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Human Sensing Using Light

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May 28th, 2021

The Rise Of Light Sensing

IMU sensors

Radio antennas

Microphone

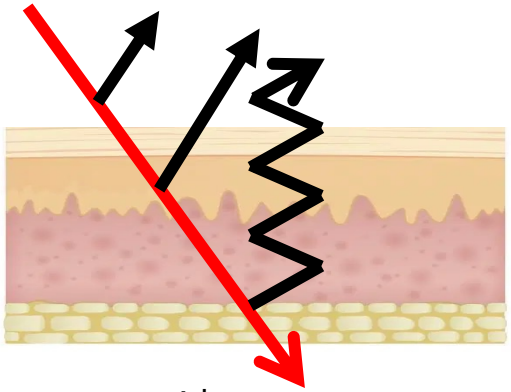
Cameras

Light As A Primary Modality For Fine-grained Human Sensing

- Sense light intensity change caused by the human **blockage**, **reflection**, and **absorption** to infer **fine-grained** human behaviors and biomarkers.

Blockage

Reflection

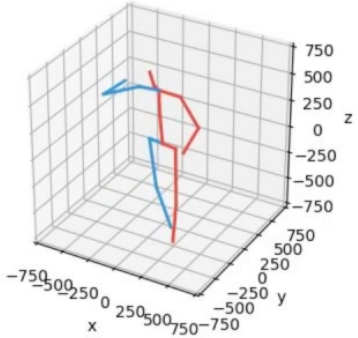


Absorption

Biomechanical sensing

Biophysiological sensing

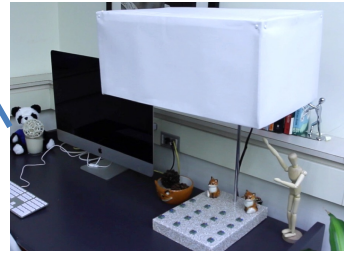
Biochemical sensing



Skeleton pose reconstruction

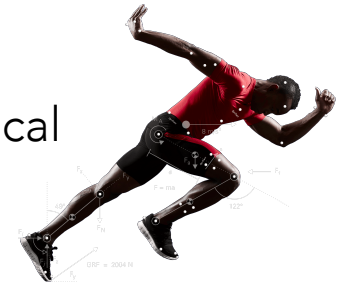
MobiCom ‘15

MobiSys ‘16



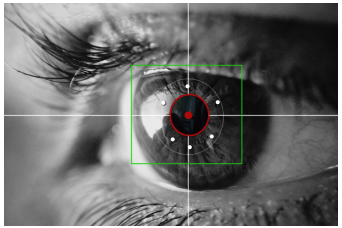
UbiComp ‘17

Biomechanical sensing



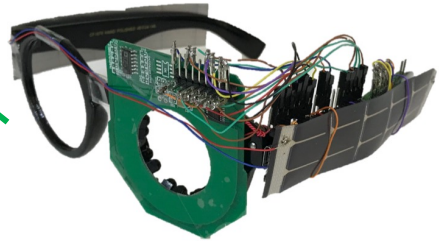
Biophysiological sensing

Biochemical sensing



Eye tracking

SenSys ‘17

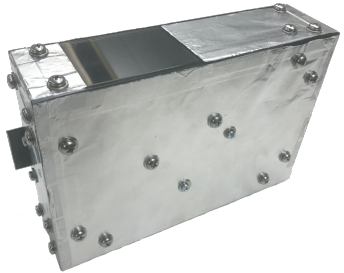


MobiCom ‘18

Biomechanical sensing

Biophysiological sensing

Biochemical sensing



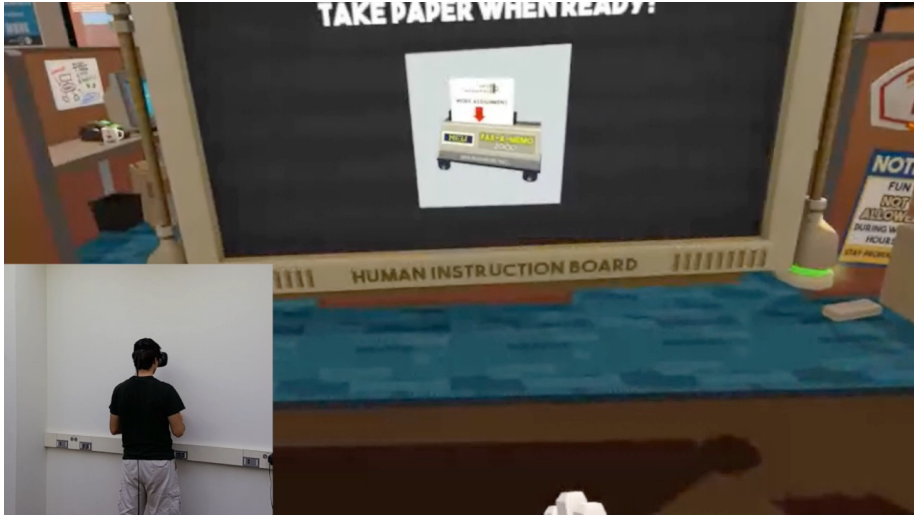
SenSys '20

Noninvasive glucose monitoring

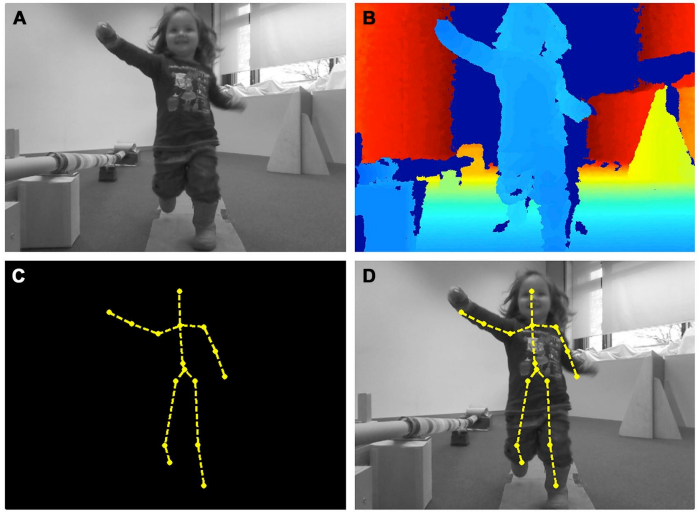
Outline

- Introduction
- Biomechanical sensing: Skeleton pose reconstruction
- Biophysiological sensing: Battery-free eye tracking
- Biochemical sensing: Noninvasive glucose monitoring
- Conclusion & Future Work

Skeleton Pose Reconstruction Applications



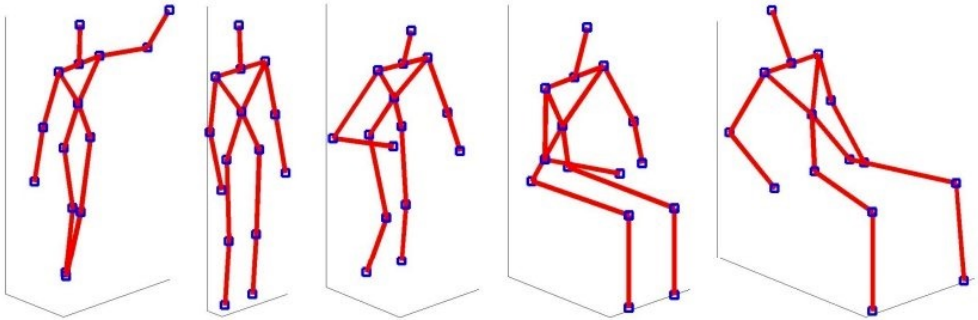
Human-computer interaction (HCI)

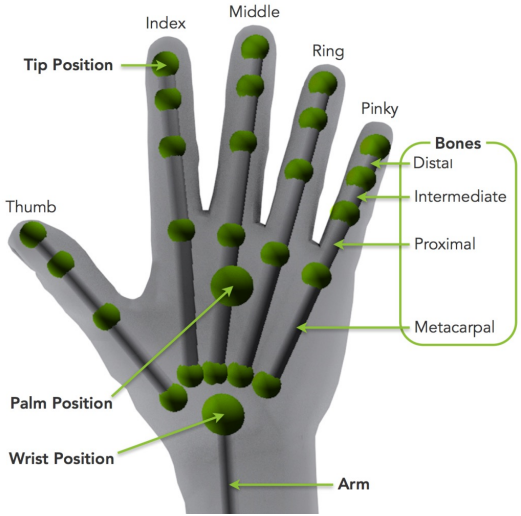


Health monitoring

Skeleton Pose Reconstruction is Challenging

- Poses are complex
  - Whole-body pose has 26 degrees of freedom.
  - Hand pose has 23 degrees of freedom.





Existing Skeleton Reconstruction Systems

Leap Motion

Microsoft Kinect

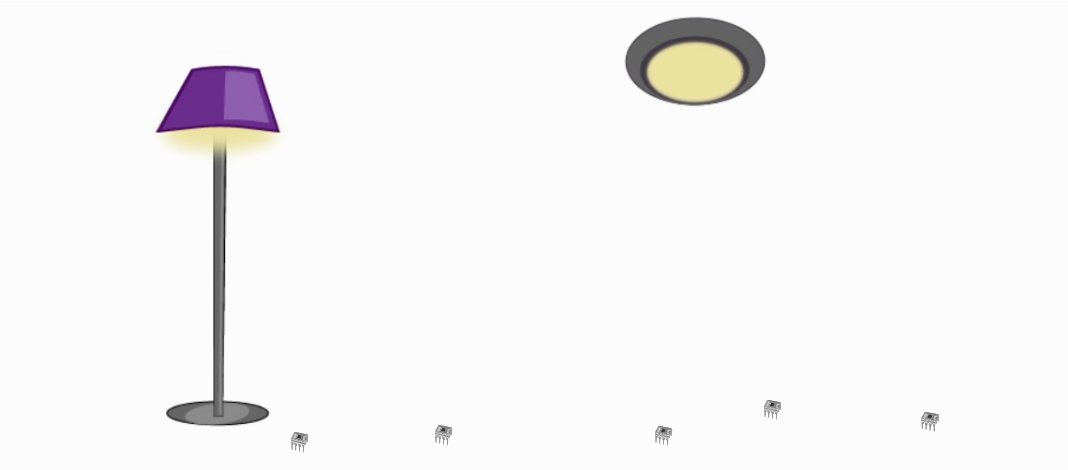
VICON

- Heavy computation overhead
- Privacy concern[1]
- Limited field of view (FoV)

SBÎRLEA, D., BURKE, M. G., GUARNIERI, S., PISTOIA, M., AND SARKAR, V. Automatic detection of inter-application permission leaks in android applications. IBM Journal of Research and Development 57, 6 (2013), 10–1.

Solution: Light Blockage Sensing

- Replace cameras with distributed photodiodes
- Measure how body block light rays
- Aggregate light-blockage information to infer 3D poses



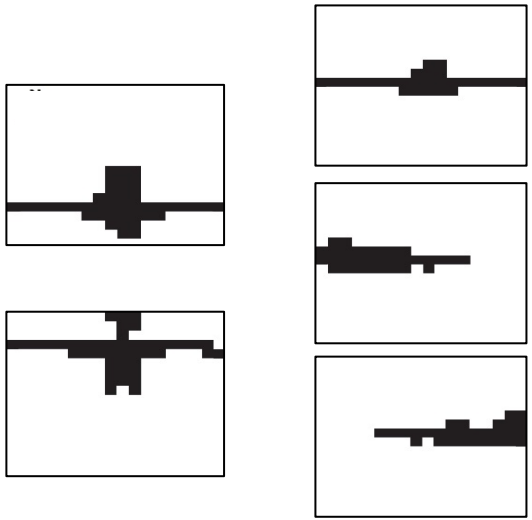
Photodiodes

Design Challenges

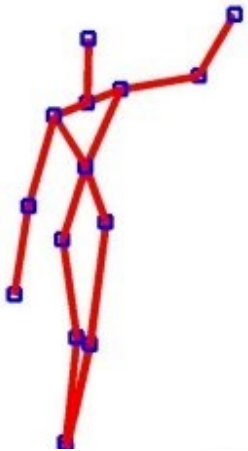
#1: Light interface with multiple light sources

Design Challenges

#2: 2D Low-resolution shadows



5 example shadows



Design Challenges

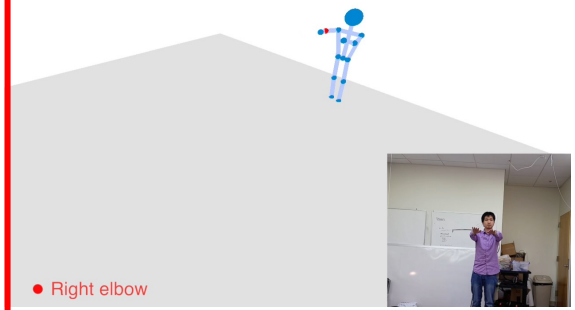
#3: Object blockage (furniture, other people, pets, etc.)

