Introduction to Behavior Imaging (Part 1)

Jim Rehg
Georgia Tech

UBIHealth Winter School
January 13, 2014

Schedule

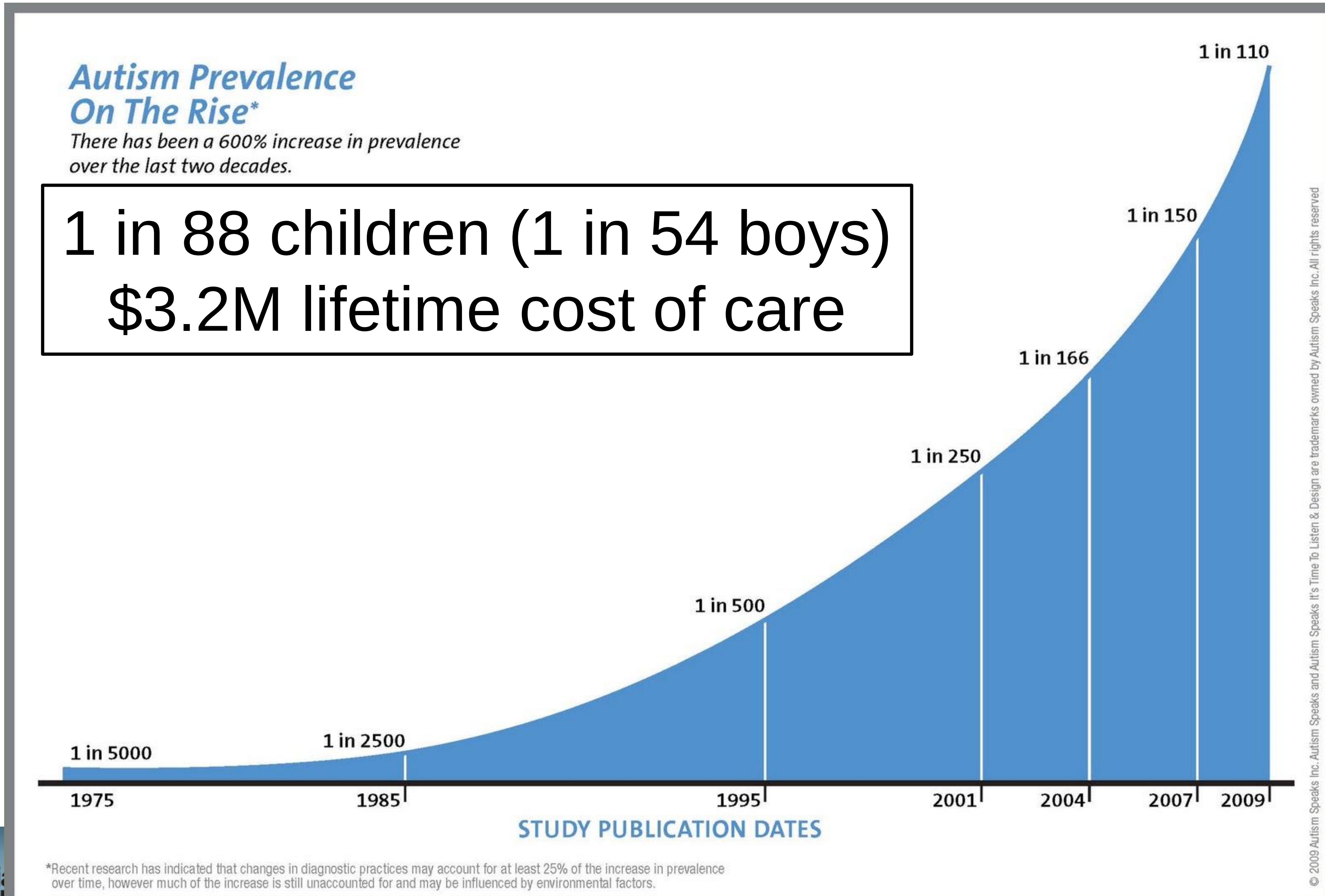
- Introduction to Behavior Imaging
- Overview of face analysis and gaze tracking
- Applications to ASD and smoking cessation


NATIONAL CENTER ON BIRTH DEFECTS AND DEVELOPMENTAL DISABILITIES
Learn the Signs. Act Early.
HARVARD'S CRISIS • THE POPE'S HOLY SUF
Newsweek
Babies And Autism
Why New Research On Infants May Hold The Key to Better Treatment
What to Watch For
A TYPICAL BABY
Autism Spectrum
In the Brain
Treatments
How Common Is It?
More Information
$12,500
$18,800
at 7 months
at 1 year
at 18 months
at 2 years
at 3 years
at 4 years
First Signs
AUTISM SPEAKS
WALK NOW FOR AUTISM
SPECIAL REPORT: MIRROR NEURONS AND THE MIND
SCIENTIFIC AMERICAN
MIRROR NEURONS AND AUTISM
DISCOVER
UNDERSTANDING AUTISM
AUTISTIC CHILD IN AREA
cure Autism now
TIME
EXCLUSIVE: NINTENDO'S NEW GAME
BIN LADEN IN HIDING: WHAT IS HE PLANNING NEXT?
Newsweek
Why 4 of 5 Autistic Children Are Male
Boys, Girls and Autism
What New Science Tells Us About How Our Brains Work
Autism Awareness
BILL, HILLARY & 2008 • THE TIP SHEET GIFT GUIDE
Newsweek
Growing Up With Autism
PARADE
Is There Hope for Autism?
People
JENNY McCARTHY
Fighting for My Autistic Son
THE COMING JOB BOOM • PAKISTAN'S SPY AGENCY • REUNION TV
TIME
INSIDE THE WORLD OF AUTISM
AUTISM: THE MUSICAL
COMING TO HBO MARCH 2008
AUTISM'S FALSE PROPHETS
PAUL A. OFFIT, M.D.

Autism Quick Facts

- A developmental brain disorder with a genetic basis, but no biological marker or cure
  - Diagnosis and characterization depends entirely on observable behavior
- Difficulties in forming social bonds with parents, peers, and care-givers
- 30-50% fail to develop spoken language
- Intellectual disability in ~50% of individuals
- First described in 1943 by Leo Kanner

Autism Prevalence on the Rise



Three Goals

- Early Detection
  - Symptoms are visible before age 2
  - Average age of diagnosis around 4 years
  - *Technology for screening* (3 times before age 3)
- Intensive Therapy
  - Therapy results in measurable improvements
  - Intensity of therapy is a key factor
  - *Technology to aid in delivering therapy*
- Autism Research
  - Social and communicative behavior in children
  - *Tools for large scale collection and analysis of data*

Behavior Imaging

Imaging technologies and medical science

- Orthopedics and dentistry — X-RAY
- Neurology — MRI / CT

Can we develop imaging technologies for the behavioral sciences?

