.78, and 0.79, respectively, suffering from two limitations. First, the observation vector included not only the features the participant whose role had to be detected but also those of all the other participants. This is due to the fact that due to the curse of dimensionality [23], which might artificially inflate results.

The second limitation is that radial kernels might turn out to be bad in infinite VC dimensionality and that can easily lead to overfitting [8].

In this paper, we investigate a new framework for functional role detection in meetings, the "influence model" [4, 12], and compare this approach with multi-class SVMs based on linear and RBF kernels, and Hidden Markov Models. Among its advantages, the

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

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Data collected from mobile phones have the potential to provide insight into the relational dynamics of individuals. This paper compares observational data from mobile phones with standard self-reporting data and finds that the two data sources are largely overlapping but distinct. For example, self-reports of proximity deviate from mobile phone records despite the fact that the two data sources overlap. These findings demonstrate that it is possible to accurately infer 95% of friendships based on the observational data alone, without relying on physical proximity and calling patterns. These behavioral patterns, in turn, allow the prediction of individual-level outcomes such as job satisfaction.

Results
Behavioral Versus Self-Report Data. The reliability of existing measures for friendships has been the subject of sharp debate since the mid-1990s [1–3], with a wide range of studies in which it was found that behavioral observations were surprisingly weakly related to reported interactions (8–10). There are several reasons for this. First, the self-reporting method asks a subject to report a behavior (11). Existing research suggests that people are good at recalling long-term, but not short-term, social interactions [12]. Second, self-reporting methods are prone to recall bias in that they are less accurate than observational methods [13].

Third, self-reporting data typically involve both limited numbers of people and a fixed time period (e.g., one day). Fourth, observational data are more likely to be biased toward recent events. A salience bias is one where memories are biased toward more vivid events. Fifth, self-reporting methods are prone to social desirability bias, in that they are less accurate than observational methods [14]. Sixth, self-reporting data are less accurate than observational methods because they are less likely to be recalled in a fixed period preceding the survey, and salience by whether the individual in question is a friend or not.

We conducted three analyses of these data. First, we examined the relationship between self-reported and behavioral data. Second, we analyzed whether behaviors identified in the mobile phone data that were characteristic of friendship. Third, we examined the relationship between behavioral data and individual satisfaction.

Engineering-social systems | relational inference | social network analysis | reality mining | relational scripts

The field devoted to the study of the system of human interactions is a relatively young discipline concerned in aspects of breadth and depth because of its reliance on self-report data. Social network analysis relies on self-report relational data typically involve both limited numbers of people and a fixed time period (e.g., one day). Social network analysis has generally been limited to examining small, well-known populations, involving a small number of snapshot observations. The field has been dominated by a fixed period preceding the survey, and salience by whether the individual in question is a friend or not.

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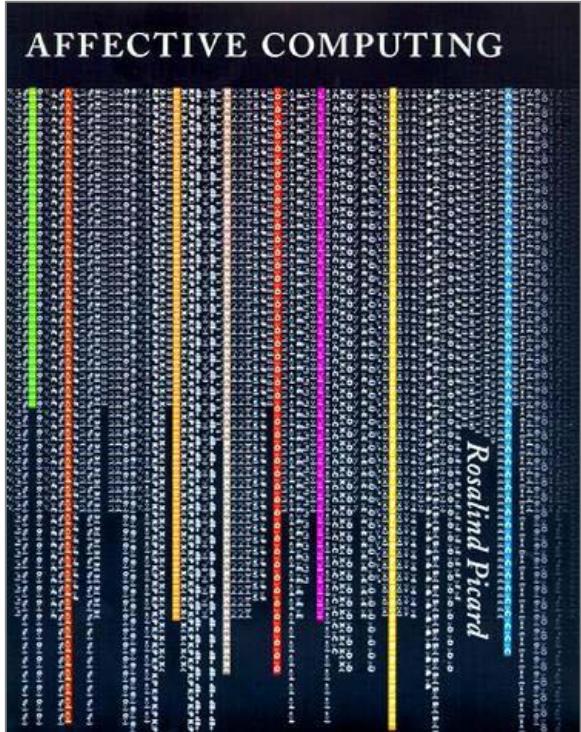
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EMOTION INFERENCE



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



UBICOMP INFERENCE SYSTEMS

EMOTION INFERENCE

AFFECTIVE COMPUTING



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

MIT Media Laboratory Perceptual Computing Section Technical Report No. 536
To appear in IEEE Transactions on Pattern Analysis and Machine Intelligence

Toward Machine Emotional Intelligence: Analysis of Affective Physiological State

Rosalind W. Picard, Elias Vyzas, and Jennifer Healey

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20 Ames St.
Cambridge, MA 01239

Abstract

The ability to recognize emotion is one of the hallmarks of emotional intelligence, an aspect of human intelligence that has been argued to be even more important than the more general verbal intelligences. This paper proposes that machine intelligence needs to include emotional intelligence and demonstrates results toward this goal: developing a machine's ability to recognize emotion from physiological state signals. We describe difficult issues unique to obtaining reliable affective data, and collect a large set of data from a subject trying to elicit different expressions of emotional state daily over multiple weeks. This paper presents and compares multiple algorithms for feature-based recognition of emotional states from this data, and shows how physiological signals can exhibit significant inter-subject variations: the features of different emotions on the same day tend to cluster more tightly than do the features of the same emotion on different days. To support the findings presented, we propose new features and algorithms to measure their performance. We find that the technique of seeking a Fisher Projection with the results of Sequential Floating Forward Search improves the performance of the Fisher Projection, and provides the highest recognition accuracy reported to date for classification of affect from physiology: 81% recognition accuracy on eight classes of emotion, including neutral.

1 Introduction

It is easy to think of emotion as a luxury, something that is unnecessary for basic intelligent functioning and difficult to encode in a

computer program; therefore, why bother giving emotional abilities to machines? Recently, a constellation of findings, from neuroscience, psychology, and computer science, suggests that emotion plays a surprising critical role in rational and intelligent behavior. Most people already know that too much emotion is bad for rational thinking; much less well known is that negative emotion states of patients who essentially have the opposite emotional needs of normal patients have significant negative impacts in intelligent day-to-day functioning, suggesting that too much emotion can impair rational thinking and behavior [1]. Apparently, emotion exists with thinking in ways that are non-obvious but important for intelligent functioning. Emotion-processing brain regions have also been found to perform better when resting before the task begins. We believe that these findings are key to our system to create mood-enabled applications. We further argue that emotion-oriented processing is believed to take place in human vision and audition [2].

Scientific studies have provided evidence that emotion is a basic component of intelligence, especially for learning preferences and adapting to what is important [2] [4]. With increasing deployment of adaptive computer systems, e.g., software agents and video retrieval systems, the ability to learn and adapt to user affective feedback is of growing importance. Emotional intelligence consists of the ability to recognize and interpret one's own emotions, coupled with the ability to regulate them, and then harness them for constructive purposes, and skillfully handle the emotions of others. The skills

of emotional intelligence are thus important to enable us to be effective in our personal or professional lives. We believe that the skills of emotional intelligence are important for basic intelligent functioning and difficult to encode in a computer program; therefore, why bother giving emotional abilities to machines? Recently, a constellation of findings, from neuroscience, psychology, and computer science, suggests that emotion plays a surprising critical role in rational and intelligent behavior. Most people already know that too much emotion is bad for rational thinking; much less well known is that negative emotion states of patients who essentially have the opposite emotional needs of normal patients have significant negative impacts in intelligent day-to-day functioning, suggesting that too much emotion can impair rational thinking and behavior [1]. Apparently, emotion exists with thinking in ways that are non-obvious but important for intelligent functioning. Emotion-processing brain regions have also been found to perform better when resting before the task begins. We believe that these findings are key to our system to create mood-enabled applications. We further argue that emotion-oriented processing is believed to take place in human vision and audition [2].