Contributions in Skeleton Pose Reconstruction

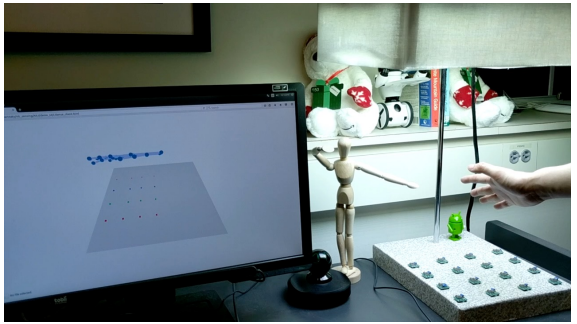
Whole-body poses

Hand poses

LiSense @ 60 Hz
(MobiCom'15)



StarLight @ 40 Hz
(MobiSys'16)



Aili @ 140 Hz
(UbiComp'17)

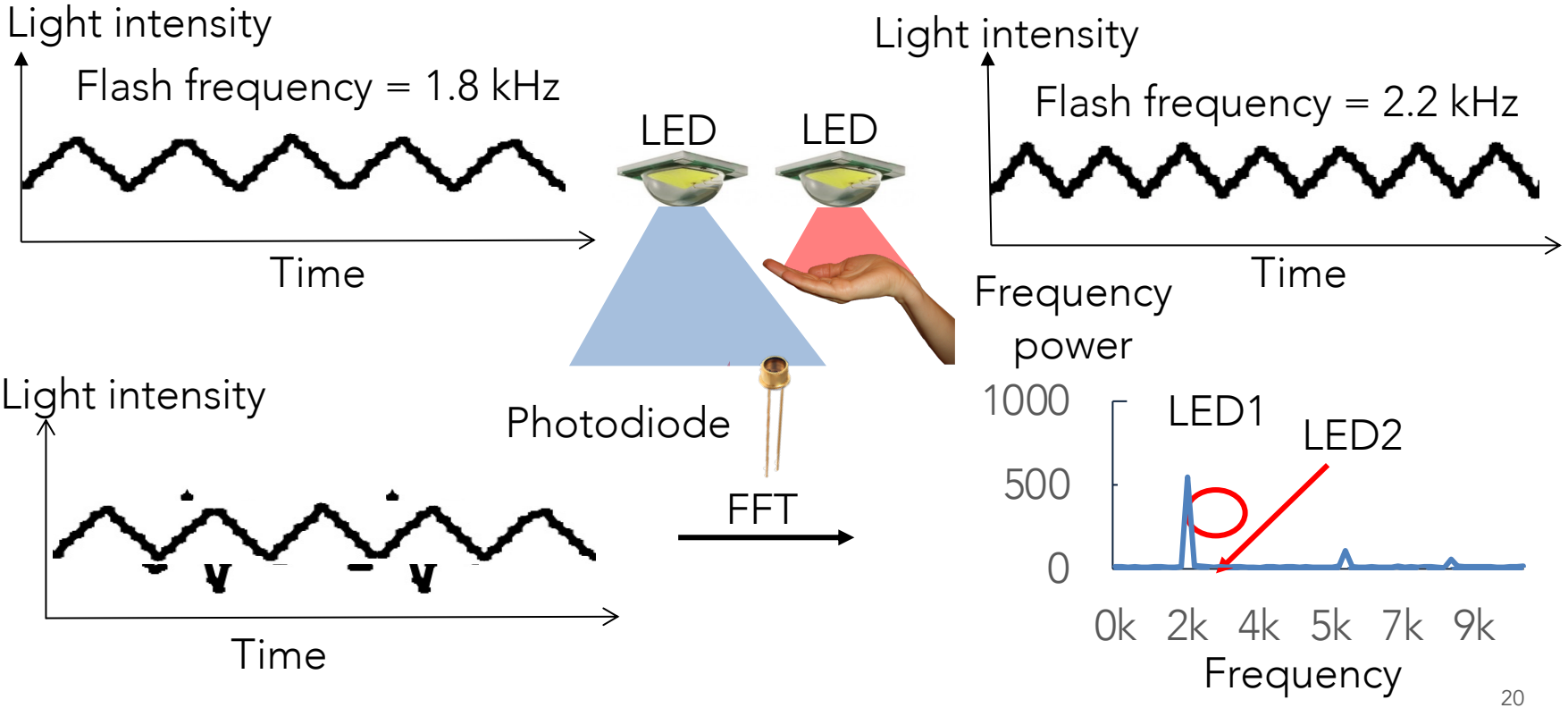
LiSense Overview

Challenge #1: Multiple light sources

↓

Separate light rays via light beacons

Light Beacon Rationale

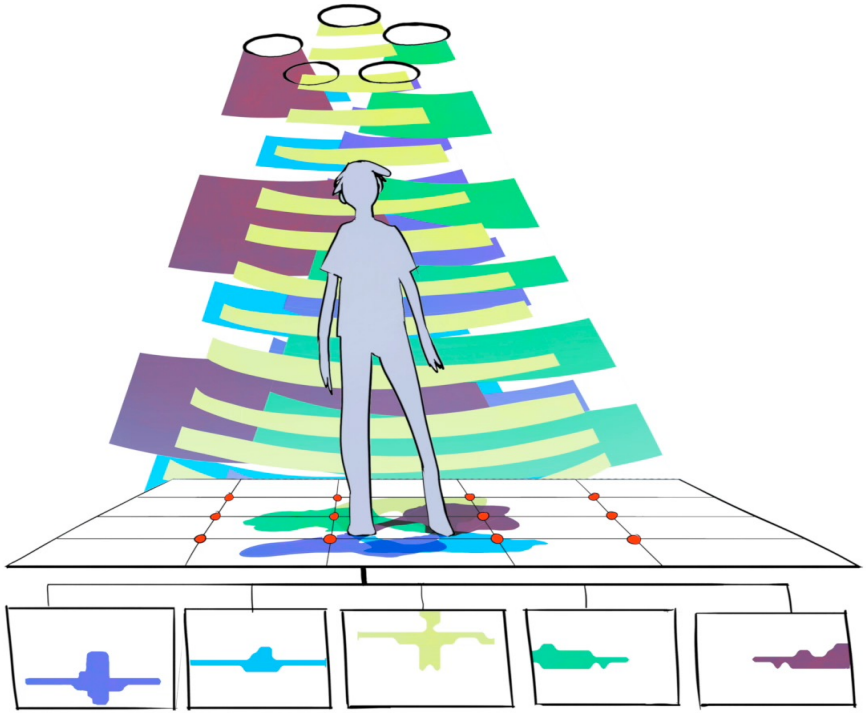


LiSense Overview

Challenge #2:
Reconstruct a 3D pose from 2D shadows

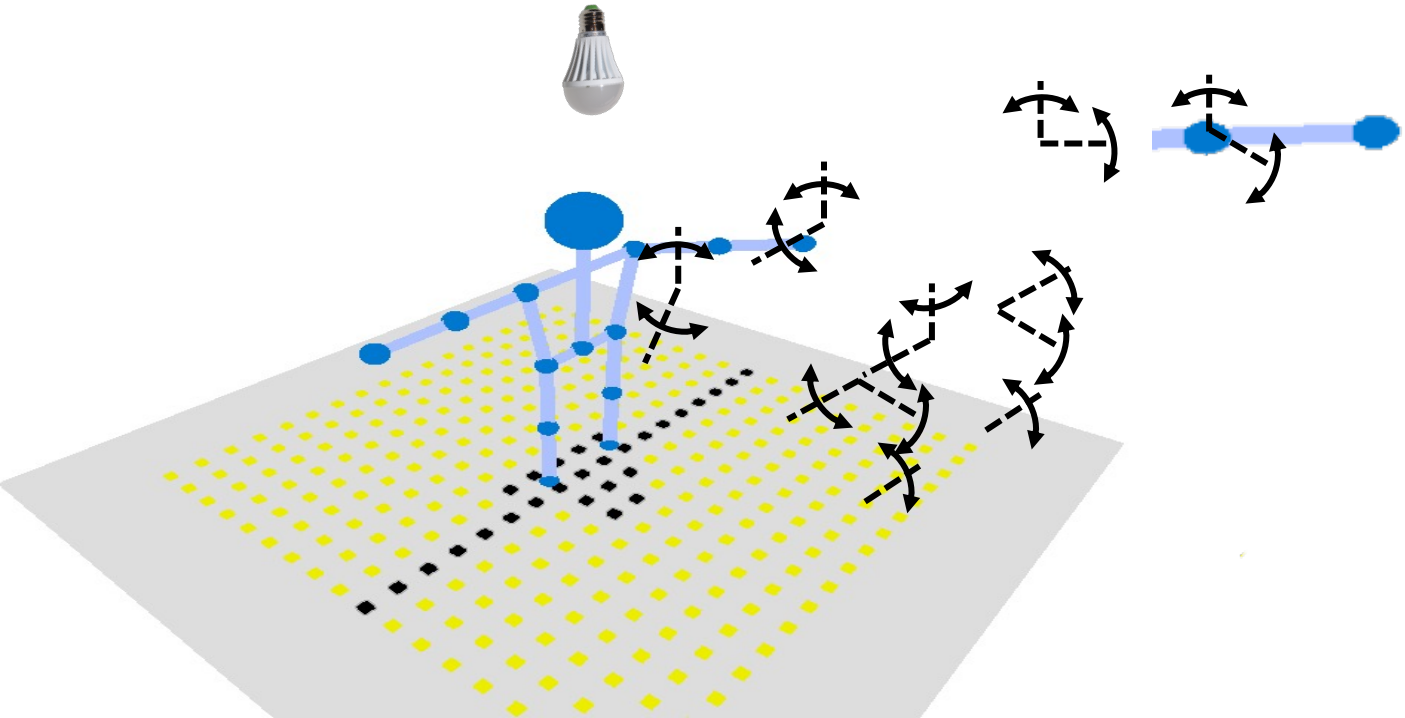
↓

Seek a posture best fitting shadows cast in multiple directions



Shadow-Based Inference

- Search for the skeleton best matching observed shadow maps



Shadow-Based Inference

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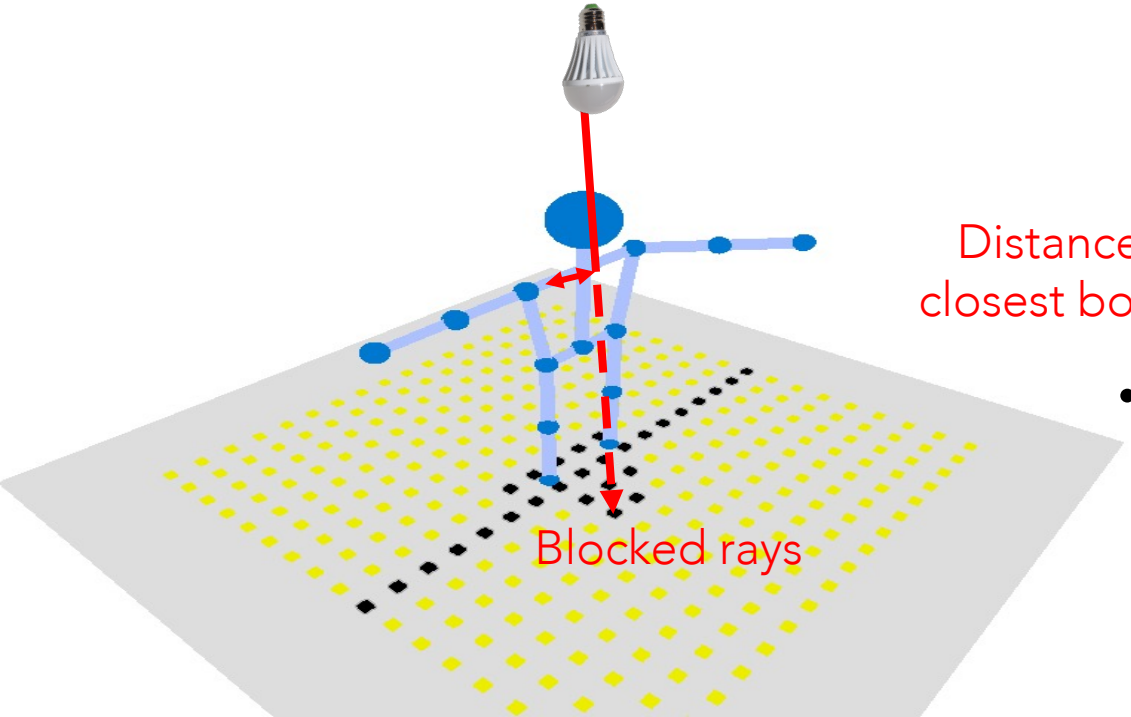


A candidate pose

$$B^* = \underset{B}{argmin}(E(B))$$

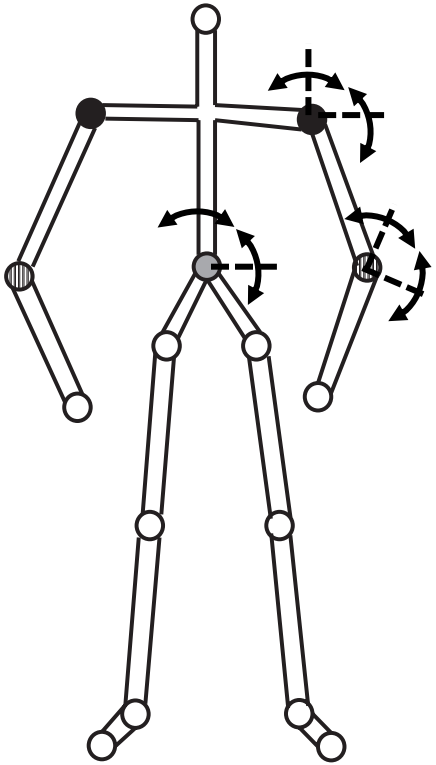
Distance between blocked rays and the closest body segment on a candidate pose