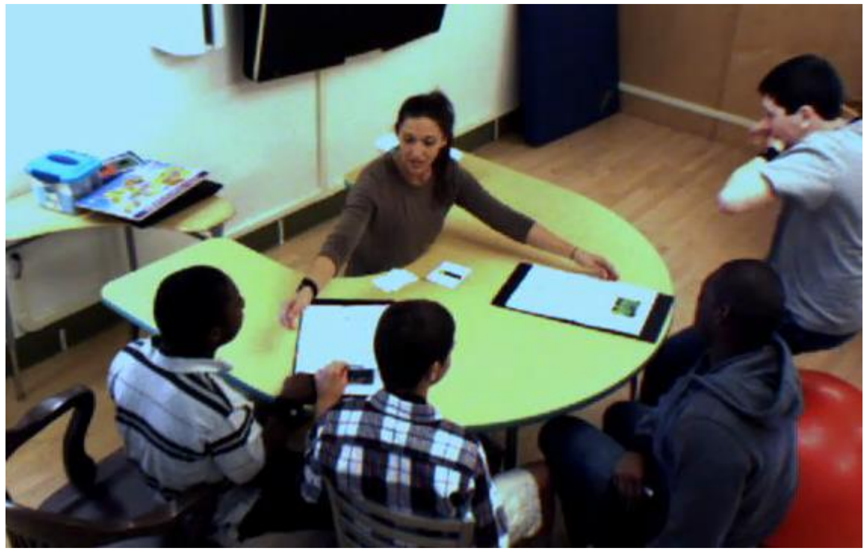
- Large-scale measurement of behavior
- Capture of behavior under natural conditions
- Visualizations over time and across populations

NSF Expeditions in Computing

- Computational methods for sensing, modeling, and analyzing social & communicative behaviors
- Focus on interactions between children and caregivers and peers in the context of autism

Rapid-ABC (GT)

Classroom (CfD)



STAT (NEU)

Catalyze Computational Behavioral Science

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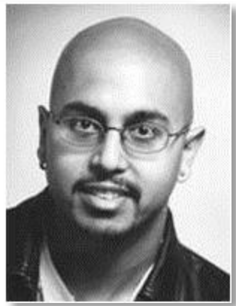

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Jeffery Cohn
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Nate Call
Marcus Inst

Rosa Arriaga
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Mario Romero
CS
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Agata Rozga
CS
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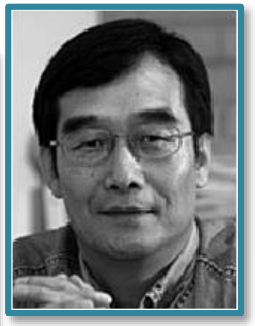

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Carnegie Mellon
Massachusetts Institute of Technology
ILLINOIS UNIVERSITY OF ILLINOIS AT URBANA-CHAMPAIGN
BOSTON UNIVERSITY
EMORY UNIVERSITY
Northeastern University
USC UNIVERSITY OF SOUTHERN CALIFORNIA
THE MARCUS INSTITUTE
Turning Disabilities Into Possibilities

Georgia Tech
CHILD STUDY LAB

Rapid-ABC

Protocol for eliciting social and communicative behavior

Greeting

Ball play

Book

Hat

Tickle

Recruitment: 15-30 month olds

Ousley, Arriaga, & Abowd

Example

Another Example

Basic Questions

- How can we sense the subtle behaviors that comprise socialization, communication, and other daily activities?
- How can we model the dynamics of social interactions?
- How can we describe concepts such as social engagement computationally?

Multimodal Dyadic Behavior Dataset

- Goal: Capture key social and communicative behaviors in children aged 18-36 months
  - Recruited from the Atlanta community
  - No special focus on at-risk children (so far)
- 160 sessions of 5-minute R-ABC interactions from 121 children
  - One follow-up session 3 months later (approx. 40 kids)
- Consented for sharing with research community
- Interested researchers must have an IRB in place to receive the data

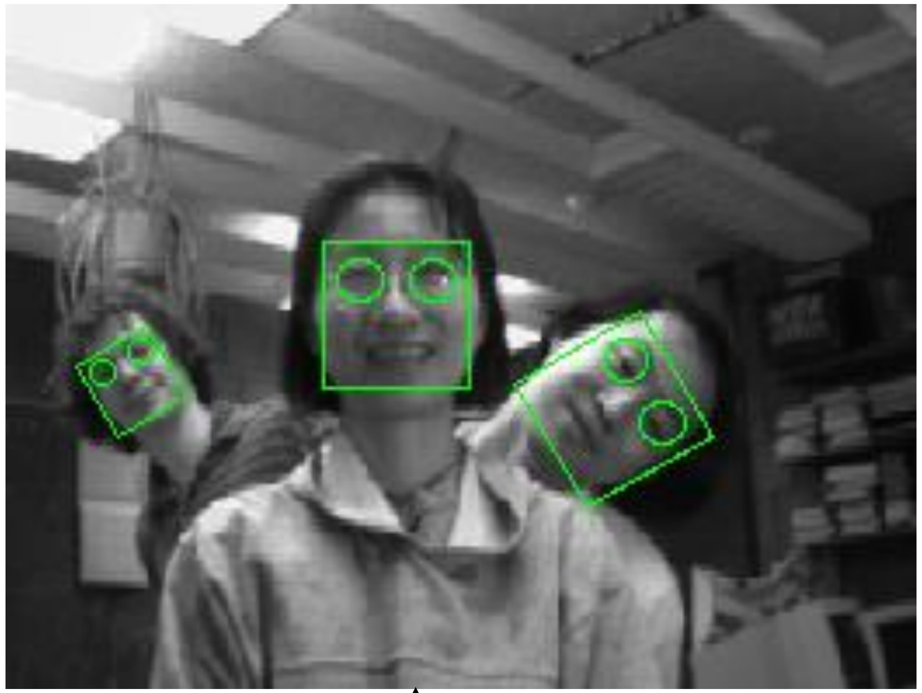
http://www.cbi.gatech.edu/mmdb/

Facial Analysis

- Faces play a key role in social behavior
- How can we automatically detect faces in images?
- How can we analyze facial expressions?

Faces: Terminology

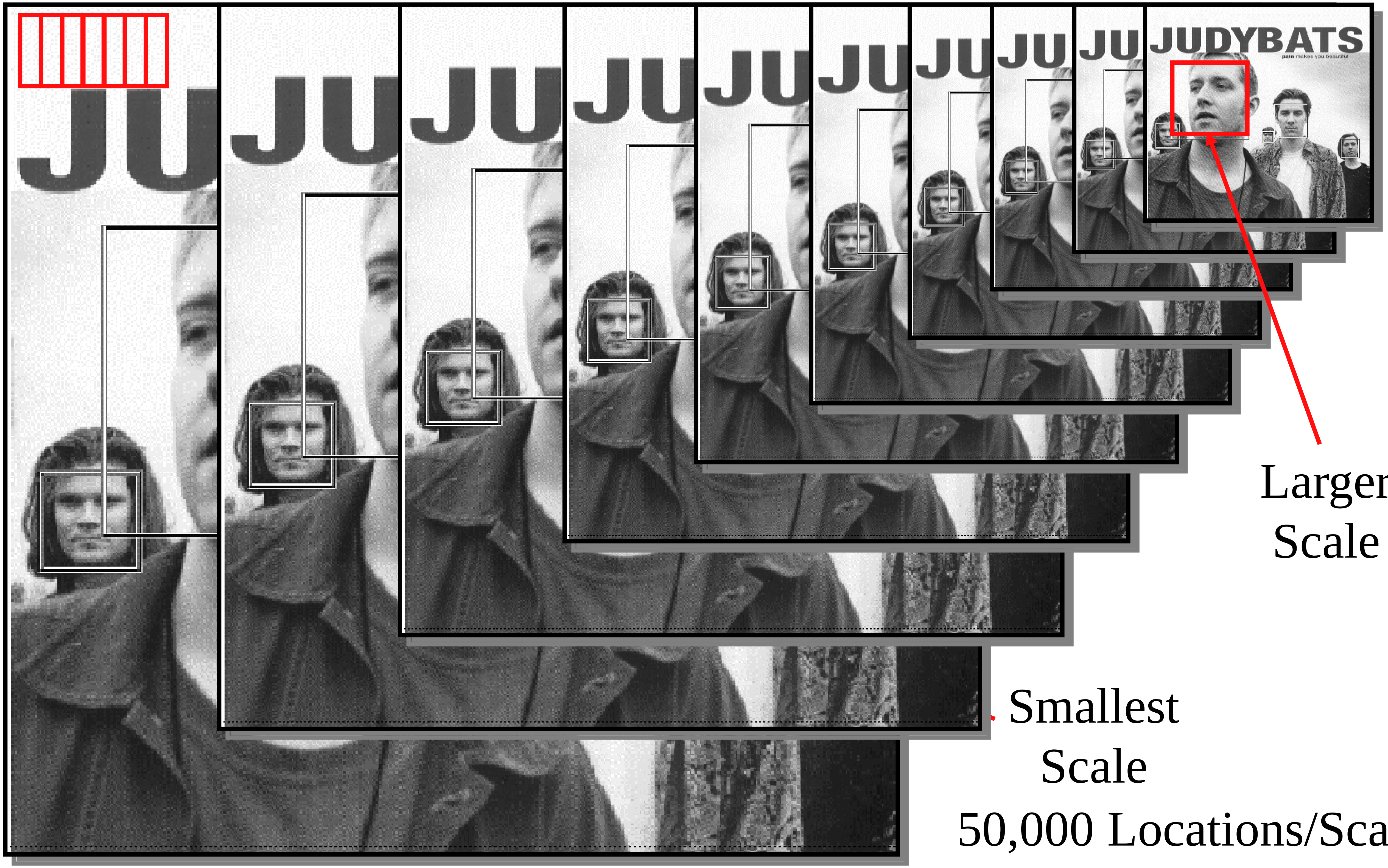
- *Detection*: given an image, where is the face?
- *Recognition*: whose face is it?
- *Expression Analysis*: what is the face configuration?