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MoodScope: Building a Mood Sensor from Smartphone Usage Patterns

Robert LiKamWa^{1†}, Yuxin Liu¹, Nicholas D. Lane², Lin Zhong¹
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ABSTRACT

We report a first-of-its-kind smartphone software system, MoodScope, which infers the mood of its user based on how the user interacts with his/her smartphone. Compared to smartphone sensors that measure accelerometers, light, and other physical properties, MoodScope is a "sense" that measures the state of the user's mind, and provides an important input to context-aware computing.

We run a formative statistical study with smartphone users to validate MoodScope's mood sensing. Through the study, we find that by analyzing communication history and application usage patterns, we can statistically infer a user's mood with an accuracy of 66%, which gradually improves to an accuracy of 93% after a short 15-day training period. Motivated by these results, we build a service, MoodScope, which analyzes usage history to act as a sensor of the user's mood. We believe that MoodScope can be developed into our system to create mood-enabled applications. We further argue that the implementation of a mood sensor as a vital next step in enhancing the context-awareness of mobile devices.

There are numerous ways to employ mood information. Video and music recommender systems such as Netflix or Spotify would benefit from mood information using collaborative filtering algorithms. By knowing the user's mood and building preferences based on previously sensed items, these providers could recommend more items that match the user's mood. MoodScope can also be used to build a mood-aware mobile application. While the system can ask the user to supply their mood, an automatic mood sensor will significantly improve the system's usability.

More importantly, mood sensing can build an interesting digital ecosystem as mood sensing can enable users to share their moods with close friends and family. Privacy concerns aside, these moods would enhance social networks by allowing users to share mood status with their friends and family. MoodScope can also help users to communicate with others. For example, parents of a son in whom a mood could decide to call to cheer him up. When text messaging, MoodScope can enable users to digitally communicate closer to the way they want in life. For mood sharing, an automatic mood sensor can be built into mobile phones. More importantly, lower the social barrier for a user to share their mood: we do not directly tell others our mood very often, but we do not do so because we are very often embarrassed.

To enable these scenarios, we consider a system that recognizes users' mood from their smartphone usage patterns. We call the system MoodScope for its ability to peer into usage data and infer a user's mood without asking the user to supply it. Our smartphones have rich information about us: where we have been, with whom we communicate, what applications we use, and even more. MoodScope attempts to leverage these patterns to infer what mood they are in different mood states. MoodScope attempts to leverage these patterns by learning about its user and associating mood states with usage patterns.

MoodScope's approach is not invasive: it does not require users to carry any extra hardware sensors or rely on the use of the microphone or camera. Instead, MoodScope passively runs in the background of the user's smartphone usage patterns. Because of this, MoodScope is also lightweight and power efficient; it does not rely on computationally intensive or power expensive data processing of audio, video, or physical sensor signals. Furthermore, MoodScope works on the general patterns of smartphone usage, making it application-independent. Consequently, MoodScope is easy to deploy on existing smartphones without any modifications to the OS or hardware.

To validate the approach of MoodScope, we conducted user studies with 32 participants. We carried out four group discussions with each participant to collect their mood information and finished a two-month field study to collect daily smartphone usage

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DOI 10.1007/s00779-015-0842-3

ORIGINAL ARTICLE

Emotions in context: examining pervasive affective sensing systems, applications, and analyses

Eiman Kanjo¹ · Lubush Al-Husain² · Alan Chamberlain³



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1 Introduction

This review article creates a platform for understanding the growing field of pervasive affective sensing and offers designers, computer scientists, and researchers from other related disciplines an opportunity to further engage with this field.

The recognition of smartphones, and sensor-based technologies has opened up new territory with respect to the development of systems that can recognize and process human affective states. One of the key challenges in such systems is the recognizing of people's feelings and related behaviors. Advances in pervasive sensing have enabled us to measure peoples' affective states in real-time situations by harnessing properties that such mobile and sensing technologies now afford.

Affect plays an important role in our daily life and is generally reported in the literature as a spontaneous mental feeling or state [1, 2]. Emotions in general can overwhelm the human being, which results through various signals such as manifested physical and psychological effects. Physical responses include facial expressions, voice intonation, gestures, and movements, whereas physiological response indicators relate to respiration, pulse rate, skin conductance, body temperature, and blood pressure. In terms of affective psychology, affective states can be categorized as follows: self-reports, physiological recordings, and behavioral observations [3]. Self-reporting is an explicit way to gather information related to a person's feelings or emotional state by using questionnaires or interviews in order to report on one's own state. Physiological recording is an implicit way to measure emotional reactions by recognizing the user's physiological changes with the use of biosensors. The behavioral observations method is used to identify the user's emotional state by

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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

...

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...

HEALTH & FITNESS

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

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and Henry B. Strub

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Abstract A sedentary lifestyle is a contributing factor to chronic diseases, and other related health problems. 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 players' 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 the game may have been more successful than led by heavier 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.

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

Lin *et al.*, UbiComp'06

724 citations

CHI 2008 Proceedings · Personal Health

April 5-10, 2008 · Florence, Italy

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

Sunny Consolvo^{1,2}, David W. McDonald², Tammy Toscos³, Mike Y. Chen¹, Jon Froehlich², Beverly Harrison¹, Predrag Klasnja^{1,2}, Anthony LaMarca¹, Louis LeGrand², Ryan Libby³, Ian Smith¹, & James A. Landay^{1,3}

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ABSTRACT

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 through their motion. These technologies have had limited success with participants in controlled and "clean" 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 system is used as part of everyday experiences, where the technology is brittle, and user reactions to activity inference 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 through their motion. These technologies have had limited success with participants in controlled and "clean" 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 system is used as part of everyday experiences, where the technology is brittle, and user reactions to activity inference and activity inference to encourage physical activity.

Our goal in this work is to investigate users' experiences with a system that uses on-body sensing and machine learning to automatically infer people's activities through their motion. This work builds upon previous work that 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 initial awareness of their activity, 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 their activities were recorded and manipulated, and participants' qualitative reactions to activity inference and manual journaling. We also discuss participants' general reactions to the system.