- Challenges:
  - No close-form solution
  - Large search area in high dimensional space

Search for Pose Candidates E(B)

- Sequential search: prioritize the search order based on the body part size

- Fixed-step search: search from large to small movement magnitude



Backbone joint

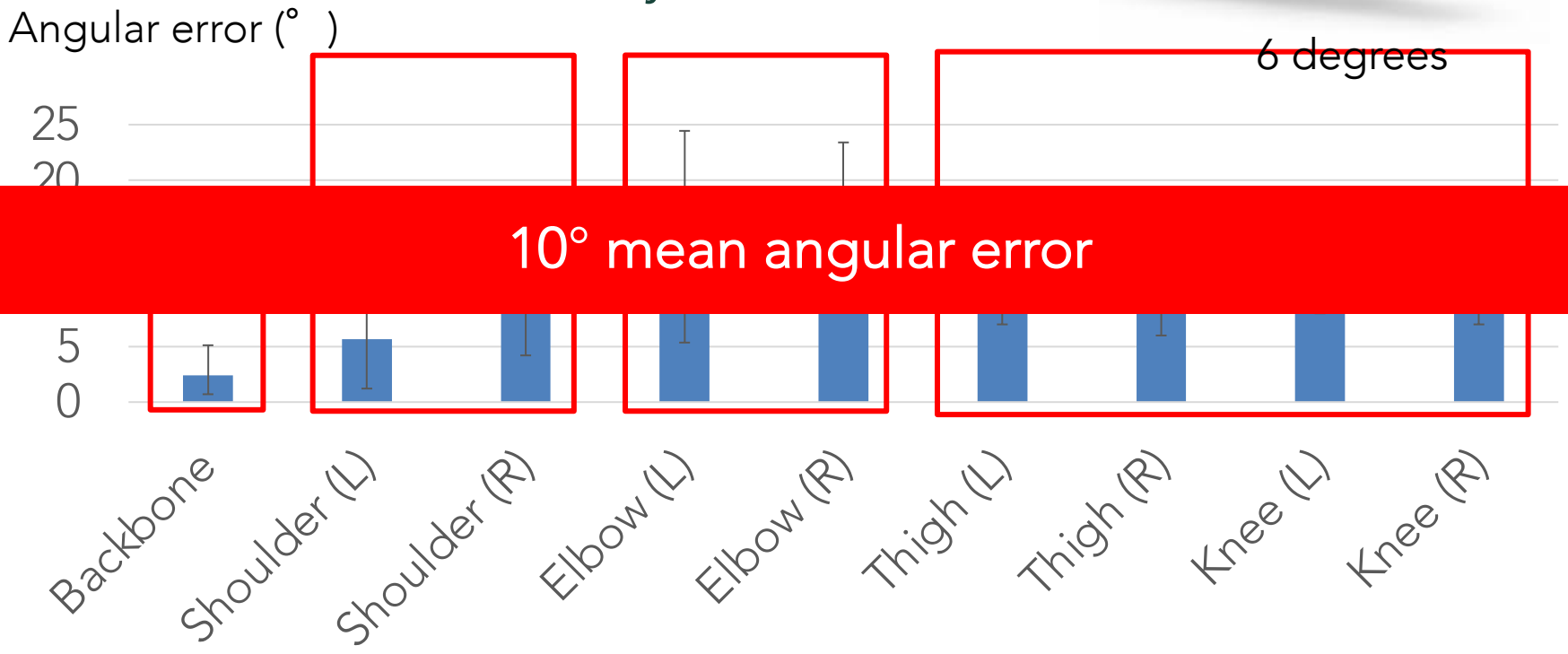
Shoulder joint

Elbow joint

Experiment Settings

- 7 users
  - 169 cm – 190 cm
  - 60 kg – 80 kg
- Ground truth
  - Human labelling using three cameras

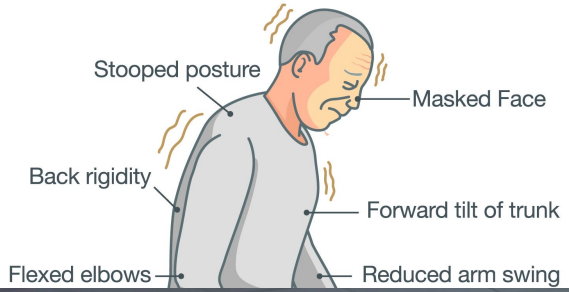
Reconstruction Accuracy



10° mean angular error

Potential Applications

- Health
  - Detect early symptoms of diseases (e.g., Parkinson's disease)
  - Help with stroke recovery
- HCI
  - Control robots with body movement
  - Virtual reality interaction
  - Translate sign language



Outline

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- Biophysiological sensing: Battery-free eye tracking
- Biochemical sensing: Noninvasive glucose monitoring
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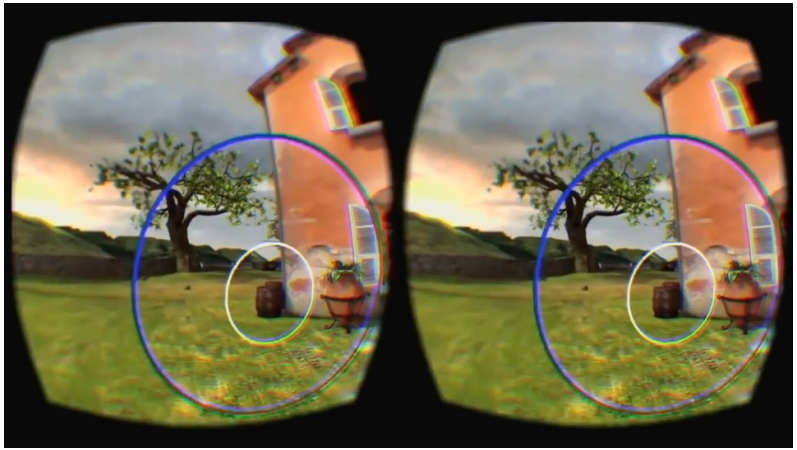
Wearable Eye Tracking in VR/AR

New interactive input



Optimized Rendering

Wearable Eye Tracking in Health

Fatigue detection

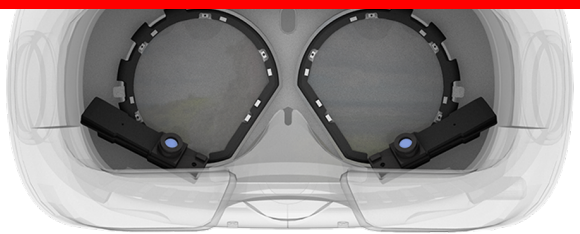
Detect early symptoms of diseases (e.g., ADHD)

Existing Wearable Eye Trackers

- Camera-based
  - ☹ High power consumption
  - ☹ Expensive

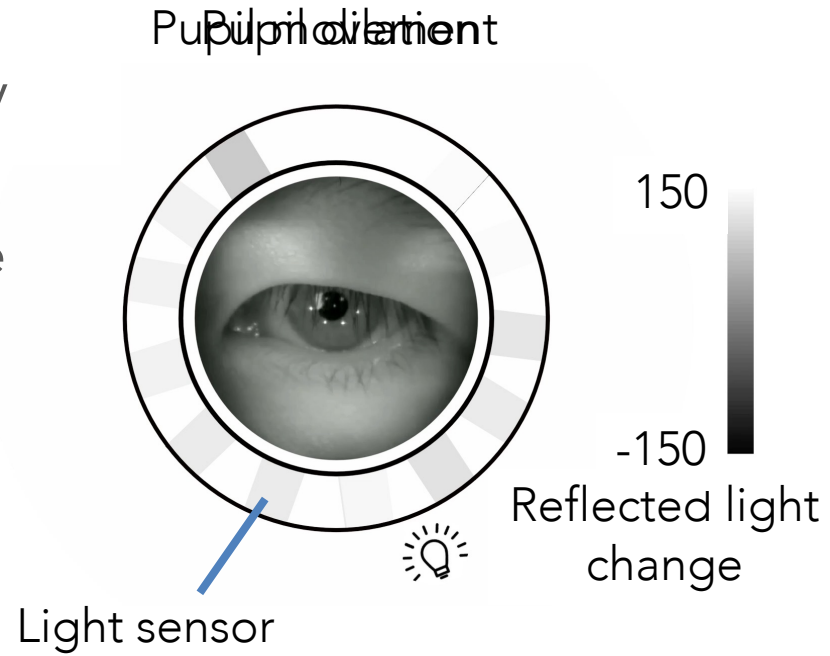
Can we design a low-power and low-cost eye tracker?

Battery pack



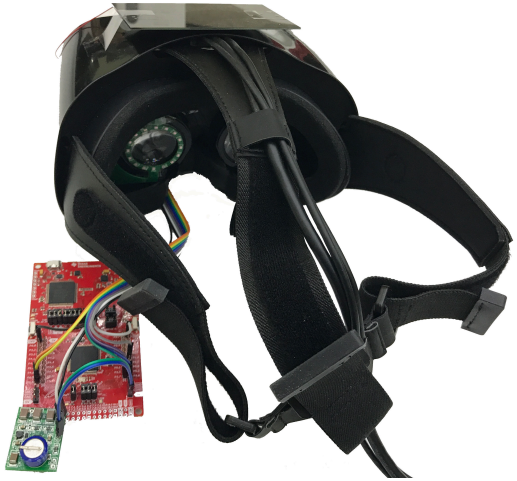
My Approach

- Pupil's light absorption property
- Array of photodiodes to sample reflected light intensity change
- Benefits:
  - Low-cost
  - Low-power