Ann is smiling

Image credit: H. Rowley

Face Detection Process



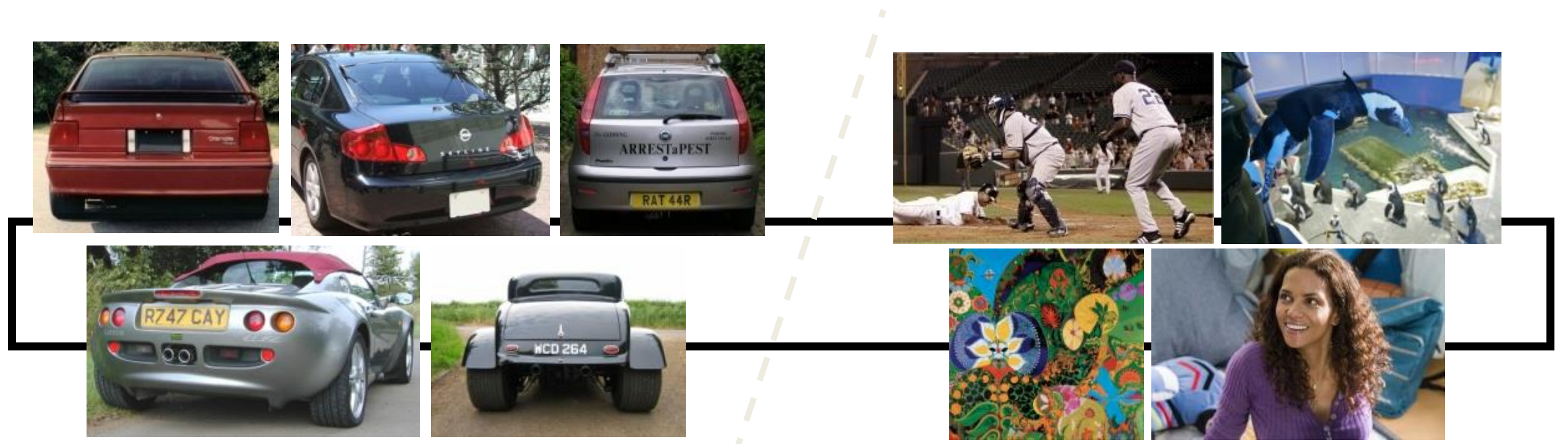
50,000 Locations/Scales

Slide courtesy of Paul Viola

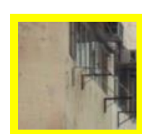
Detection via Classification: Main idea

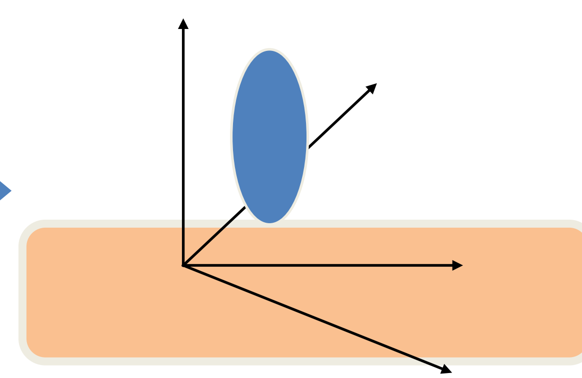
We need to:

1. Obtain training data
2. Define features
3. Define classifier



Training examples





Feature extraction

Car/non-car Classifier

Slide by K. Grauman, B. Leibe

Example: Face Detection

- Frontal faces are a good example of a class where global appearance models + a sliding window detection approach fit well:
  - Regular 2D structure
  - Center of face almost shaped like a "patch"/window

- Now we'll take AdaBoost and see how the Viola-Jones face detector works

Slide by K. Grauman & B. Leibe

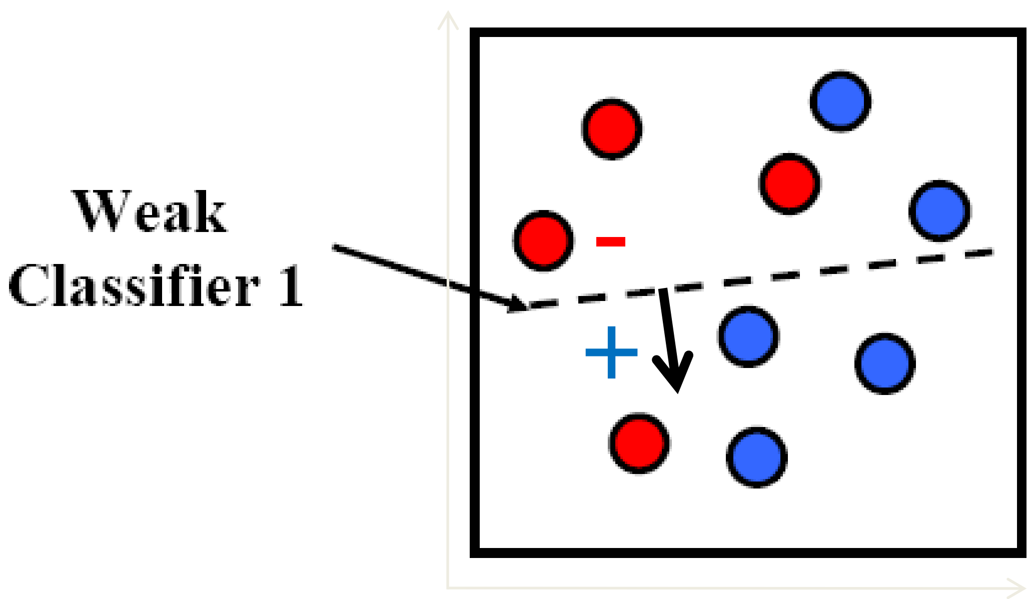
Boosting

- Build a strong classifier by combining number of "weak classifiers", which need only be better than chance
- Sequential learning process: at each iteration, add a weak classifier
- Flexible to choice of weak learner
  - including fast simple classifiers that alone may be inaccurate

- We'll look at Freund & Schapire's AdaBoost algorithm
  - Easy to implement
  - Base learning algorithm for Viola-Jones face detector

K. Grauman, B. Leibe

AdaBoost: Intuition



Consider a 2-d feature space with positive and negative examples.