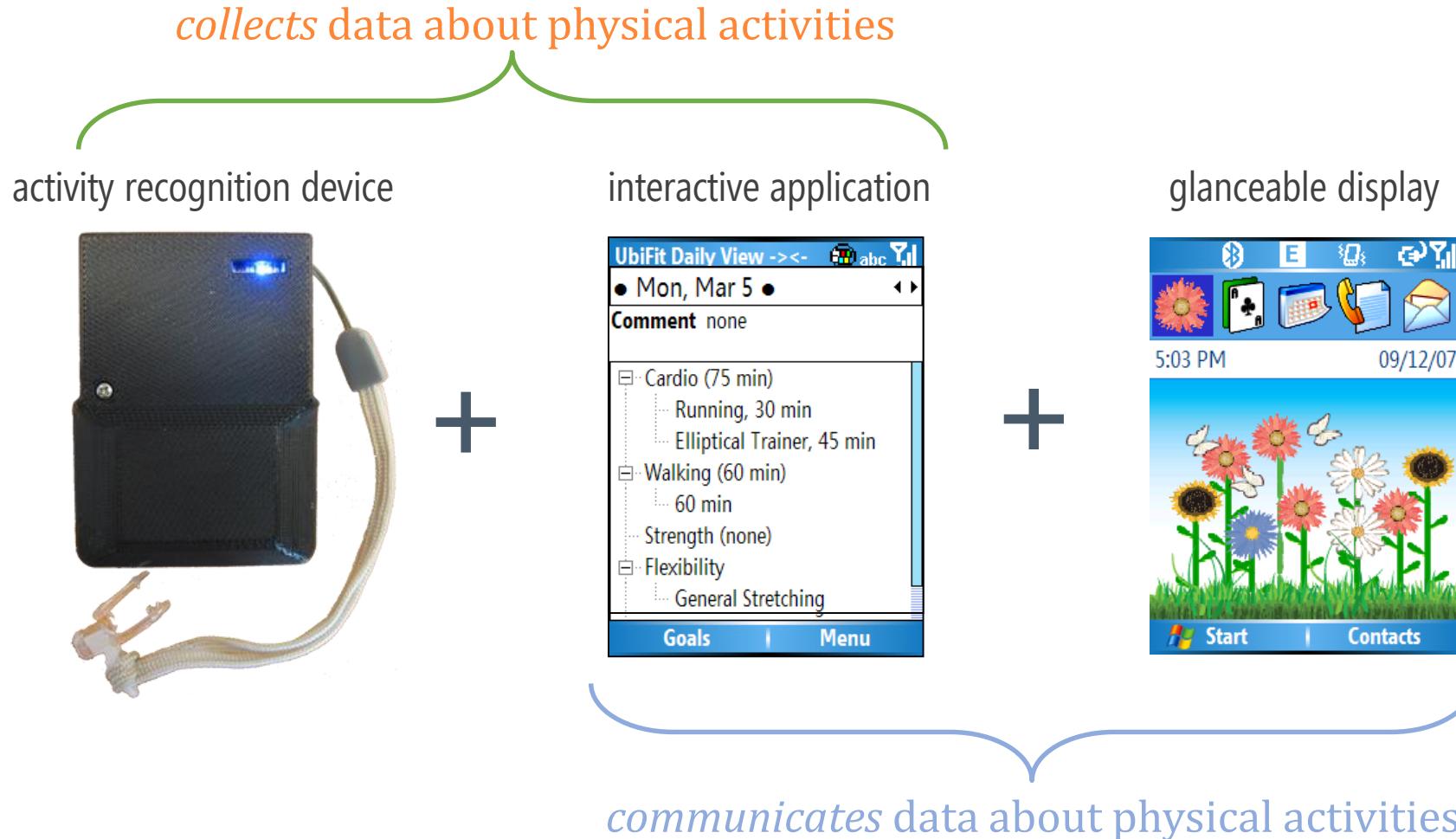
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CHI 2008, April 5–10, 2008, Florence, Italy.
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Activity Sensing in the Wild: A Field Trial of UbiFit Garden

Consolvo *et al.*, CHI'08

989 citations

HEALTH & FITNESS: UBIFIT

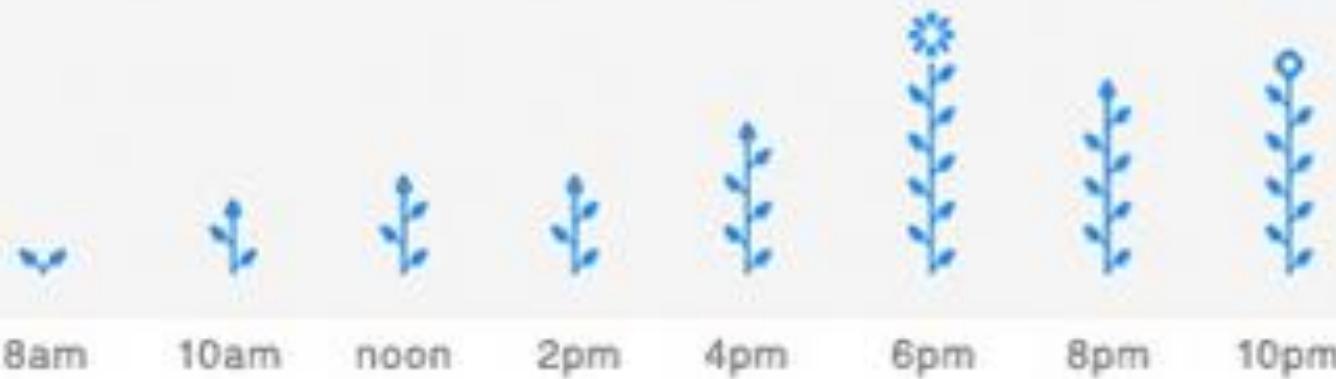


HEALTH & FITNESS: UBIFIT



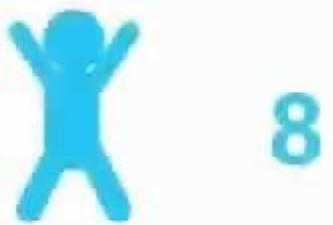
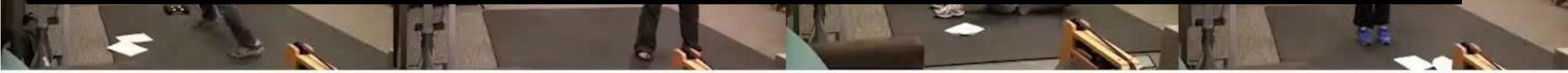
HEALTH & FITNESS: COMMERCIAL SYSTEMS

Your flower's health:



In addition to the feedback on Fitbit's website, the sensor displays a virtual flower that grows as your activity level changes.

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





HEALTH MONITORING & DIAGNOSTICS

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

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

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

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

INTRODUCTION
Spirometry is the most widely employed objective measure of lung function [17] and is central to the diagnosis and management of chronic lung diseases, such as asthma, chronic obstructive pulmonary disease (COPD), and cystic fibrosis. During a spirometry test, a patient's forcefully exhaled through a flow-measuring device, or mouthpiece, which is attached to a flow meter and pressure-exhaled volume (Figure 1). Spirometry is generally performed in medical offices and clinics using conventional spiroimeters, but home spirometers with portable devices is slowly becoming popular [6,26]. Home spirometry at home allows patients and physicians to more regularly monitor for trends and detect changes in lung function that may need evaluation or treatment. Home spirometry has the potential to result in earlier treatment of exacerbations.

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Figure 1: Subjects using SpiroSmart (left) and a clinical spirometer (right).

The first two authors are equal contributors to this work.

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

BiliCam: Using Mobile Phones to Monitor Newborn Jaundice

Lilian de Greef¹, Mayank Goel¹, Min Joon Seo¹, Eric C. Larson², James W. Stout MD MPH¹, James A. Taylor MD³, Shwetak N. Patel^{1,2}
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ABSTRACT
Health sensing through smartphones has received considerable attention in recent years because of the device's low cost and portability, making it ideal for tracking medical conditions. In this paper, we focus on using smartphones to monitor newborn jaundice, which manifests as a yellow discoloration of the skin. Although a degree of jaundice is normal in newborns, early detection of extreme jaundice is essential to prevent permanent brain damage or death. Current detection techniques, however, require clinical tests with blood samples and other specialized equipment. Currently, newborns often depend on visual assessments of their skin color at home, which can be unreliable. To this end, we present BiliCam, a low-cost system that uses smartphone cameras to monitor newborn jaundice. We evaluate BiliCam on 100 newborns, yielding a 0.85 rank order correlation with the gold standard blood test. We also discuss usability challenges and design solutions to make the system practical.