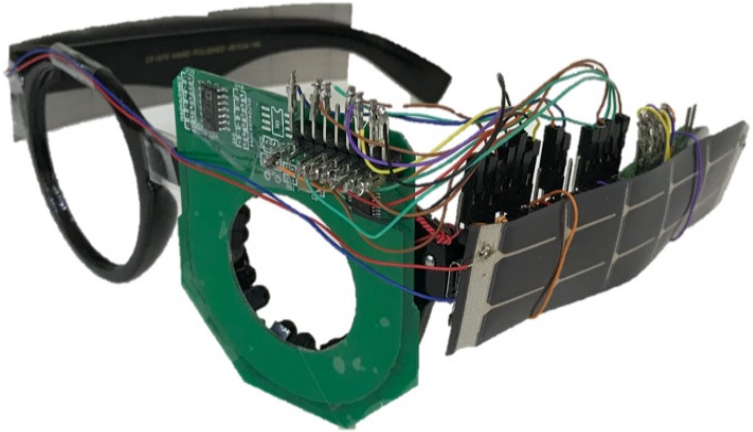
Contributions in Eye Tracking

VR headset



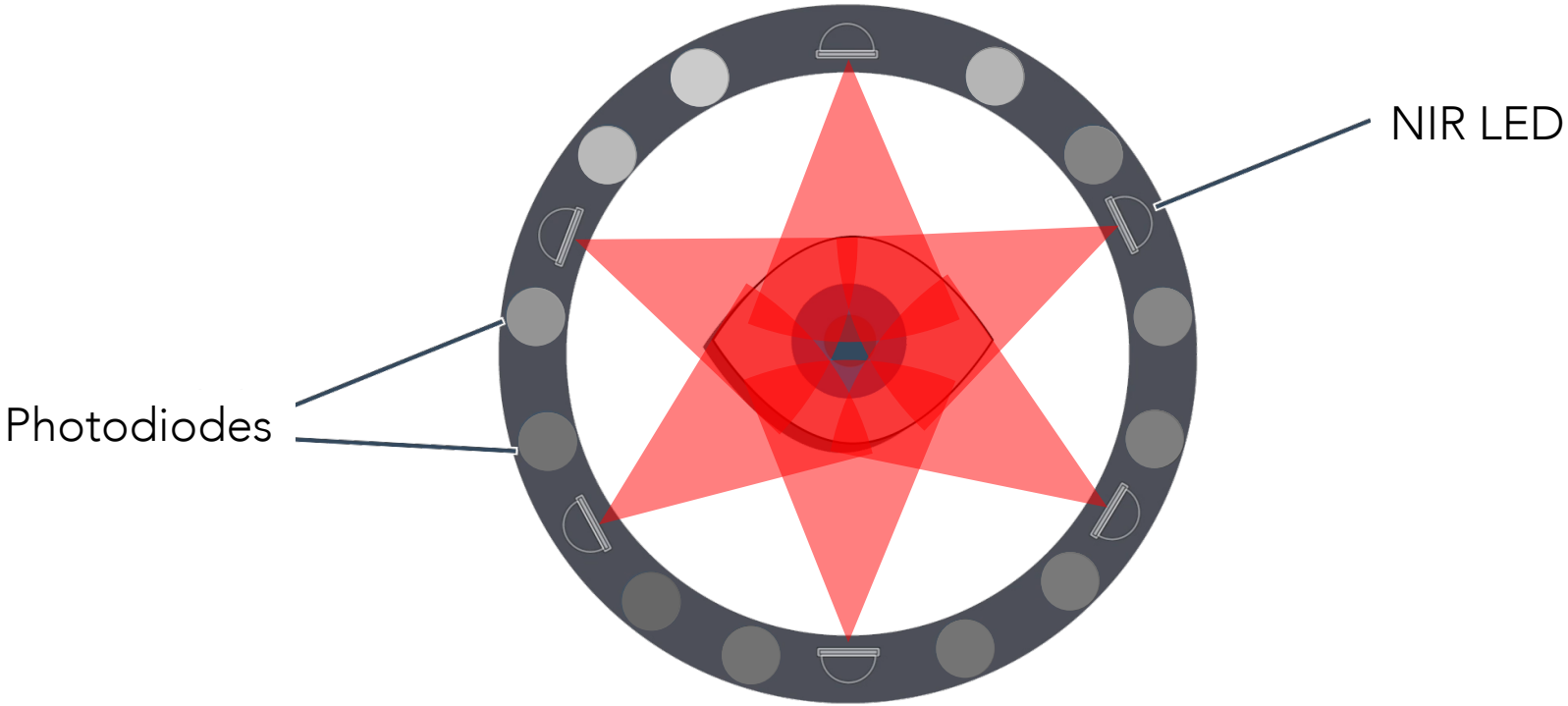
SenSys'17

Regular/AR glasses

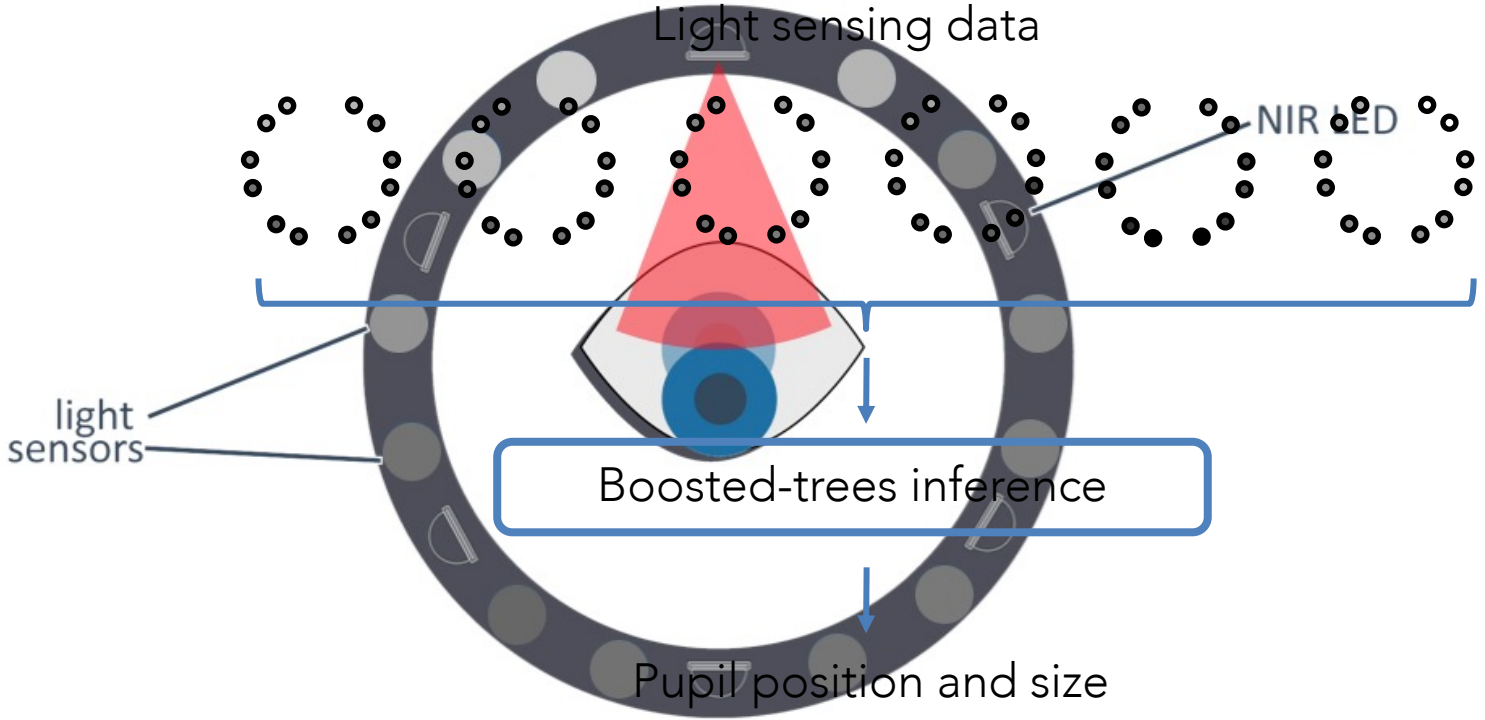


MobiCom'18

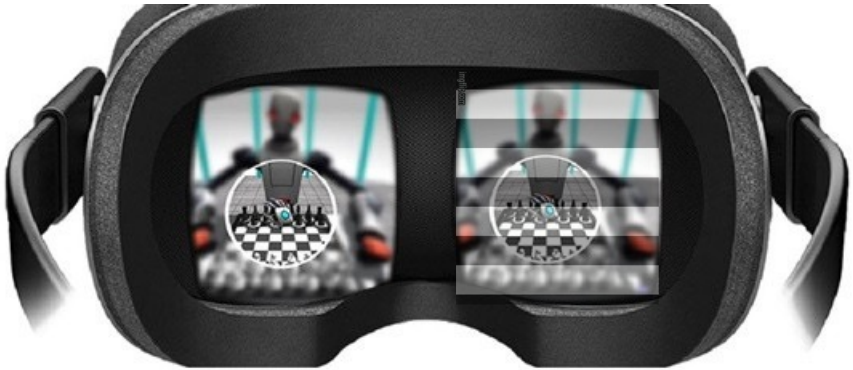
Sensing with Multiple NIR LEDs



Sensing with Multiple NIR LEDs



High Tracking Rate is Essential!



VR

> 90 Hz

Health

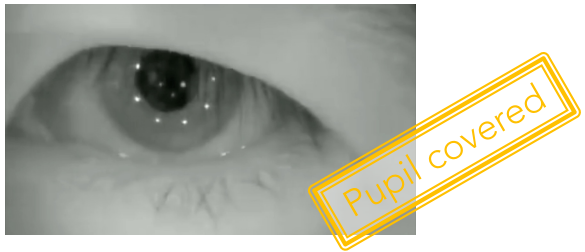
> 120 Hz

Predictability of Eye Movements

- Characteristics of four types of eye movement

Fixation

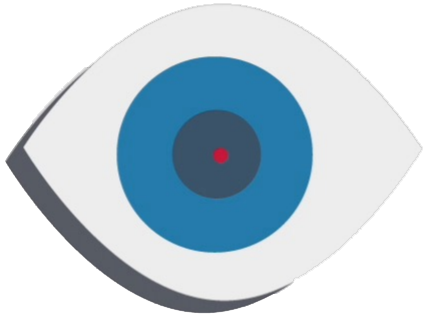
Smooth pursuit



Blink

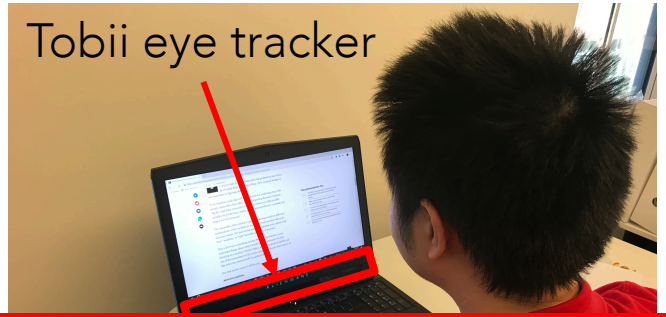
Saccade

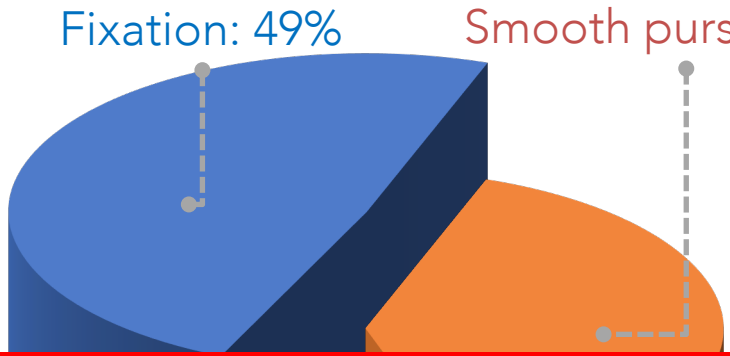
Pupil Movement is Jerky…



Saccadic movement occupies a small portion!