Each weak classifier splits the training examples with at least 50% accuracy.

Examples misclassified by a previous weak learner are given more emphasis at future rounds.

Figure adapted from Freund and Schapire

AdaBoost: Intuition

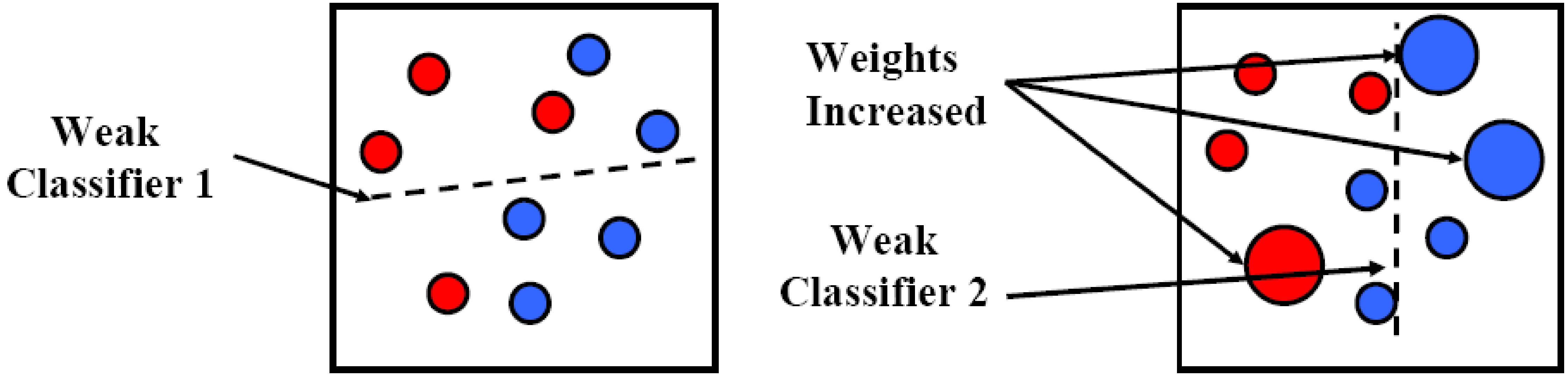


Figure adapted from Freund and Schapire

AdaBoost: Intuition

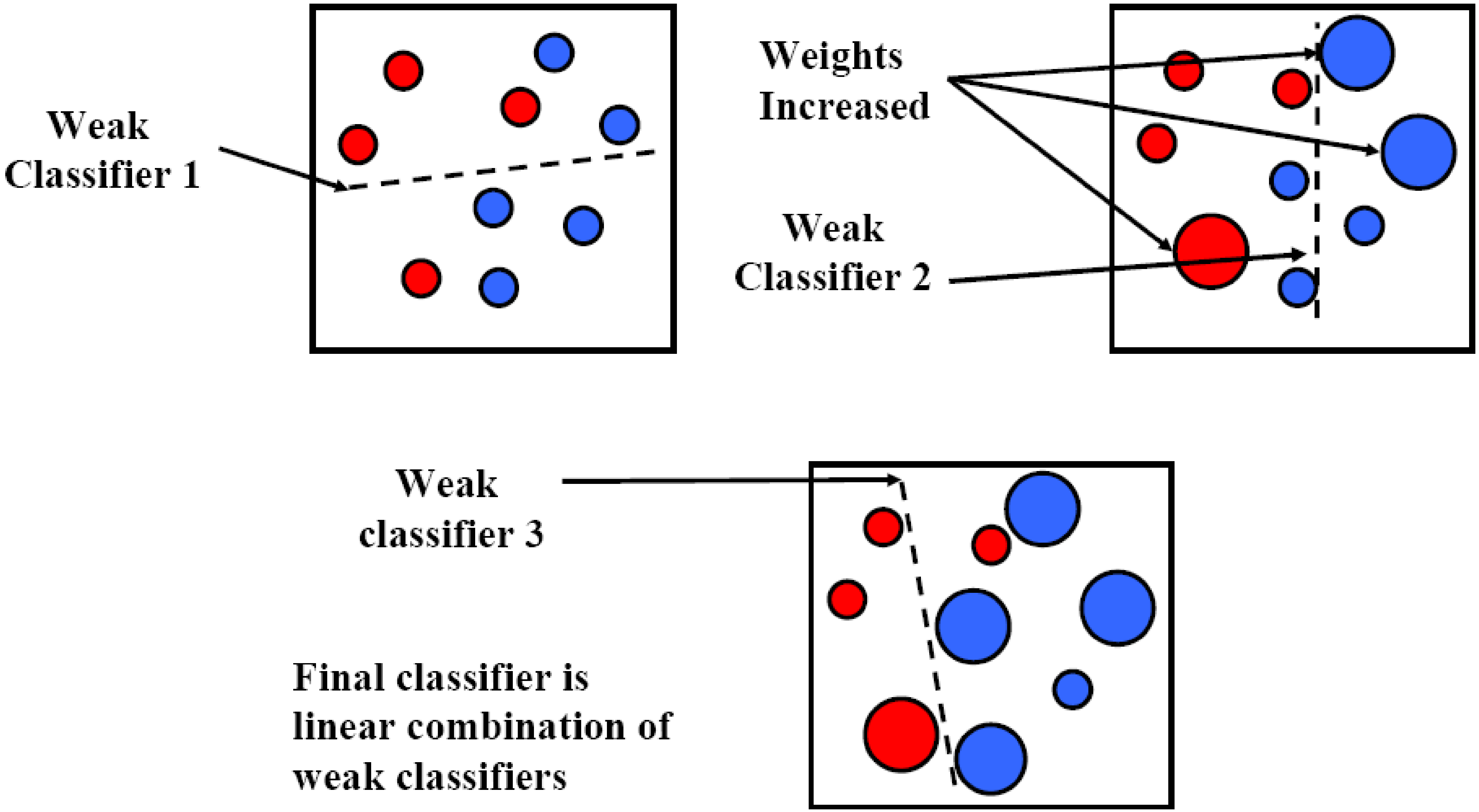
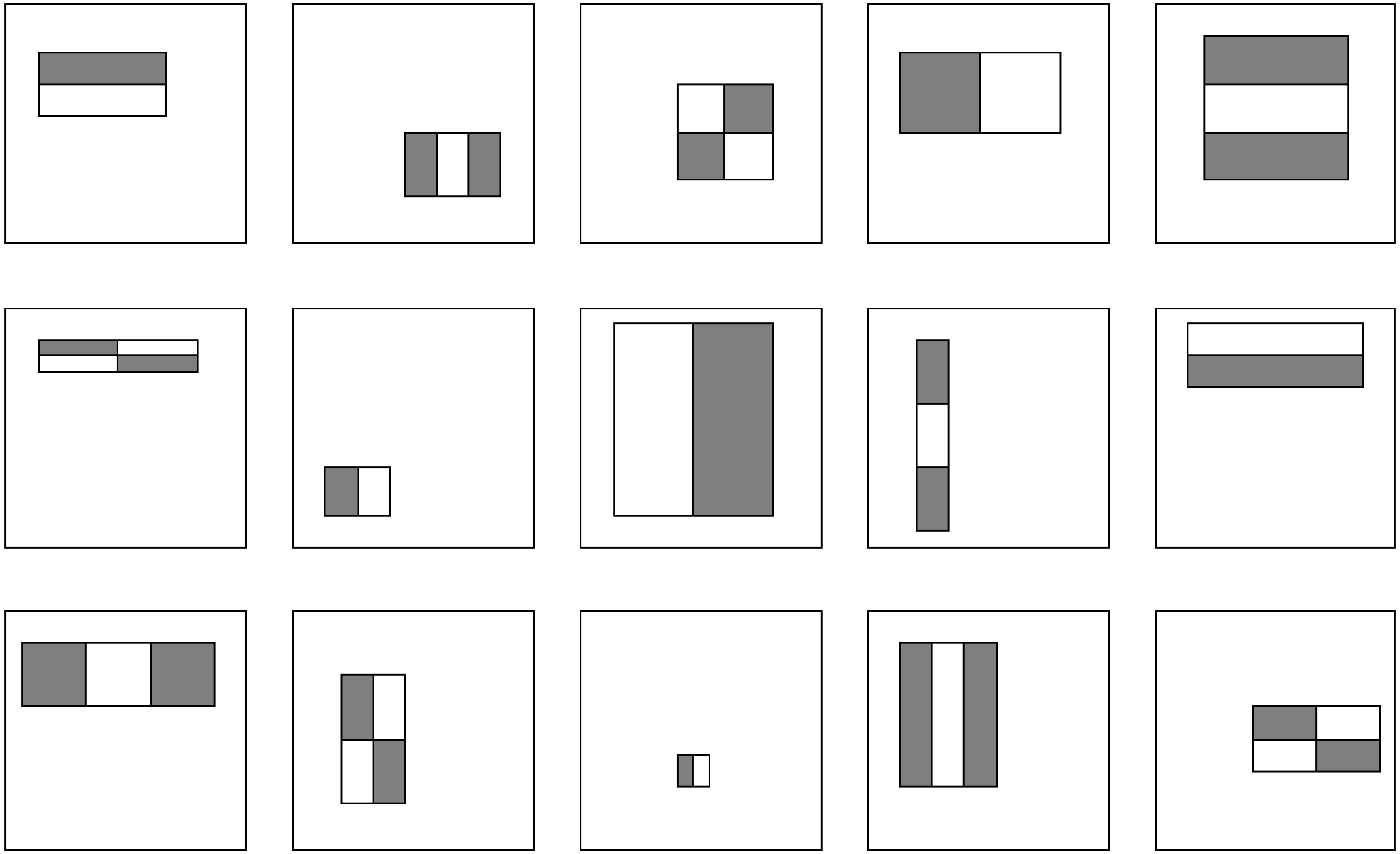