Author Keywords
Health sensing, mobile phones, neonatal jaundice, bilirubin, image processing.

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

INTRODUCTION
A number of smartphone-based medical devices are becoming increasingly common for fitness [13], heart rate permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are made on behalf of the author(s) or publisher for internal distribution only, and to servers or to redistribute to lists, requires prior permission from the author(s) or publisher. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires specific permission and/or a fee.
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Figure 1: Parents or medical practitioners can monitor a newborn's jaundice with their smartphones through BiliCam.

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

HemaApp: Noninvasive Blood Screening of Hemoglobin using Smartphone Cameras

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ABSTRACT
We present HemaApp, a smartphone application that noninvasively monitors blood hemoglobin concentration using the camera of a smartphone. Hemoglobin measurement is a standard clinical tool commonly used for screening anemia and assessing a patient's response to iron supplement treatments. Given a degree of difficulty in obtaining a blood sample, early detection of extreme jaundice is essential to prevent permanent brain damage or death. Current detection techniques, however, require clinical tests with blood samples and other specialized equipment. Currently, newborns often depend on visual assessments of their skin color at home, which can be unreliable. To this end, we present BiliCam, a low-cost system that uses smartphone cameras to monitor newborn jaundice. We evaluate BiliCam on 100 newborns, yielding a 0.85 rank order correlation with the gold standard blood test. We also discuss usability challenges and design solutions to make the system practical.

Author Keywords
Hemoglobin; Mobile Health; Photoplethysmography; Anemia; Camera; Blood Screening

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

INTRODUCTION
Smartphone-based medical devices have grown increasingly common for heart rate monitoring [18-19], point-of-care diagnostics [14-15], and mobile health applications [1]. These devices have the capabilities and ubiquity of modern smartphones, make them excellent candidates for clinical and health platforms, despite their inherent sensing limitations. In this paper, we present the design and critical evaluation of a noninvasive hemoglobin detector using a smartphone in a study with 100 newborns. Our prototype, BiliCam, is a smartphone-based medical device that uses the embedded camera and a paper based color calibration card to estimate hemoglobin levels.

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593

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

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ABSTRACT

Stress has long term adverse effects on individuals' physical and mental well-being. Changes in the speech production process is one of many physiological changes that happen during stress. Microphone enabled smartphones and carried ubiquitous by people, provide the opportunity to continuously and non-intrusively monitor stress in real-life situations. We propose StressSense for unconstrained stress detection using smartphones.

We investigate methods for adapting a one-size-fits-all stress model to individual users and scenarios. We demonstrate that StressSense can robustly identify stress in multiple individuals in diverse acoustic environments using model adaptation. StressSense achieves 81% and 76% accuracy for indoor and outdoor environments, respectively. StressSense runs in real-time. To the best of our knowledge, StressSense represents the first system to consider voice based stress detection and model adaptation in diverse real-life conversational situations using smartphones.

INTRODUCTION
Stress is a universally experienced phenomenon in our modern lives. According to a 2007 study by the American Psychological Association, 75% of Americans experience stress on a regular basis [1]. Stress has been shown to affect cognitive, emotional, and physical processes [1]. Stress has shown that stress can play a role in psychological or behavioral disorders, such as depression, and anxiety [2]. The amount of cumulative stress in daily life may have broad consequences on social and economic outcomes, which even have negative impact upon daily health and mood [2] and also contributes significantly to health care costs [3].

Because stress impacts negative public health consequences, it is advantageous to consider automatic and ubiquitous methods for stress detection. Ubiquitous stress detection can help identify individuals who are stressed in their daily life.

Meanwhile, distributed stress monitoring may allow health professionals the ability to examine the extent and severity of stress across populations.

Many physiological symptoms of stress may be measured with sensors, e.g., by chemical analysis, skin conductance measurement, heart rate, etc. However, most of these methods are inherently intrusive upon daily life, as they require direct interaction between users and sensors. We therefore seek less intrusive methods to monitor stress. Researchers have widely acknowledged that behavioral stress is influenced by stress [4, 5, 6, 7]. This fact poses the human voice as a potential target for stress detection. In this paper, we argue that smartphones and their microphones are an optimal computer-sensor combination for the non-intrusive identification of daily stress.

To be operational in real life, a voice-based stress classifier needs to deal with both the diverse acoustic environments encountered everyday and the individual variability of people's stress. Most previous work on stress detection and speech has focused on a single acoustic environment using high-quality microphones. This paper presents a method for detecting the occurrence of stress using smartphone microphones and adapting universal models of stress to specific individuals or scenarios using Maximum A Posteriori

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http://dx.doi.org/10.1145/2623076

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

HEMAAPP: NONINVASIVE BLOOD SCREENING OF HEMOGLOBIN USING SMARTPHONE CAMERAS





UBICOMP APPLICATION AREAS

ELDER CARE

CHI 2001 • 31 MARCH - 5 APRIL

Papers

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

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ABSTRACT
A growing social problem in the U.S., and elsewhere, is supporting older adults who want to continue living independently, as well as those who need some level of assistance. One part of this complex problem is providing awareness of senior adults' day-to-day activities, promoting peace of mind for extended family members. In this paper, we introduce the concept of a digitally augmented portrait that provides a visual representation of a family member's daily life. Leveraging a familiar household object, the picture frame, our design populates the frame with iconic imagery every 28 days. In a final implementation, the digital family portrait would gather information from sensors in the home.

Keywords: ubiquitous computing, light-weight interaction, aging, visualization, home

INTRODUCTION
The world's population is aging, and this aging will have far ranging economic and social effects. According to the U.S. Census Bureau, in 1996 there were approximately 550 million adults age 60, and this number is projected to approach 1.2 billion by 2025. In the U.S. alone, there were nearly 44 million adults age 60 in 1996, and the projected number for 2025 is approximately 82 million (over 20% of the total population).

A growing social concern is the support of aging adults in a manner that allows them to continue an independent lifestyle in their own homes, rather than moving to some form of institutional care. For example, a digital portrait, such as a traditional portrait, providing a qualitative sense of the activity of his elderly mother, or a digital day-to-day awareness is key to providing peace of mind for family members concerned about an elderly relative who potentially lives far away from them.

To meet this need, we introduce our design of a digital portrait, providing a qualitative sense of a person's daily activity and well-being from available sensor information. Like a traditional portrait, it is designed to be mounted on a wall or presented on a table top, with housed decorative instead of a static frame, the digital frame changes daily, reflecting a portion of the person's life. From general measurements of activity, to indications of the person's health, our design attempts to capture the observations that would normally occur to someone living in the same house or next door.

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**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

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For more than just economic reasons, a primary goal of many older individuals is to maintain an independent lifestyle [15]. Thus, many older adults live in private homes, typically either alone or with family [13]. While some are generally living safely, many others are experiencing many new challenges that lead to a profound sense of loss. Our research addresses those who wish to remain in the family home, where they may benefit from the benefits that can be derived from institutional living.