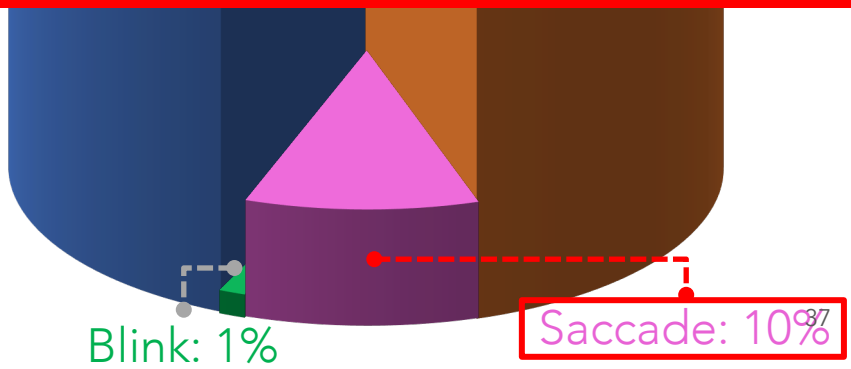
User Study on Eye Movement Patterns



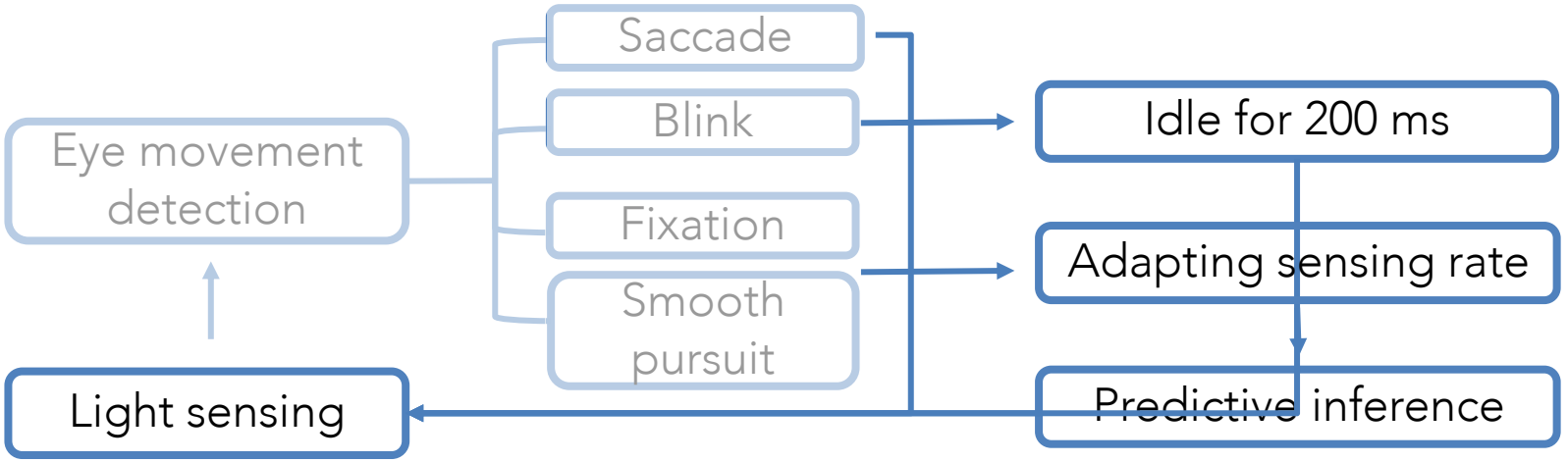


Most eye movements are predictable

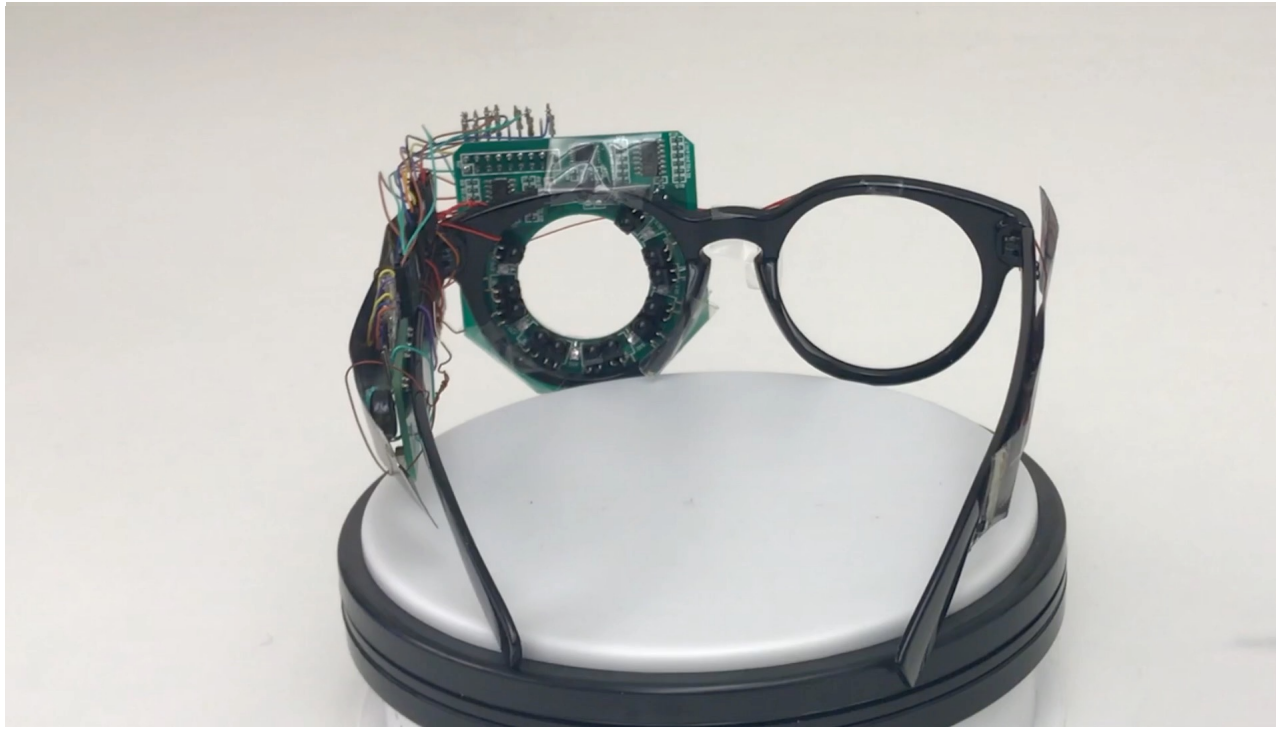
- 10 x
- 5 activities: slow reading, fast reading, watching videos, playing games, in conversation



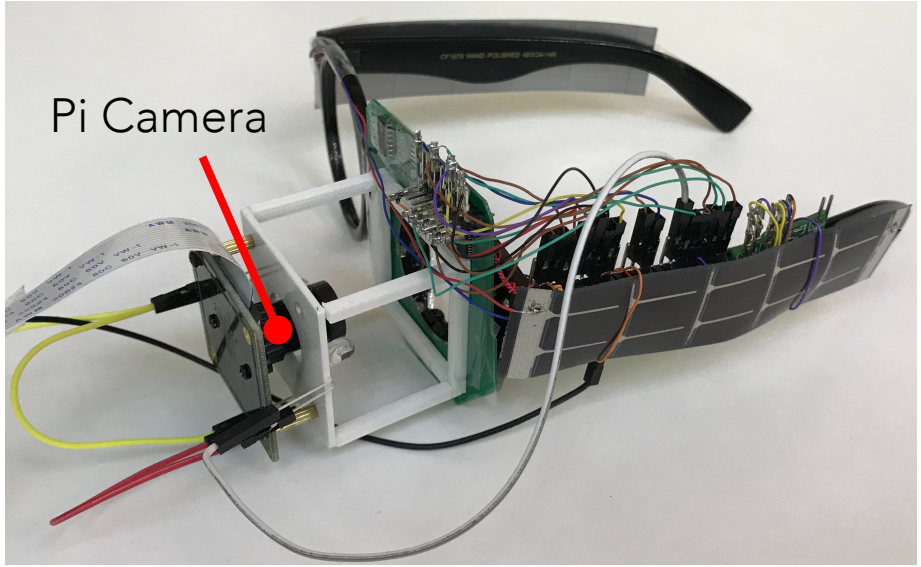
Adaptation Based On Eye Movement



Prototype



Experiment Setups



Pupil Lab API + human label

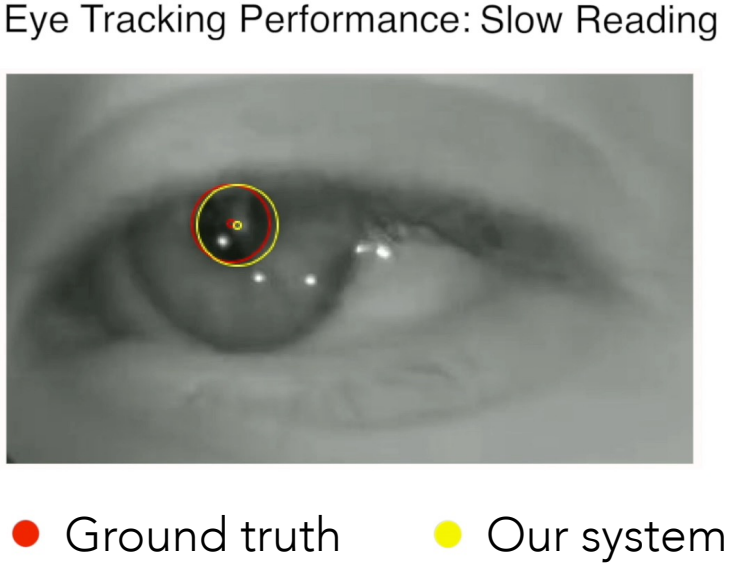
- 22 x

		# of users
Eye color	Black	16
	Blue	5
	Green	1
Skin color	White	6
	Yellow	11
	Black	5

- 5-min training data
- 5 activities (10 mins each)
  - slow reading
  - fast reading
  - watching videos
  - playing games
  - conversation

Tracking Accuracy

- Pupil position error
  - 0.8-mm mean error
  - Only 0.4 mm larger than the most accurate camera-based wearable eye tracker
- Pupil diameter error
  - 0.3-mm mean error



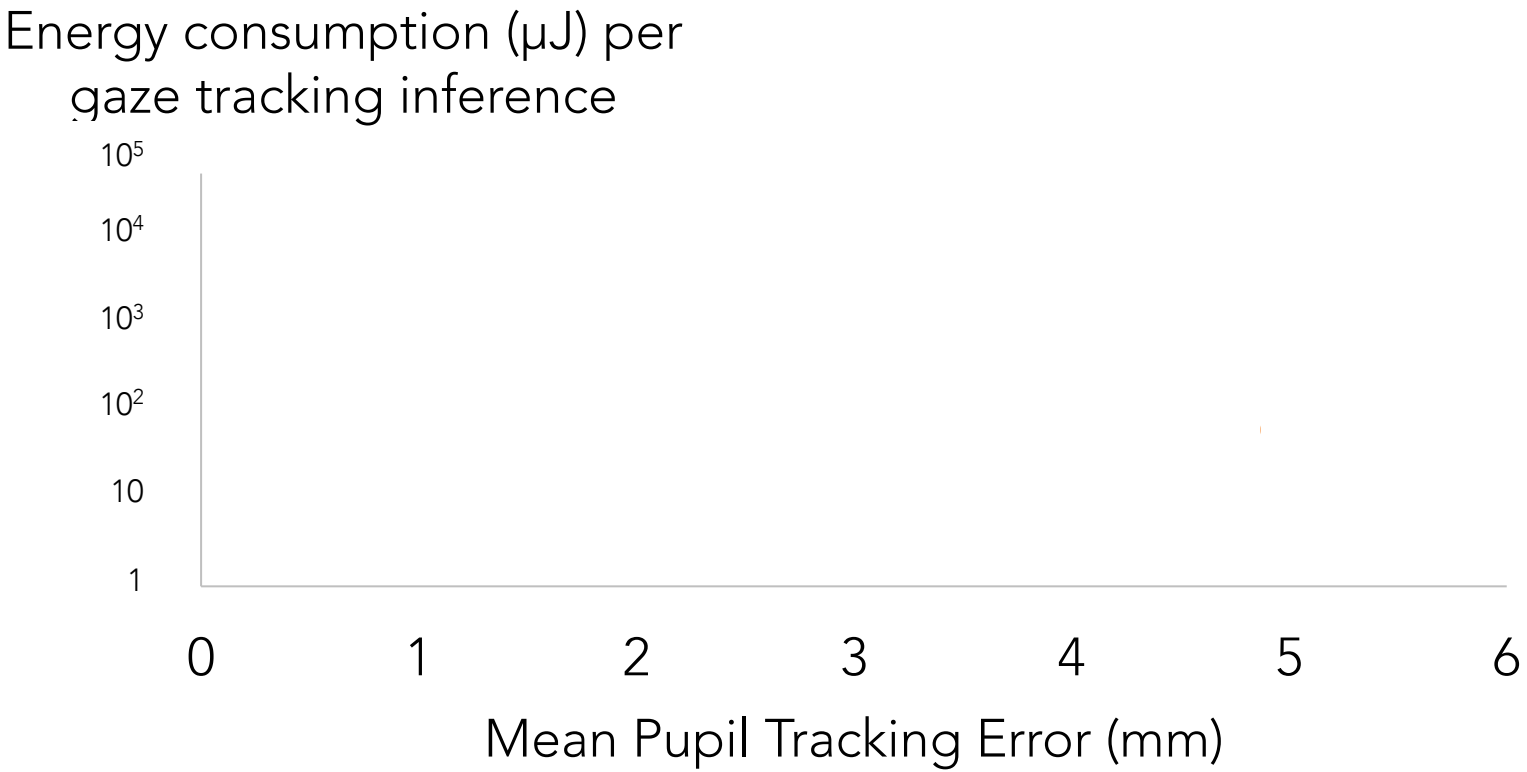
Energy Analysis

Avg. power consumption: 395 μW < Avg. harvested power: 450 μW

- Power Consumption

- Power Consumption

Our System vs. Existing Eye Trackers



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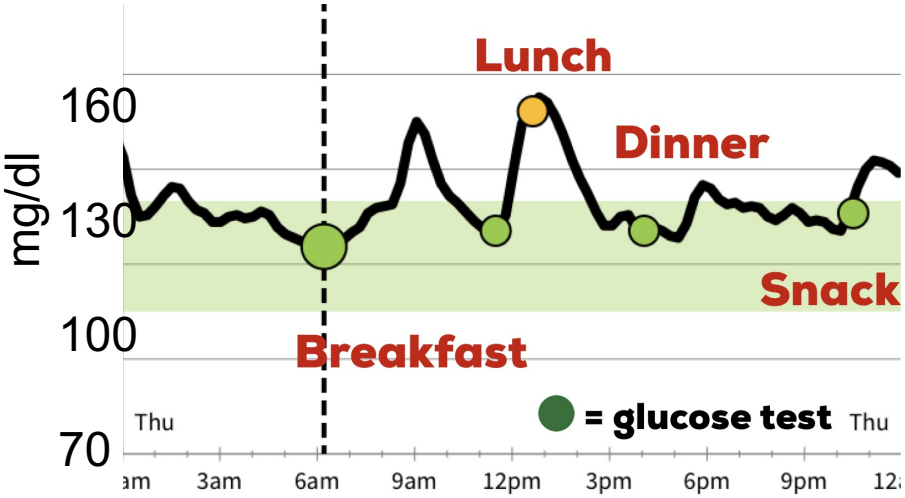
The Importance Of Glucose Monitoring

- 30+ million Americans have diabetes
- Glucose monitoring can manage diabetes conditions
  - Require > 3 times a day



- Normal: 70-140 mg/dl
- High: > 140 mg/dl
- Low: < 70 mg/dl

Existing Method #1: Finger Pricking

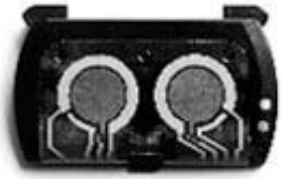
☹ Painful, invasive

Existing method #2: Continuous Glucose Monitoring (CGM)