Figure adapted from Freund and Schapire

Large library of filters



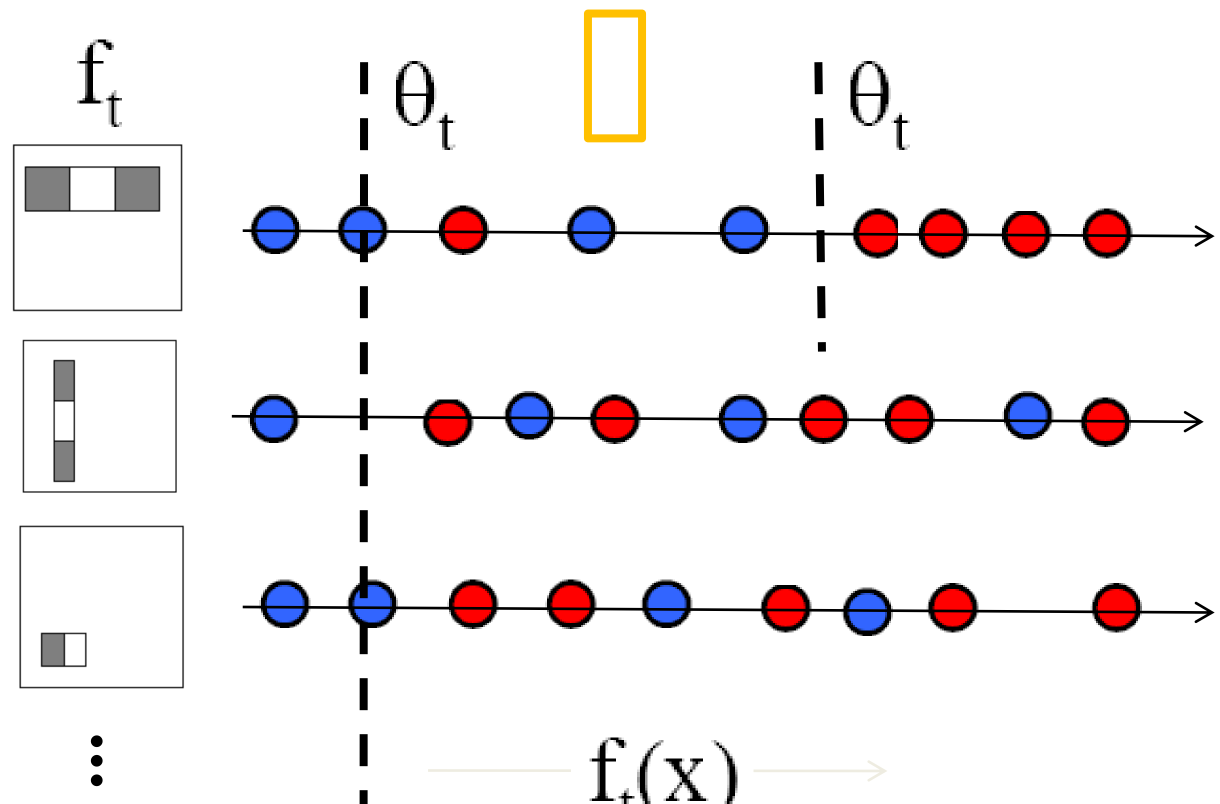
Considering all possible filter parameters: position, scale, and type:

180,000+ possible features associated with each 24 x 24 window

Use AdaBoost both to select the informative features and to form the classifier

AdaBoost Feature Selection

- Want to select the single rectangle feature and threshold that best separates positive (faces) and negative (non-faces) training examples, in terms of *weighted* error.



Resulting weak classifier:

$$h_t(x) = \begin{cases} +1 & \text{if } f_t(x) > \theta_t \\ -1 & \text{otherwise} \end{cases}$$

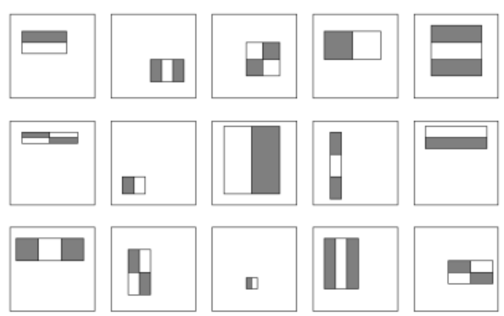
For next round, reweight the examples based on errors, choose another filter/threshold combo.