The aging adult's desire to remain in the familiar setting of the family home frequently must be balanced against their extended family's desire to keep them safe. Clearly, this balance becomes more precarious as age increases. An aging couple can support one another, but if one becomes incapacitated, can the other support himself? Not always, as we have learned from our research. The insights we have gained from knowing that one aging parent can support the other. Additionally geographic distance between extended family members exacerbates the problem by denying the natural contact that naturally occurs when families are co-located. Providing a means of remaining aware of a distant family members' day-to-day activities that could be called "cognitive memory" may ameliorate this concern and provide the emotional support that is often necessary for those senior family members to age in place.

Our goal is to support awareness of the long-term health, activity, and social well-being of senior adults living by themselves, answering questions such as "Has she been active today?" or "Is he getting enough exercise?"

For example, a display on an adult child's bookcase could provide a qualitative sense of the activity of his elderly mother. This kind of day-to-day awareness is key to providing peace of mind for family members concerned about an elderly relative who potentially lives far away from them.

When robbed of the ability to use tools as basic as a coffee maker due to a disease such as Alzheimer's, people are forced to rethink their everyday priorities and assumptions about how they will interact with the world. Bill's struggle is unfortunately typical of those faced by the millions who care for elders with declining capabilities and consequent lifestyle changes. And like Gerry, who cannot remember what he has learned late in life, many can no longer interact with relatively recently acquired and novel home devices, such as computers and remote controls.

Cognitive decline may well invite reconsideration not only among sufferers but also the ubiquitous computing community. In particular, concepts such as ubiquity, adaptivity, contextual awareness, location-based services, and usability may take on new meaning. What might be learned about general ubiquitous computing principles

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**New Perspectives on
Ubiquitous Computing from
Ethnographic Study of Elders
with Cognitive Decline**
Morris *et al.*, UbiComp'03
96 citations

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

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Abstract. A rapidly growing elder population is placing unprecedented demands on health care systems around the world. Cognitive decline is one of the most taxing health problems in terms of both its relation to elders' overall functioning and the cost of care. We present findings and implications of an ethnographic study of elderly computing solutions that help the local members of an elder's care network provide her day-to-day care. We describe the CareNet Display's design and discuss results of a series of in-home deployments of the device. We report how the CareNet Display was used and its impact on elders and their informal network members. Based on our findings, we offer lessons about how ambient display technologies could be improved to further benefit this growing user community.

1 Introduction

Though the potential benefits of ambient displays have been discussed [4,7,8,10,11,14], little has been shared about users' experiences with deployments of actual ambient displays in the home environment. Previously, we introduced the area of Commodity Ubiquitous Computing for Care (CSCC) [3] which described the many people involved in the care of an elder and the challenges of helping them do so. This paper, however, focuses on the details of our first CSCC prototype, the CareNet Display. The CareNet Display is an interactive digital picture frame that augments a photograph of an elder with information about her daily life and provides mechanisms to help the local members of her care network coordinate care-related activities. We describe the CareNet Display's design and its deployments in the homes of several members of four different care networks for three weeks at a time. In these deployments, we show that the CareNet Display was collected from daily interviews with the elders and their caregivers. From our findings of these deployments, we suggest how CSCC tools can help elders and the members of their care networks. We also discuss the lessons we learned about the use of an ambient display in the home that we believe can be of benefit to other designers.

Because caring for an elder is often a secondary, yet important focus for the care network, the CareNet Display also attempts to accommodate this role. This idea was previously explored by the Digital Family Portrait project [14] from the perspective of offering *peace of mind to distant* family members who are concerned for an elder. In our research, we are targeting the *local* members of an elder's care network who are responsible for providing the elder's *day-to-day care*. This change

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The CareNet Display: Lessons Learned from an In-Home Evaluation of an Ambient Display
Consolvo *et al.*, UbiComp'04
274 citations

Pers Ubiquit Comput (2010) 14:389–400
DOI 10.1007/s00779-009-0277-9

ORIGINAL ARTICLE

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

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B. J. A. Kröse

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Abstract An activity monitoring system allows many applications to assist in care giving for elderly in their homes. In this paper we present a wireless sensor network for elderly care, observe in the home and show the potential of generative and discriminative models for recognizing activities from such observations. In previous work a variety of sensing modalities has been used. One approach is to tag a large number of objects in a house with RFID tags. An RFID reader in the form of a bracelet is worn by the user to detect which objects are used [6]. The observed events are then used to infer the user's activity [21]. Another approach is to use video. Dong et al. [5] use four cameras to capture a scene from different angles. From the videos they extract the location of a user and use it for activity recognition. Wu et al. [37] use a single camera connected to a computer and a sensor network to compare the performance of a model using only video to a model using both video and RFID. The results show equal performance suggesting RFID does not add any information.

Keywords Activity recognition · Machine learning · Wireless sensor networks

1 Introduction

As the number of elderly people in our society increases so does the need for assistive technology in the home. Elderly people need to be able to continue living in their daily routine, i.e. to get older. Activities of daily living (ADLs), such as bathing, toileting and cooking, are good indicators of the cognitive and physical capabilities of elderly [10]. Therefore, a system that automatically recognizes these activities allows automated health monitoring [3, 18, 19, 28, 31]. A system for monitoring elderly persons [7] provides an alternative classifier for nursing personnel. In [10] the system can also be used to support people with dementia by reminding them which steps to take to complete an activity when almost all activities in this dataset [16].

Although RFID does not seem to give very good results, both video and wall-mounted sensors appear to be suitable sensing modalities. However, because an activity monitoring system is installed in a home setting it is important that a non-intrusive sensing modality is used. Because the acceptance of video cameras in a home is still questionable,

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**An Activity Monitoring System
for Elderly Care Using Generative
and Discriminative Models**
Van Kasteren *et al.*, Pers. & UbiComp'10
163 citations

ELDERCARE: THE CARENET DISPLAY

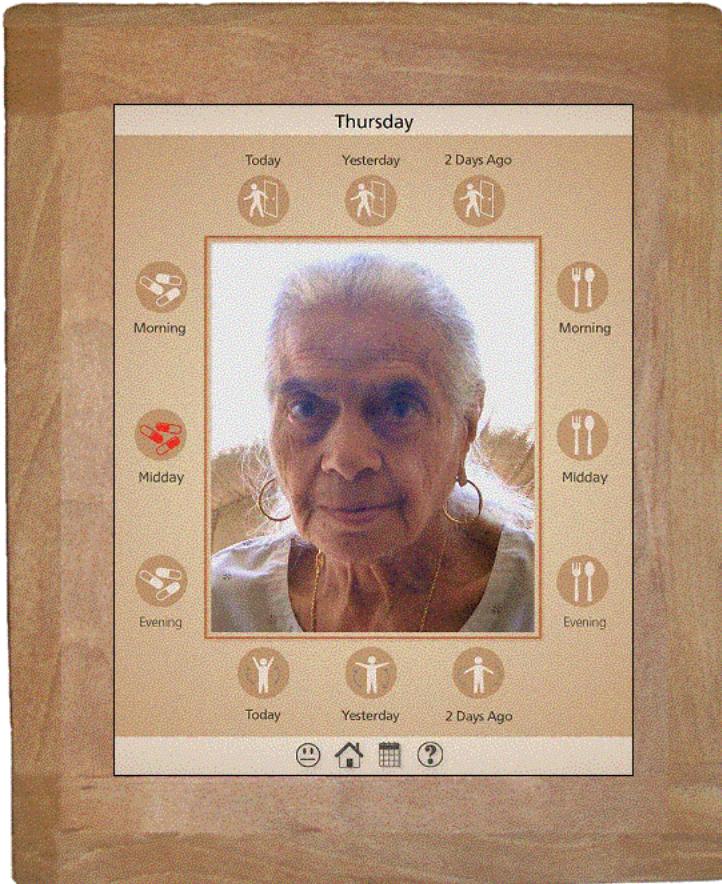


Figure 2. The CareNet Display prototype used in the deployments. The prototype uses a touch-screen tablet PC housed in a custom-built beech wood frame