☹ Invasive needle

Existing Noninvasive Glucose Monitoring

☹ Skin irritation
☹ Environmental factors



AutoSensor

icoWatch® Biographer

Optical Noninvasive Glucose Monitoring

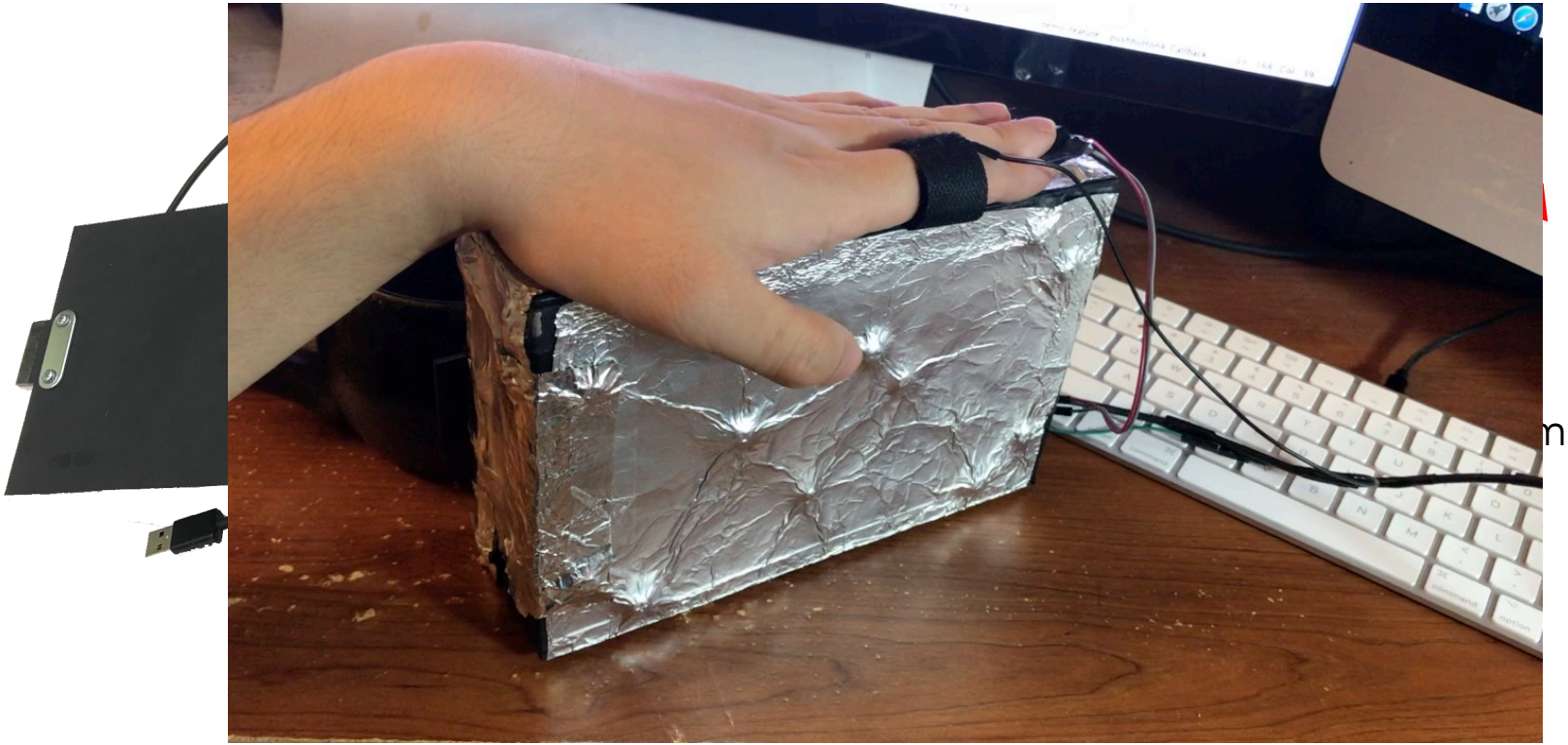
- Light absorption

We need a noninvasive, accurate, and low-cost glucose monitoring system!

☹ Expensive and bulky

☹ Lacking clinical evaluations

Prototype In Use



5 cm

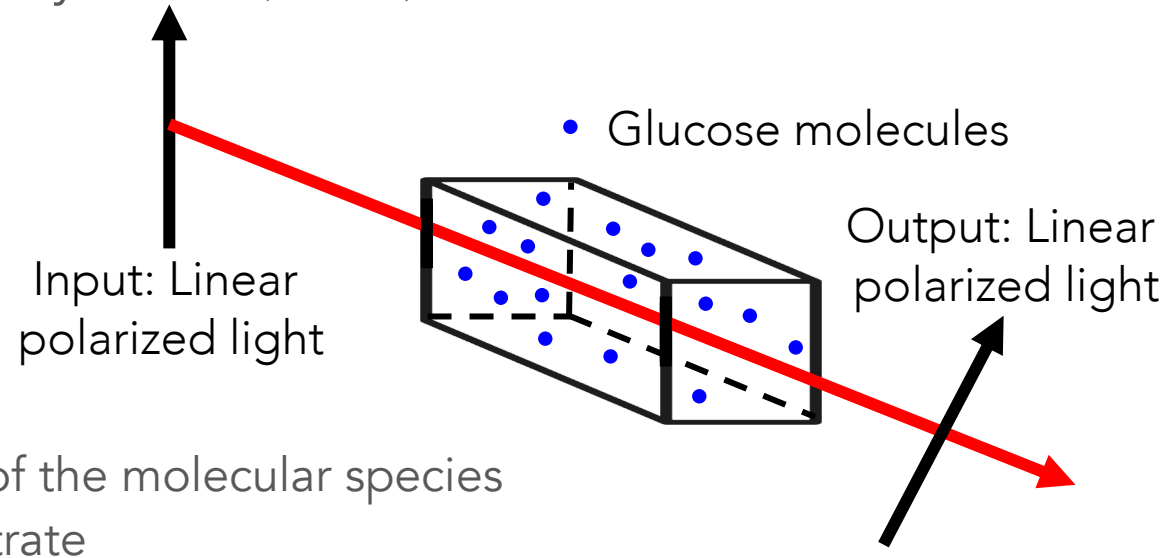
m

Rationale

- Glucose is an optically active (chiral) molecule

Difficult to compute in vivo

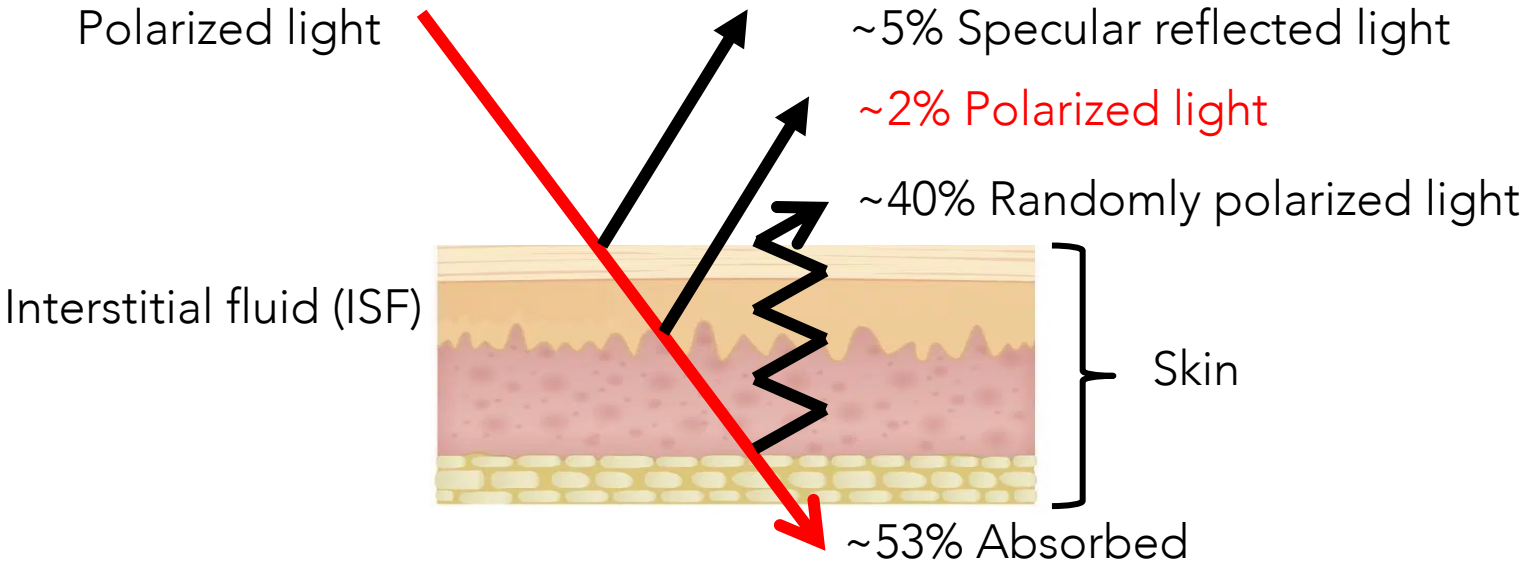
$$\alpha = R(\lambda, T) \cdot C \cdot L$$



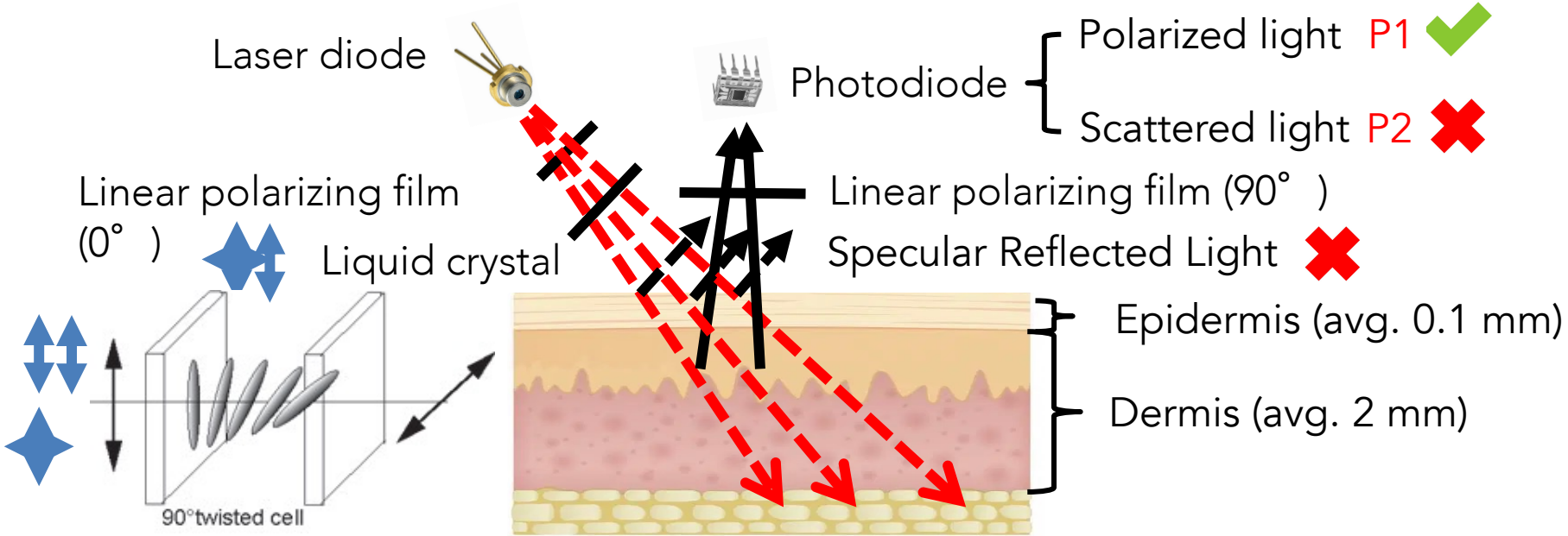
- α: Optical rotation
- R: Rotatory power of the molecular species
- C: Glucose concentrate
- L: Optical path

Challenges

- #1: Skin scattering



Sensing Changes In Light Polarization



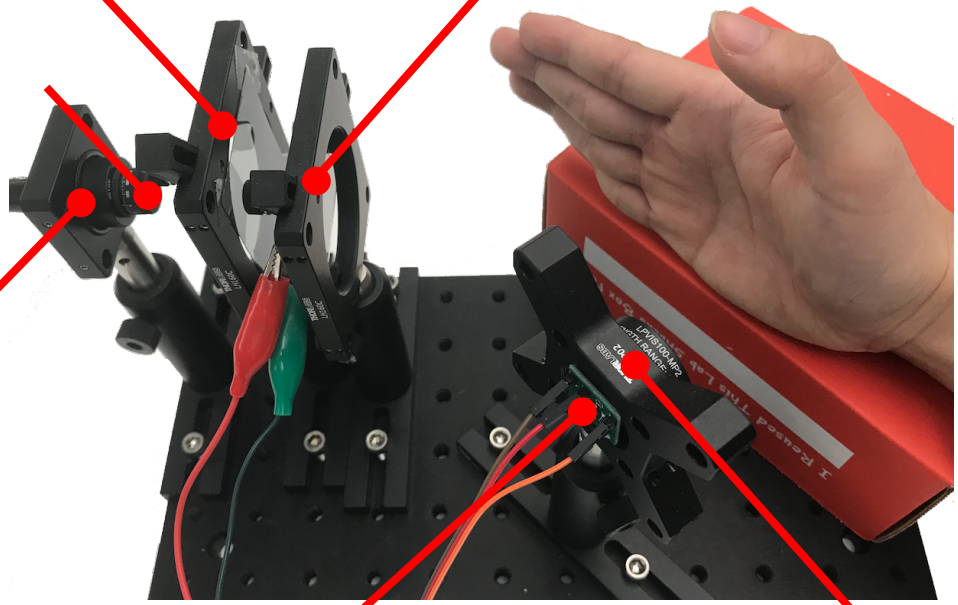
Experiment Setup

Liner polarizing film (0°)

Diffuser

Red laser diode

Liquid crystal



Photodiod

Liner polarizing film (90°)