Slide by K. Grauman & B. Leibe

Viola-Jones Face Detector: Summary

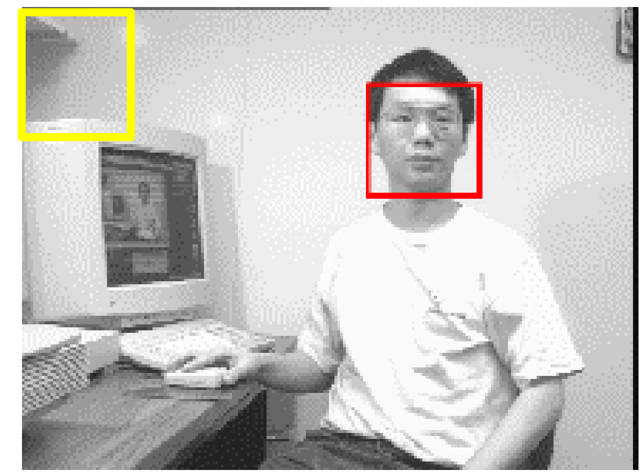
Non-faces

Train cascade of classifiers with AdaBoost



Selected features, thresholds, and weights

Apply to each subwindow



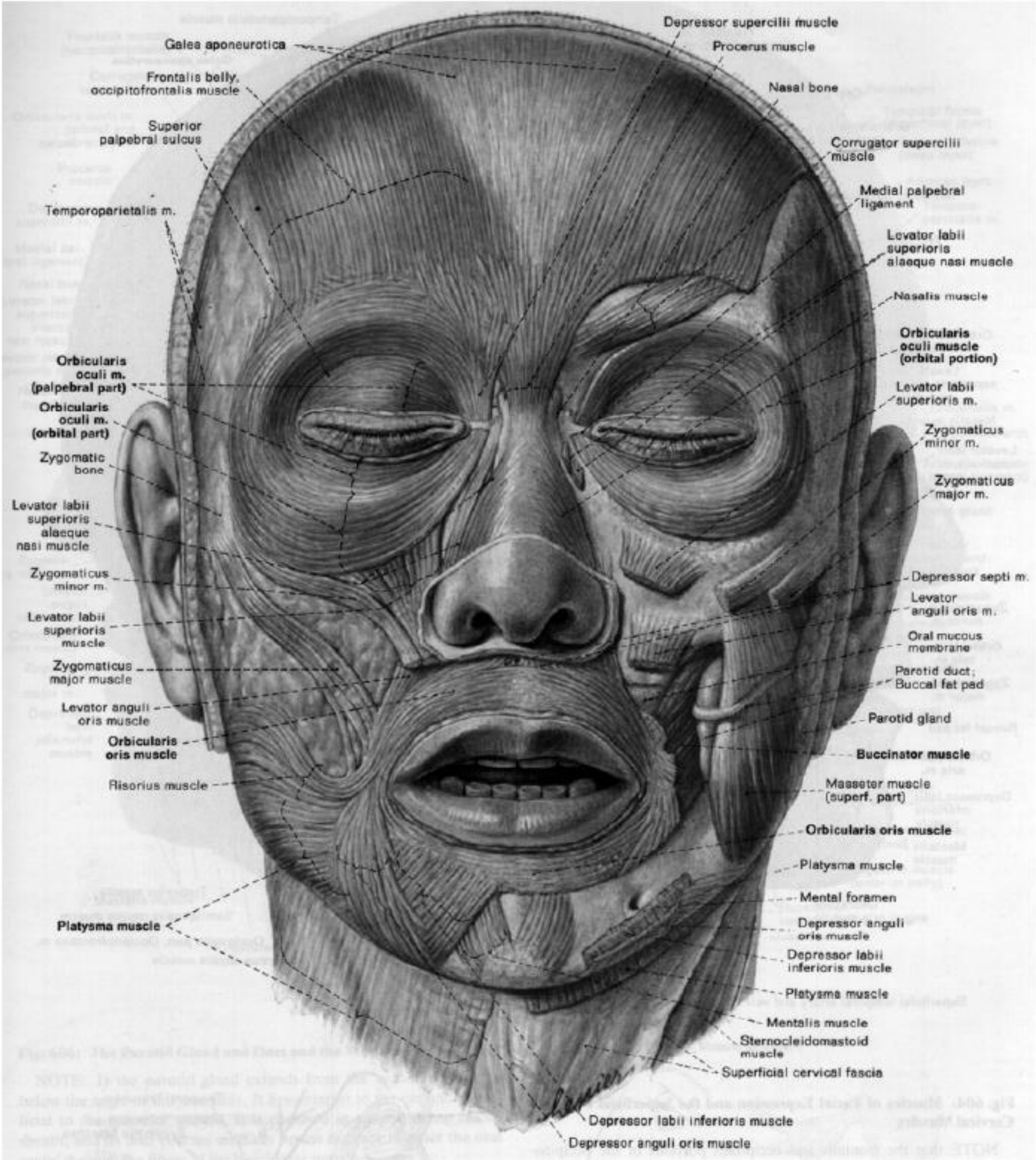
New image

- Train w/ 5K positives, 350M negatives
- Real-time detector w/ 38 layer cascade
- 6061 features in final layer
- Implementation available in OpenCV

Slide by K. Grauman & B. Leibe

Representing Facial Expression

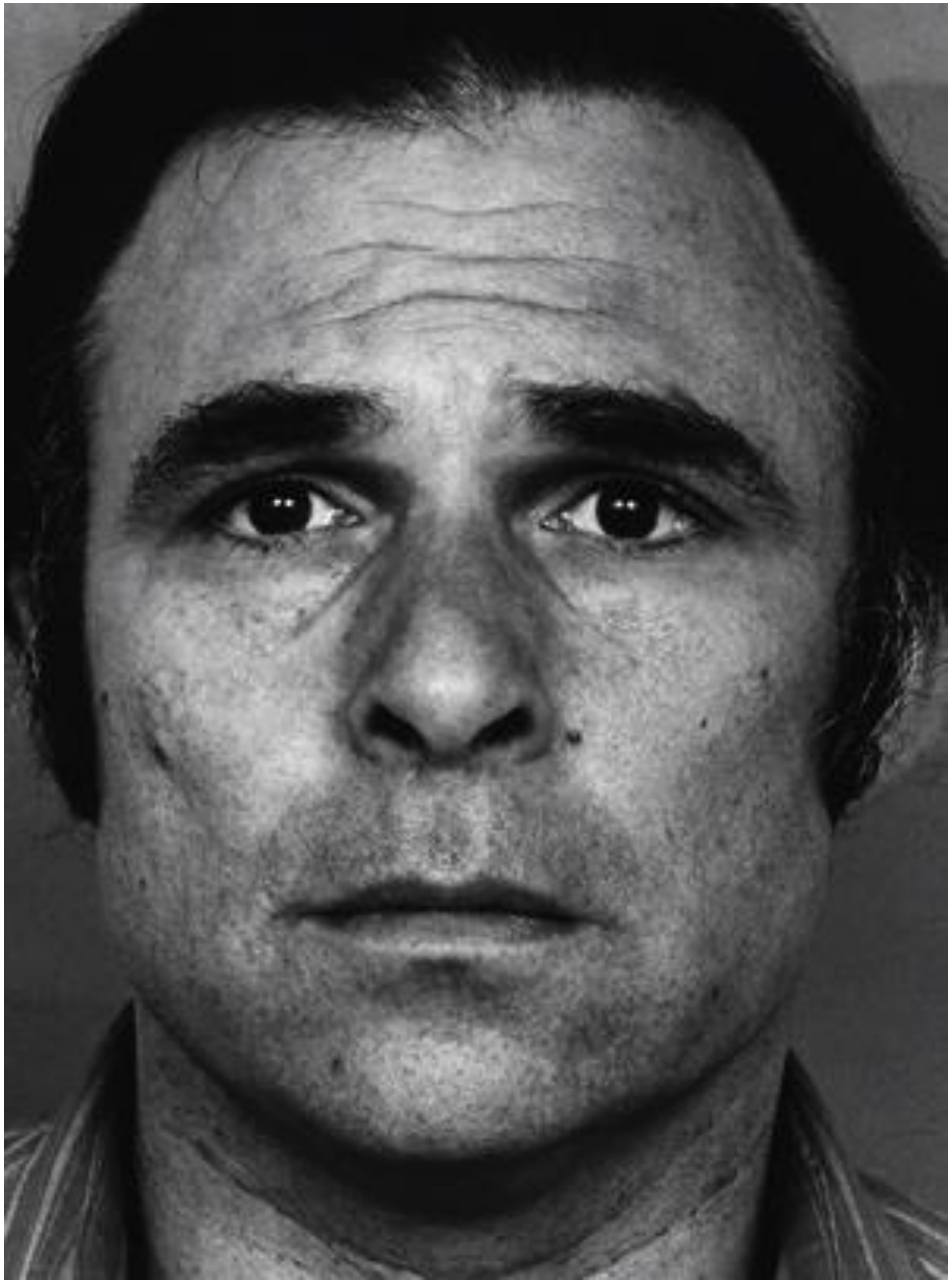
- Facial expressions result from actions of facial muscles on skin and connective tissue
- Facial Action Coding System (FACS) by Paul Ekman and Wallace Friesen provides a systematic description of muscle action
- Provides an objective and quantitative description of facial expressions
- Affect (positive or negative) defined in terms of FACS codes