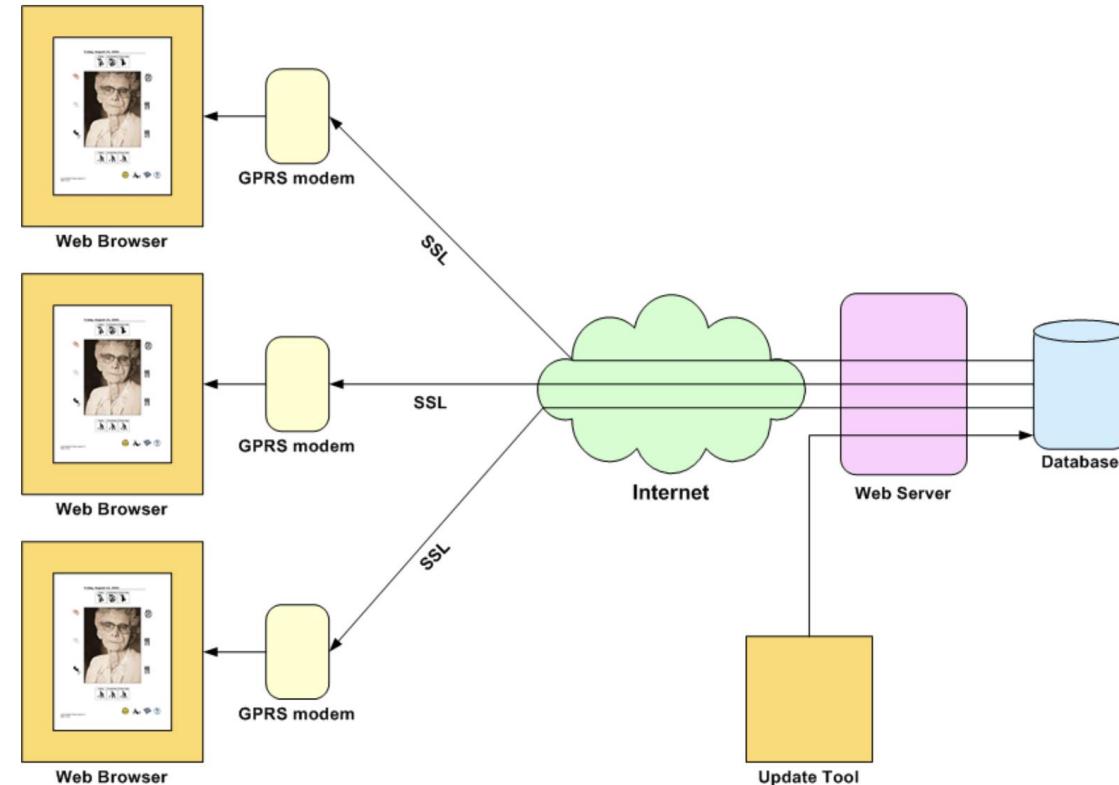
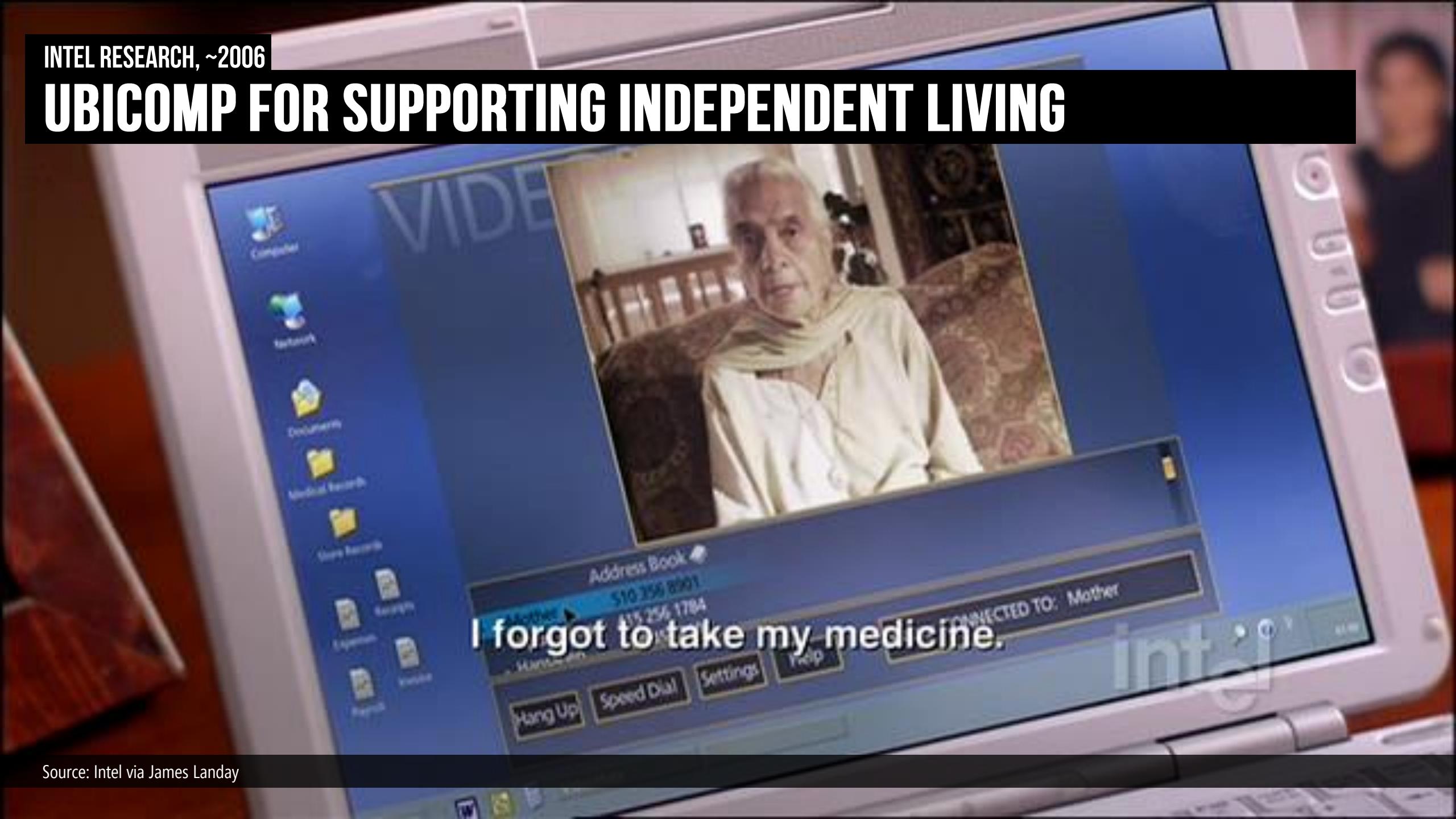


Figure 3. CareNet Display Prototype Architecture. Updates were made by evaluators through a web-based tool. Data was pushed to the displays through an always-on connection from a GPRS modem

INTEL RESEARCH, ~2006

UBICOMP FOR SUPPORTING INDEPENDENT LIVING



Source: Intel via James Landay



I forgot to take my medicine.