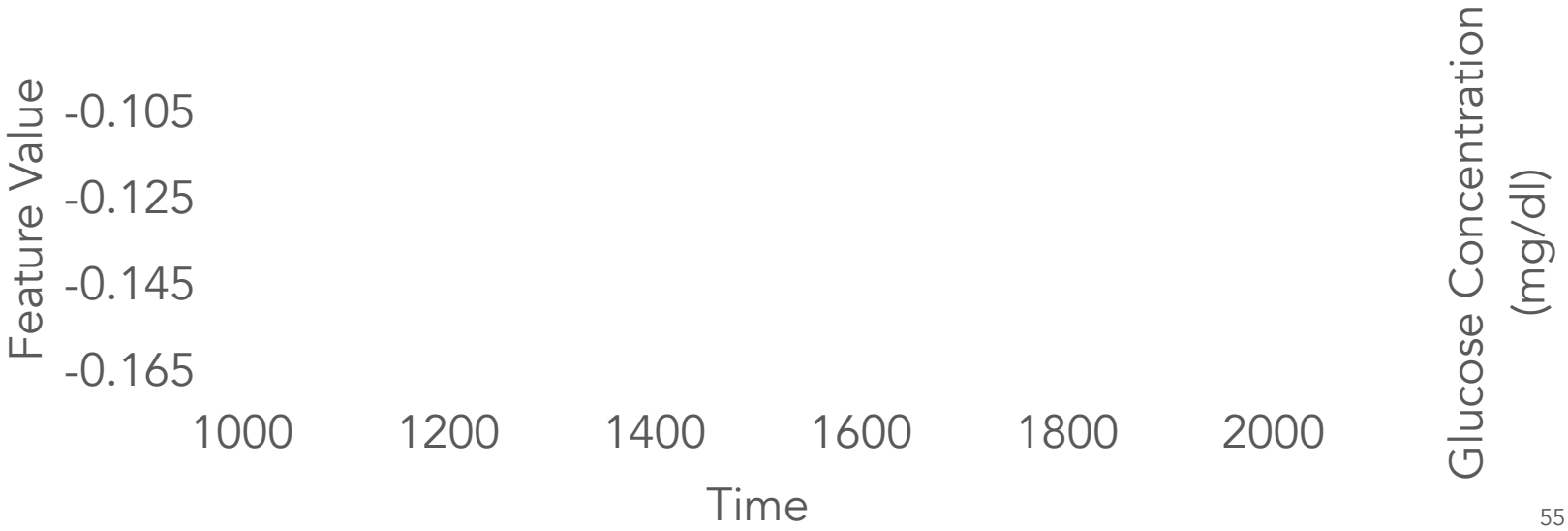
Results

I_{per} = P1 + 0.5 x P2

I_{par} = 0.5 x P2

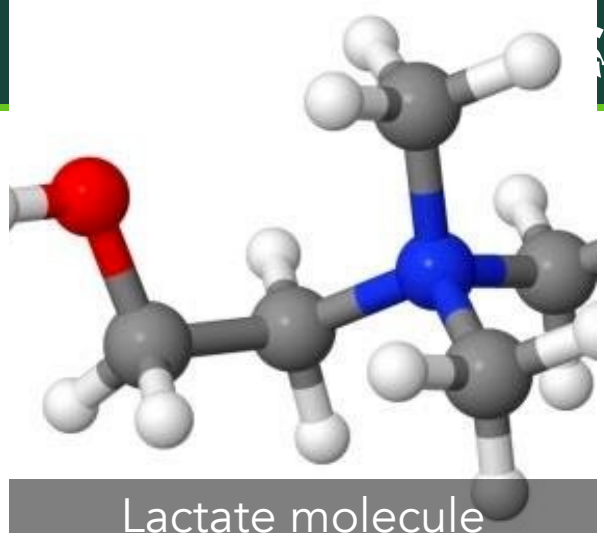
$Feature\ value = I_{per} - I_{par}$

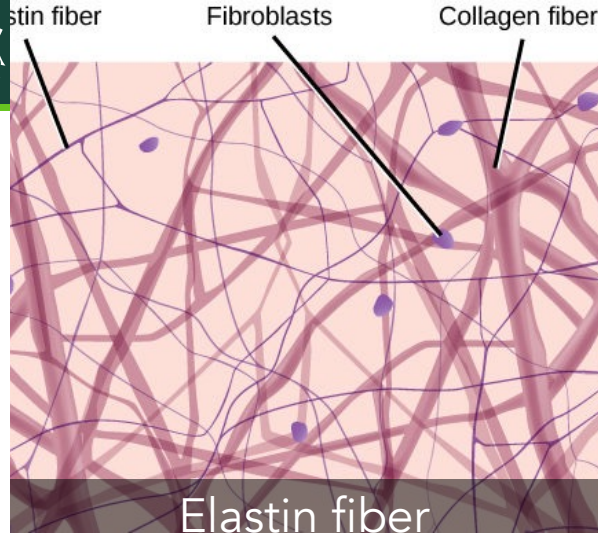
R = 0.86, p < 0.05



Challenges

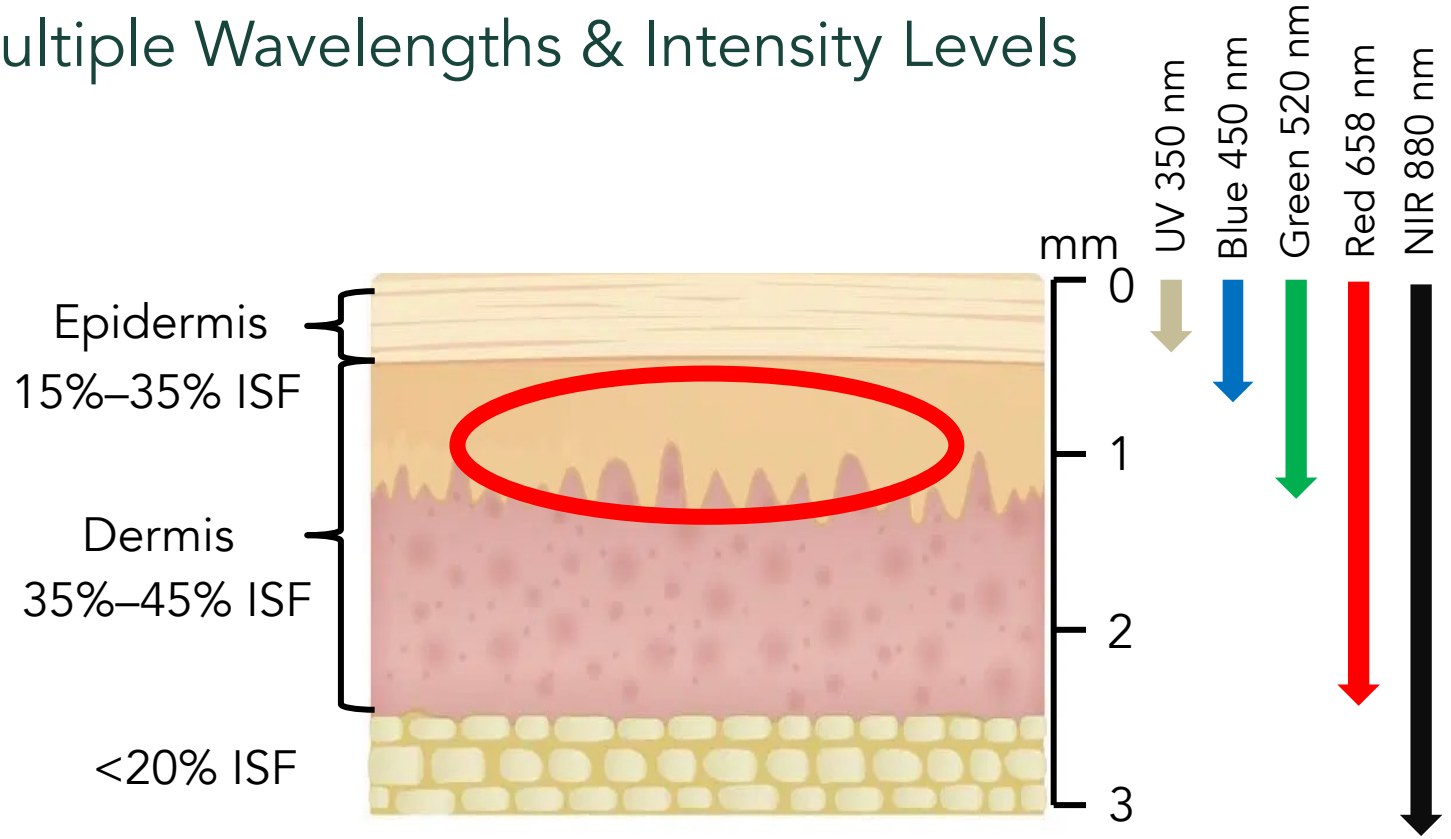
- #1: Skin scattering
- #2: Confound factors
- #3: User diversity