Muscles of the face

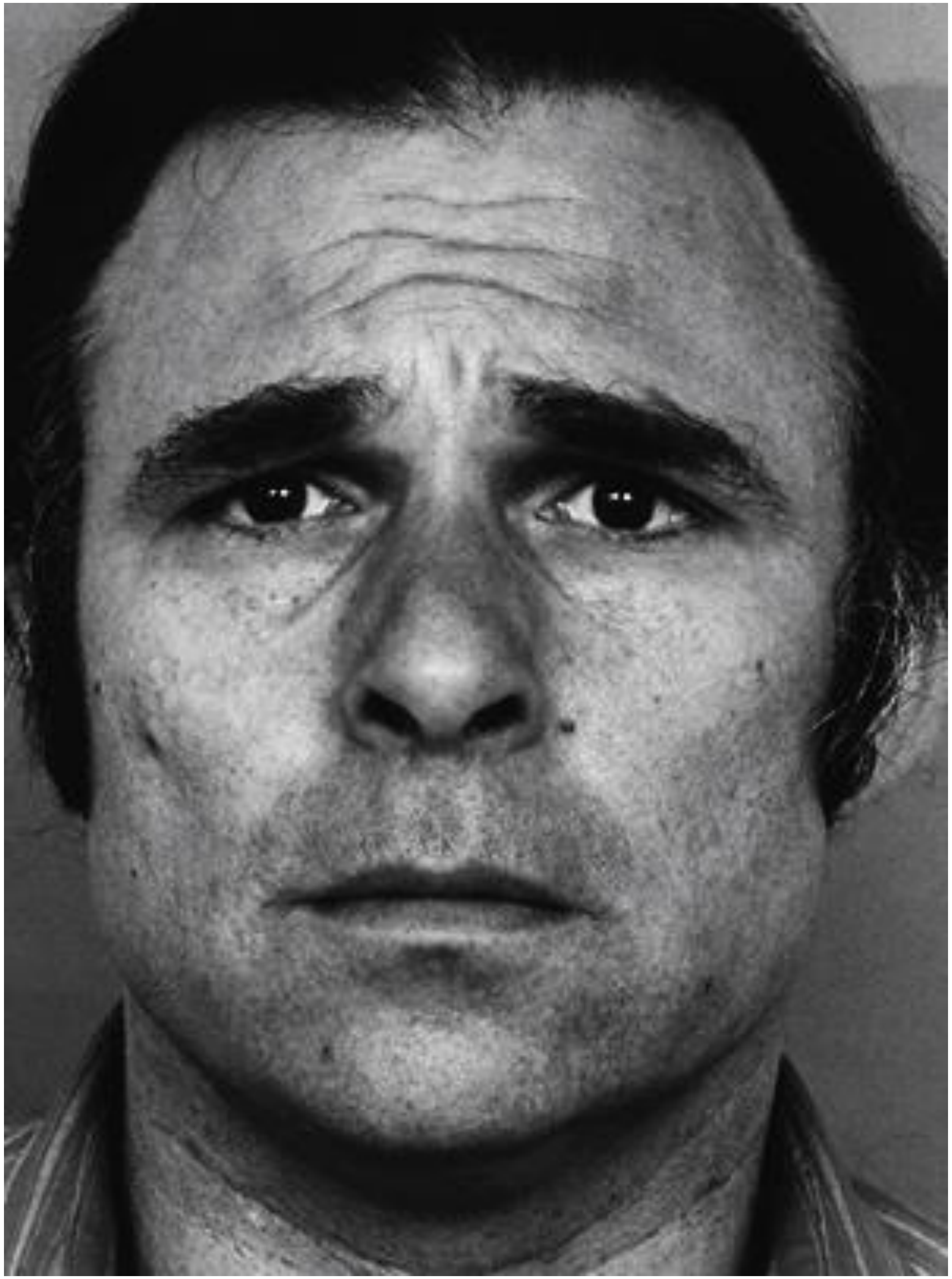
(From : Facial Action Coding System. Investigator's Guide by Paul Ekman, Wallace V. Friesen & Joseph C. Hager. Download from: http://face-and-emotion.com/dataface/facs/guide/FACSIV1.html
)

Inner Brow Raiser (AU1)