Address Book

510 256 8991

510 256 1794

CONNECTED TO: Mother

Hang Up

Speed Dial

Settings

Trac

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

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Figure 1. 12-year old Kevin has Duchenne Muscular Dystrophy. He is operating his PC by using two hands to control the stylus on a Palm running Remote Commander.

ABSTRACT
People with Muscular Dystrophy (MD) and certain other muscular and nervous system disorders lose their gross motor control while retaining fine motor control. The result is that they lose the ability to move their wrists and arms, and therefore cannot use a mouse or keyboard to control a pencil or stylus, and thus can use a handheld controller such as a Palm. We have developed software that allows the handheld to substitute for the mouse and keyboard of a PC, and report on four people (ages 12, 27 and 53) with MD. The 12-year old lost the ability to use a mouse and keyboard, but with our software, he was able to use the Palm to access email, the web and computer games. The 27-year-old reported that he found the Palm so much better than a keyboard and mouse that he stopped using a mouse. The other two subjects said that our software was much less tiring than using the conventional input devices, and enabled them to use computers for longer periods. We report the results of these case studies, and the adaptations made to the software for people with disabilities.

Keywords: Assistive Technologies, Personal Digital Assistants (PDAs), Handicapped, Disabilities, Hand-held computers, Palm pilot, Muscular Dystrophy, Pebbles.

INTRODUCTION
About 250,000 people in the United States have Muscular Dystrophy (MD), which is the same given to a group of noncongenital genetic disorders where the voluntary muscles that control movement progressively degenerate. One form, called Duchenne Muscular Dystrophy, affects about one in every 4,000 newborns. With Duchenne boys start to be affected between the ages of 2 and 6, and all voluntary muscles are eventually affected [10]. First affected are the muscles close to the trunk, and nearly all children with the disease become wheelchair-bound between ages 7 and 12. In the ten years, activities involving the arms, legs or trunk require assistance. Becker Muscular Dystrophy is a much milder version, and the onset can be in late adulthood. A related disorder, Spinal Muscular Atrophy, causes progressive weakness of the voluntary muscles in the neck, back, and legs. It is usually fatal before the person reaches the age of 10. If you are working with a person or classroom use a period without a space provided that copies bear this notice and the full citation on the first page. It is illegal to reproduce prior specific permission and/or a fee.

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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

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Abstract. We present an automated transportation routing system, called "Opportunity Knocks," whose goal is to improve the efficiency, safety and independence of individuals with mobility impairments. Our system uses GPS and a camera on a PDA-based handset that broadcasts GPS data, a GPRS-enabled cell-phone, and remote activity inference software. The system uses a novel inference engine that does not require users to explicitly provide information about the start or end points of their trip. By using a novel inference engine, we can learn from users' past behavior. Furthermore, we demonstrate how route errors can be detected and how the system helps to correct the errors with real-time transit information. In addition we present a novel solution to the problem of labeling positions with place names.

1 Introduction

For many individuals, mobility in the community means using public transportation. It is key to their social life, their employment, and their ability to receive medical services. Unless they can successfully move through their community they cannot lead an independent life. Public transportation, however, can be daunting for anyone who is born with below average cognitive abilities or whose cognitive abilities have begun to decline. Never the slightly. There is often no choice for them but to rely on potential forms of independent transport. One of the most common forms of these are given or family members; a healthy individual is needed to detect situations where a mistake made by a cognitively disabled person may cause distress or harm. Thus, the inability to use public transportation has been a barrier of life as well as that of their formal and informal caregivers. About 1-3 billion, if measured correctly, have cognitive compensatory cognitive aids to help them use public transportation; their independence and safety would improve, they would have new opportunities for socialization and employment, and stress on their families and care givers would be reduced.

We developed a ubiquitous computing system, called "Opportunity Knocks," (OK) to explore the feasibility of just such a cognitive aid. This system targets

people with these and related disorders, like the rest of the population, are increasingly using computers. Unfortunately, these disorders often make it difficult for them to move their arms, wrists and fingers, and therefore conventional keyboards and mice become difficult or impossible to use. However, a handheld computer, such as the Palm, can be used to enable people with disabilities to access their PCs (see Figure 1).

This paper reports on how we have adapted our Pebbles software for the Palm to facilitate its use by people with motor impairments. In particular, we adapted the Pebbles Remote Commander, which allows the Palm to be controlled via a keyboard and mouse. In addition, the Pebbles project is studying many ways the handheld computers can interoperate with PCs, with each other, and with smart appliances [11]. These applications are available at <http://www.pebbles.hci.cmu.edu/>. Pebbles stands for PDAs for the Entry of Both Bytes and Locations from External Sources.

In a preliminary case study of four people with MD, we found that our modified Pebble applications successfully allowed the use of the PC for extended periods of time for

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

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ABSTRACT
In this paper we present a new system that assists blind users in orienting themselves in indoor environments. We developed sensor modules that enable a blind user to walk in a blind user and use our system for specific tasks within the three-dimensional environment. By pressing keys, inquiries concerning object characteristics, position, orientation and navigation can be sent to a central server. The server processes the requests and sends back providing models of the environment. Finally these inquiries are accurately answered over a text-based speech engine.

Categories and Subject Descriptors
H.5.2 [User Interfaces]: User-centered design, Prototyping;
K.4.2 [Social Issues]: Assistive technologies for persons with disabilities

General Terms
Measurement, Design, Experimentation, Human Factors

Keywords
Indoor navigation, blind users, impaired vision, mobile computing

UBICOMP APPLICATION AREAS

NOVEL INTERACTIONS

Enabling Always-Available Input with Muscle-Computer Interfaces

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Previous work has demonstrated the viability of applying offline analysis to interpret forearm electromyography (EMG) and classify finger gestures on a physical surface. We extend those results to bring us closer to using muscle-computer interfaces for always-available input in everyday applications. We leverage existing technologies of natural human grips to develop a gesture set covering interaction in free space even when hands are busy with other objects. We present a system that can detect gestures in real-time and we demonstrate its use in a manual paradigm that enables an interactive system. We report experimental results demonstrating four-finger classification accuracies averaging 79% to 88% while holding a mug, 78% while holding a bag, and 88% when carrying a water bottle. We further show generalizability across different arm postures and explore the tradeoffs of providing real-time feedback.

ACM Classification: H.1.2 [User/Machine Systems]; H.5.2 [User Interfaces]: Input devices and strategies; B.4.2 [Input/Output Devices]: Channels and controllers

General terms: Design, Human Factors
Keywords: Electromyography (EMG), Muscle-Computer Interface, input, interaction.

INTRODUCTION
Our desire to control them have evolved over thousands of years, yielding an amazing ability to precisely manipulate tools. As such, we have often crafted our environments and technologies to take advantage of this ability. For example, we have developed tools that require physical devices such as keyboards, mice, and joysticks. Even future looking research systems often focus on physical input devices [5]. However, as computing continues to move towards the cloud, we will find ourselves in scenarios where we either cannot, or prefer not, to explicitly interact with a physical device in hand.

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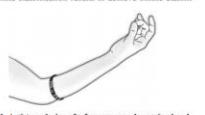


Figure 1. Artist rendering of a forearm muscle-sensing hand.