Lactate molecule



Elastin fiber

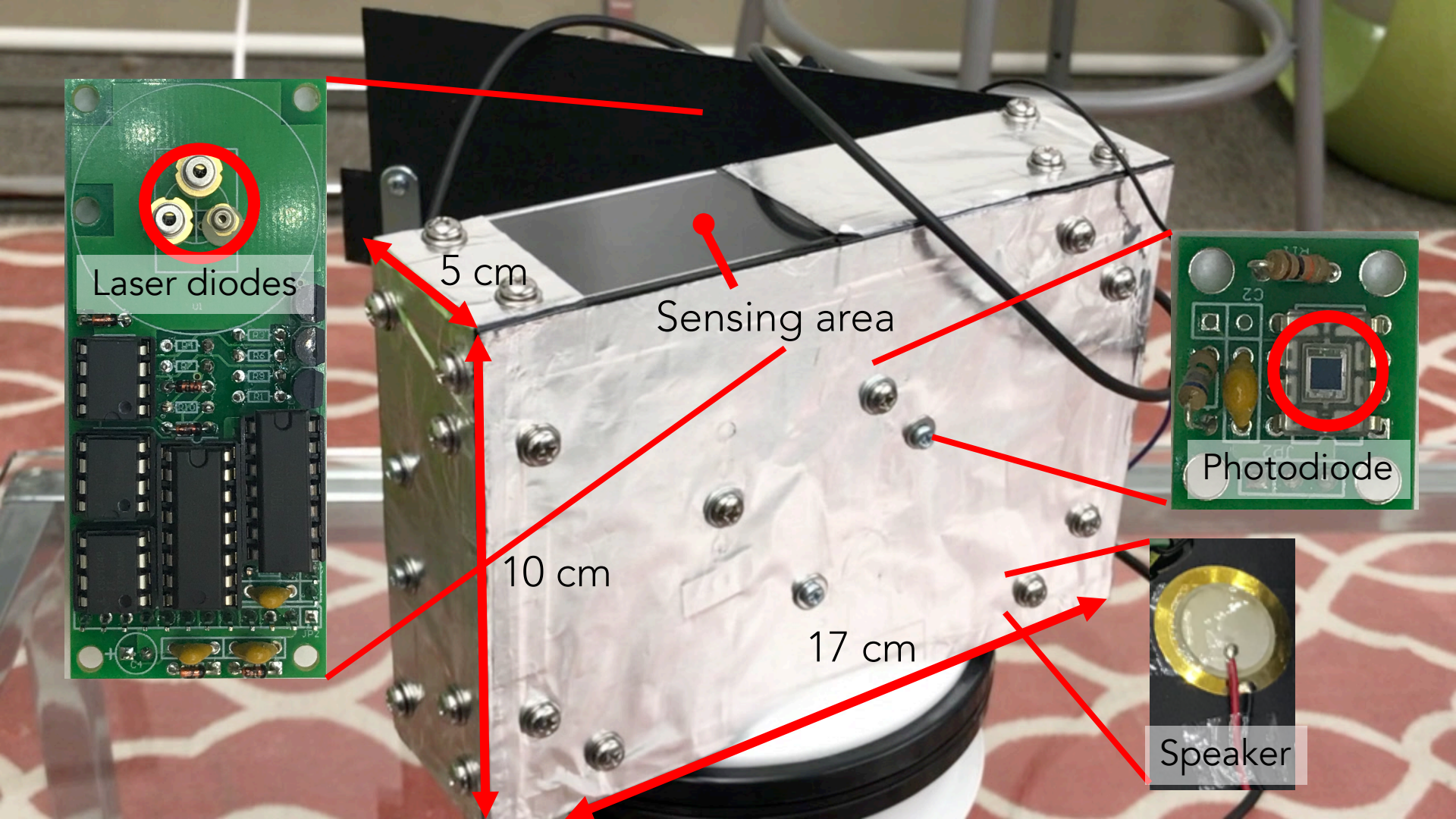
Multiple Wavelengths & Intensity Levels



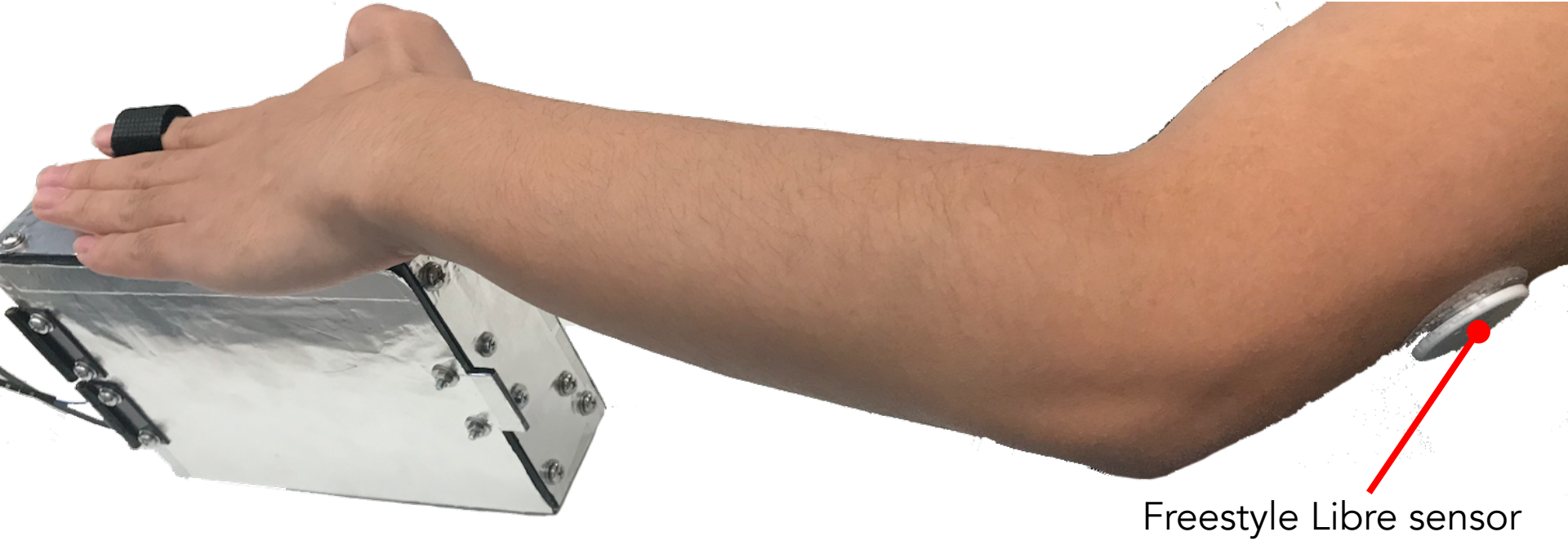
Results

- RGB lights with 7 intensity levels (21 features)

ID	Age	Gender	Race	R	
				Single W&I	Multi W&I
1	31	M	Asian	0.86	0.86
2	23	M	Asian	0.64	0.83
3	18	M	Asian	0.6	0.78
4	24	M	Asian	0.63	0.81
5	23	F	Asian	0.65	0.74
6	23	M	White	0.71	0.75
7	25	M	African American	0.46	0.78
8	24	M	American Indian	0.51	0.74
9	33	F	Asian	0.48	0.75


Laser diodes
5 cm
Sensing area
Photodiode
10 cm
17 cm
Speaker

Experiment Setup



Study Participants

- 50 participants (41 patients and 9 healthy people)

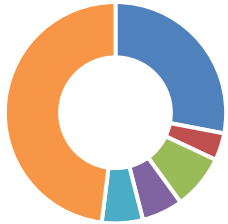
Gender

Male Female

Age

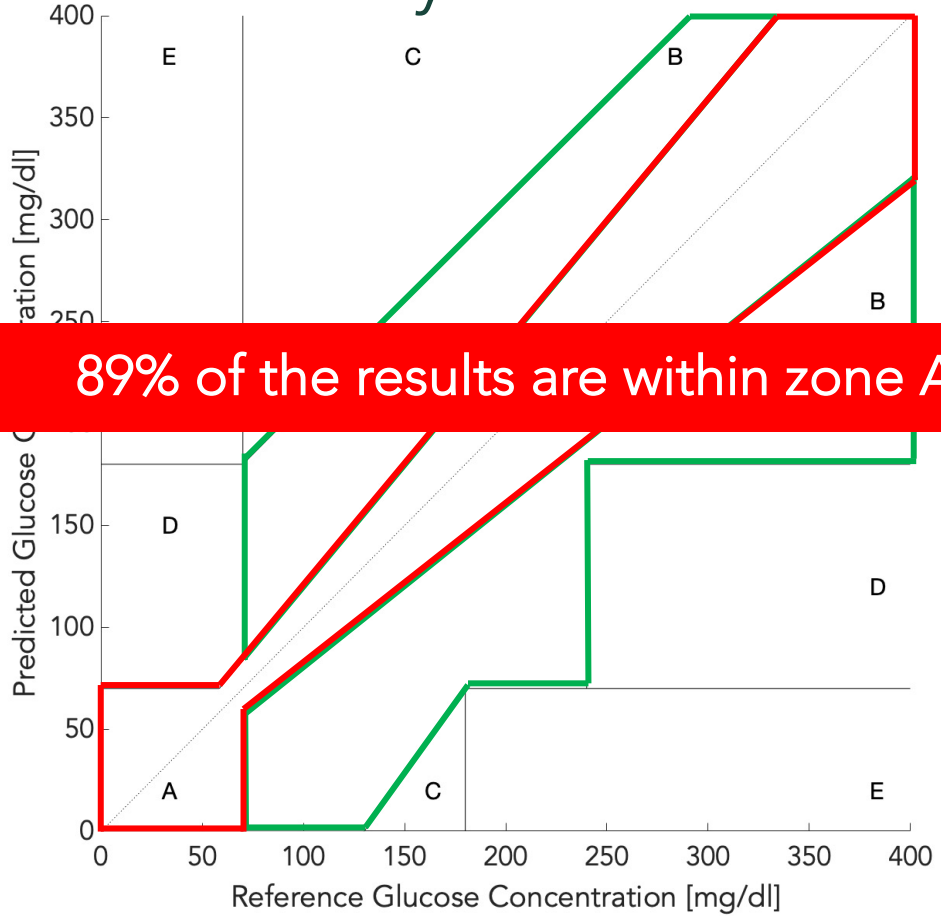
18-30 30-50 >50

Race



Asian
American Indian
African American
Hispanic or Latino
Native Hawaiian
White

Clarke Error Grid Analysis



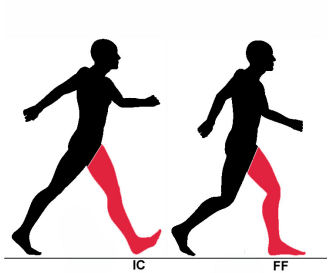
89% of the results are within zone A

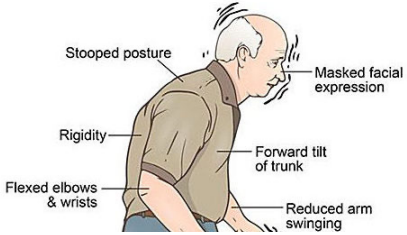
Outline

- Introduction
- Biomechanical sensing: Skeleton pose reconstruction
- Biophysiological sensing: Battery-free eye tracking
- Biochemical sensing: Noninvasive glucose monitoring
- Conclusion & Future Work

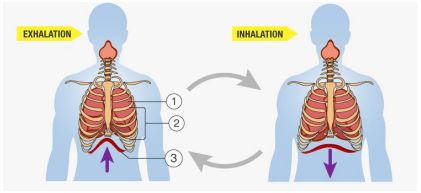
Future Direction: Human Sensing In The Light

Biomechanical sensing

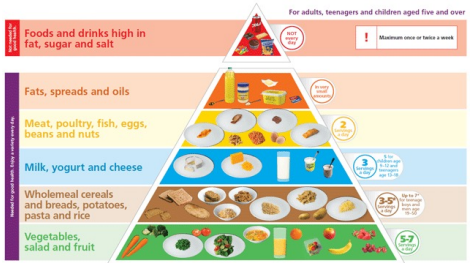




Biophysiological sensing

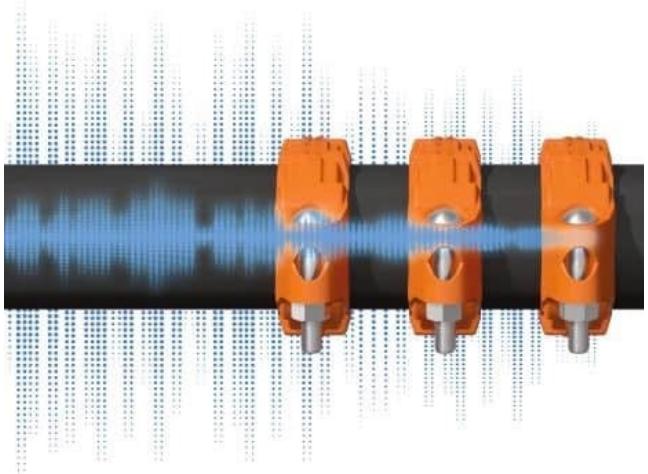


Biochemical sensing

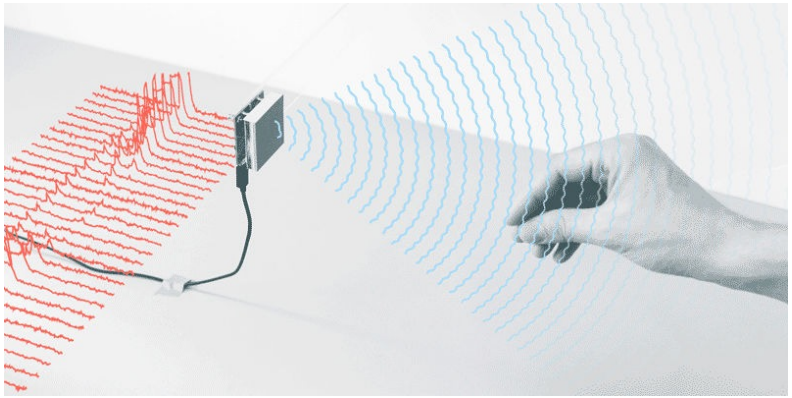


Future Direction: Emerging Privacy and Security Risks

Future Direction: Light + Other Emerging Modality For Human Sensing

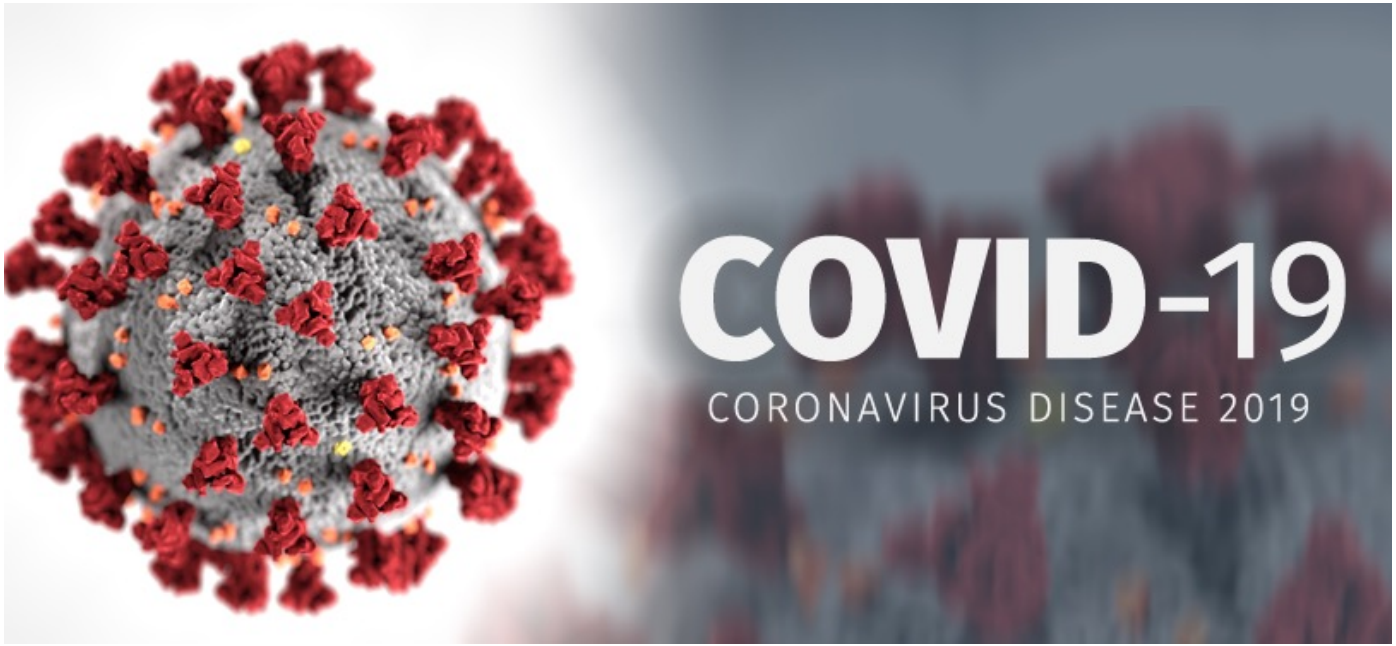


Vibration/Acoustic sensing



Mm-wave sensing

Current projects



Human Sensing Using Light

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May 28th, 2021