Enabling Always-Available Input with Muscle-Computer Interfaces

Saponas *et al.*, UIST'09
228 citations

Optically Sensing Tongue Gestures for Computer Input

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Salem et al. create what amounts to a joystick that the user can control with their tongue [5, 6]. Specifically, a commercial device from New Abilities Systems embeds pressure-sensitive buttons into a dental retainer placed on the roof of the user's mouth (www.newabilities.com).

These devices treat the tongue much as a finger and do not exploit its unique ergonomics. In this paper, we describe a novel approach of using infrared optical sensors embedded within a dental retainer to sense tongue gestures. The tongue is a highly flexible skeletal muscle most often used for generating speech as well as breathing and swallowing food. However, these muscles require a large degree of control over tongue shape and position, and suggest opportunities for designing more natural and richer gesture spaces.

Researchers who have realized this opportunity have tried to track complex movements by instrumenting the tongue with metal contacts and a magnetometer [4, 6].

The movement of the unattached segments within the tongue can then be detected either by a dental retainer worn in the mouth or by a separate device worn outside the mouth. Unfortunately, these tongue angle sensors are quite coarse and while they can be surgically attached to the dental retainer with four other options, do not make them appealing to otherwise healthy individuals.

In our work, we embed optical sensors into orthodontic dental retainers worn in the mouth. These sensors provide data with no physical contact, are explicit and complete tongue movement. Building the sensing device into a dental retainer creates a form factor that is both easy to don, but also largely undetectable to an observer. This is important to distribute the benefit of this technology to a wide range of users, as well as healthy individuals when traditional forms of computer control are inadequate. Furthermore, many people already wear dental retainers or explicit tongue gestures for communication and control.

The most obvious way to exploit direct control with the tongue is to provide physical transducers that can actuate or manipulate. For example, both Peng et al. and Ferreira et al., the cranial nerves which control organs such as the eye, jaw, and tongue, often are unaffected even in severe injuries and neuromuscular diseases. While there has been quite a bit of work applying techniques such as eye-tracking and speech recognition to these scenarios [2, 3], most of it has been placed in expert medical domains. In fact, many people already wear dental retainers or explicit tongue gestures for communication and control.

Figure 1 shows the optical tongue sensing retainer. We have developed a system that can detect four-finger gestures on a physical surface even when hands are busy with other objects. We report experimental results demonstrating four-finger classification accuracies averaging 79% to 88% while holding a mug, 78% while holding a bag, and 88% when carrying a water bottle. We further show generalizability across different arm postures and explore the tradeoffs of providing real-time feedback.



Figure 1. Our prototype optical tongue sensing retainer.

Optically Sensing Tongue Gestures for Computer Input

Saponas *et al.*, UIST'09
59 citations

Session: Brain & Body

CHI 2012, May 5–10, 2012, Austin, Texas, USA

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

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ABSTRACT
Touché proposes a *Smart Frequency Capacitive Sensing* technique that can not only detect a touch event, but also recognize complex configurations of the human hands and body. By attaching a simple sensor to a dental retainer placed on the palate, we can detect the tongue to push or pull objects located on the palate is potentially awkward and tiring. In fact, the tongue is a highly flexible skeletal muscle most often used for generating speech as well as breathing and swallowing food. However, these muscles require a large degree of control over tongue shape and position, and suggest opportunities for designing more natural and richer gesture spaces.

Researchers who have realized this opportunity have tried to track complex movements by instrumenting the tongue with metal contacts and a magnetometer [4, 6].

The movement of the unattached segments within the tongue can then be detected either by a dental retainer worn in the mouth or by a separate device worn outside the mouth. Unfortunately, these tongue angle sensors are quite coarse and while they can be surgically attached to the dental retainer with four other options, do not make them appealing to otherwise healthy individuals.

In our work, we embed optical sensors into orthodontic dental retainers worn in the mouth. These sensors provide data with no physical contact, are explicit and complete tongue movement. Building the sensing device into a dental retainer creates a form factor that is both easy to don, but also largely undetectable to an observer. This is important to distribute the benefit of this technology to a wide range of users, as well as healthy individuals when traditional forms of computer control are inadequate. Furthermore, many people already wear dental retainers or explicit tongue gestures for communication and control.

Figure 1 shows the optical tongue sensing retainer. We have developed a system that can detect four-finger gestures on a physical surface even when hands are busy with other objects. We report experimental results demonstrating four-finger classification accuracies averaging 79% to 88% while holding a mug, 78% while holding a bag, and 88% when carrying a water bottle. We further show generalizability across different arm postures and explore the tradeoffs of providing real-time feedback.

Author Keywords: touch; capacitive sensing; ubiquitous interfaces; general purpose computing; channels and controllers

ACM Classification: H.2.1 [User/Machine Systems]; H.5.2 [User Interfaces]: Input devices and strategies; B.4.2 [Input/Output Devices]: Channels and controllers

General terms: Design, Human Factors

Keywords: Tongue-Computer Interface, infrared, gestures.

INTRODUCTION

Traumatic brain and spinal cord injuries as well as medical conditions such as Lou Gehrig's disease often result in severely impaired hand function. Many of these patients retain significant functional cognitive abilities and there is great value in creating alternate input modalities that allow them to interact with computers and with the world around them.

Fortunately, the cranial nerves which control organs such as the eye, jaw, and tongue, often are unaffected even in severe injuries and neuromuscular diseases. While there has been quite a bit of work applying techniques such as eye-tracking and speech recognition to these scenarios [2, 3], most of it has been placed in expert medical domains. In fact, many people already wear dental retainers or explicit tongue gestures for communication and control.

The most obvious way to exploit direct control with the tongue is to provide physical transducers that can actuate or manipulate. For example, both Peng et al. and Ferreira et al.



Figure 1. Touché applications: (a) on-body gesture sensing; (b) a smart doorknob with a "gesture password"; (c) interacting with water; (d) hand postures in touch screen interaction.

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

Harrison *et al.*, CHI'12
219 citations

Session: Novel Interfaces

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AirWave: Non-Contact Haptic Feedback Using Air Vortex Rings

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Figure 1: AirWave prototype filled with fog to visualize a vortex ring being used for providing precise non-contact haptic feedback.

vise and provide direct mechanical stimulation. However, this assumption is no longer valid, as non-contact and at-a-distance sensing (e.g., computer vision and speech recognition) have become prevalent in our computing environments. The Microsoft Kinect, for example, allows immersive gaming and media control through computer vision and speech recognition, which require no physical contact between the user and the computer. This presents a new challenge to haptic feedback systems, and our core research question:

How do we restore haptic realism to virtual environments when the user is meters away from the computer, and is neither carrying nor wearing an interface device?

In order to restore haptic realism to at-distance, non-contact interfaces, we investigate the use of *air vortex rings* as a technique for providing haptic feedback. We believe vortexes form a natural medium for haptic feedback, as they subsume the need to build intricate foundations. We then discuss a prototype, *AirWave*, that provides at-a-distance haptic feedback that does not require physical contact or instrumentation of the human body. We provide an analysis of the spatial resolution of this prototype, and we analyze how interactions are perceived by users. We also show how users can perceive haptic feedback at different locations on the body. In a study with 10 users, we found that the mean error between the intended target point and where users sensed the vortex was less than 10 cm, at a distance of 2.5 meters.

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The specific contributions of this paper are:

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Enabling Always-Available Input With Muscle-Computer Interfaces

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</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