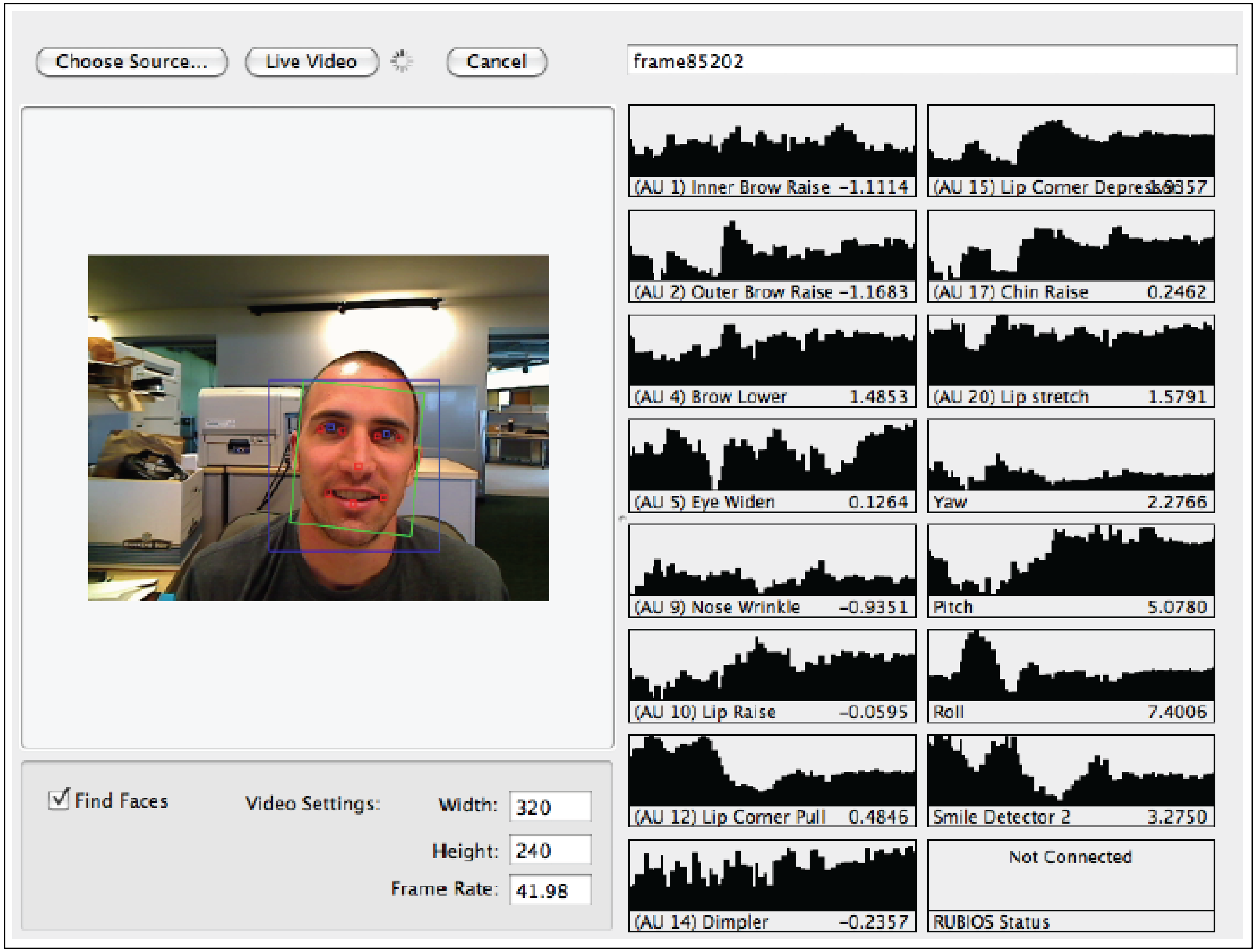
Images from
FACS manual

Inner brow raiser & brow lowerer (AU 1 + 4)



Images from
FACS manual

Goal

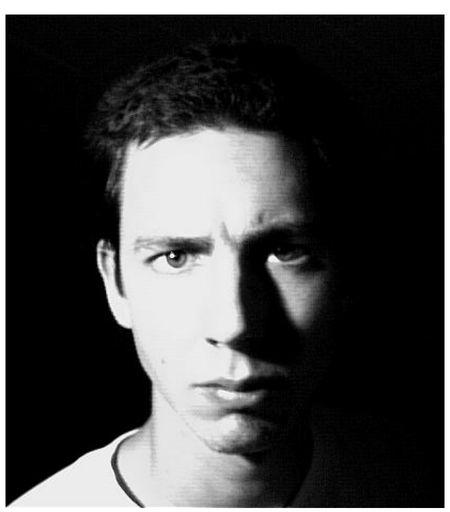


Littlewort et. al. Face & Gesture 2011

Challenges

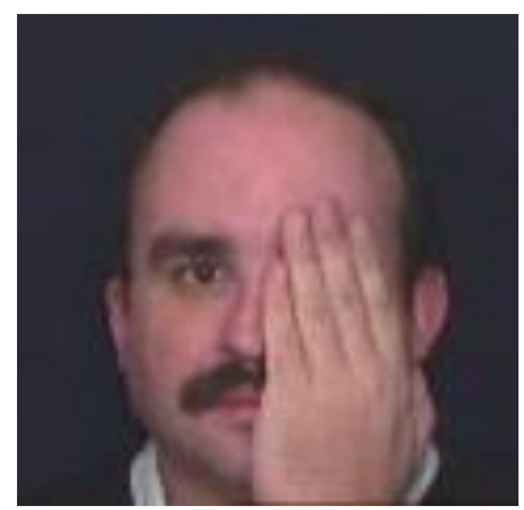
Pose

Race



Lighting

Expression

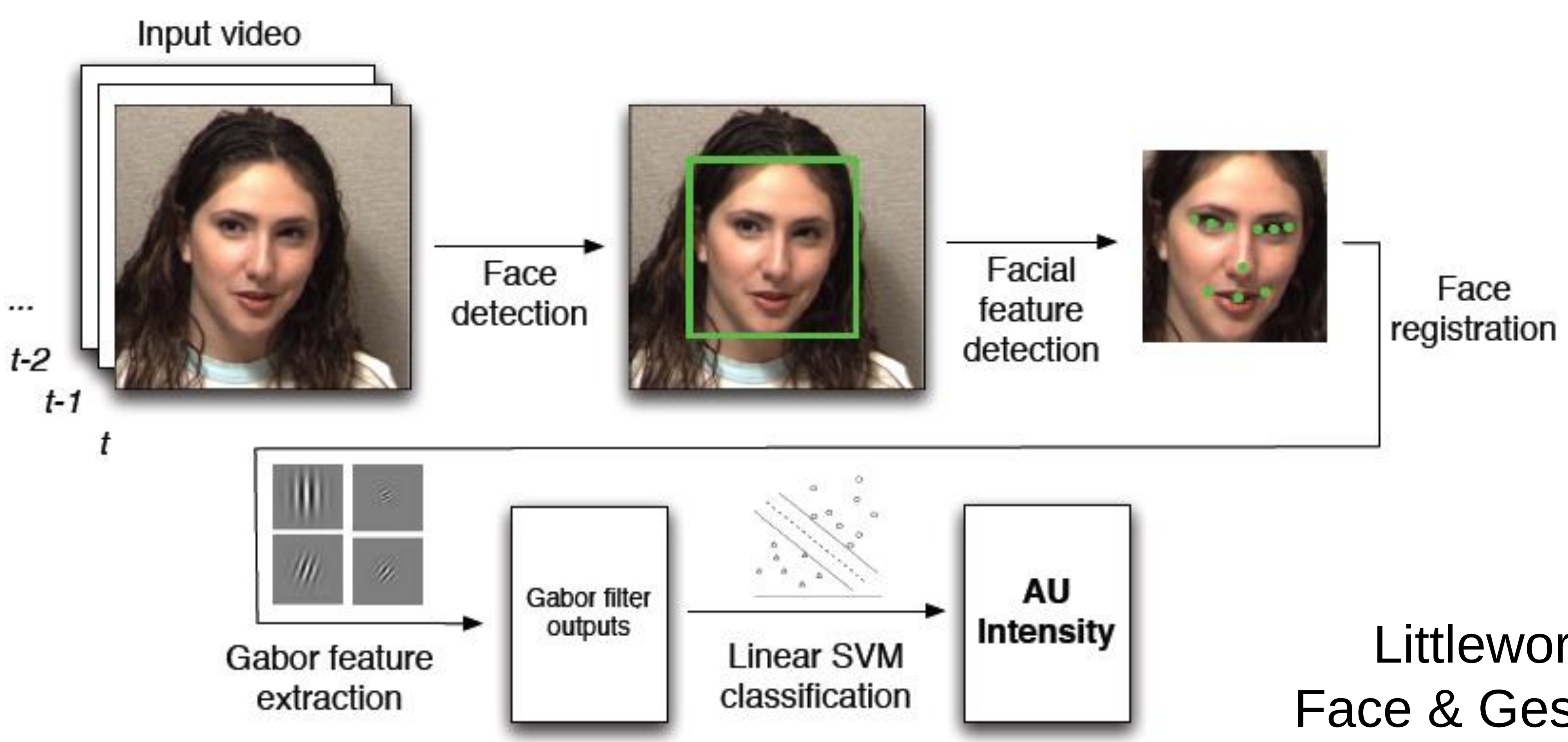


Occlusion

Resolution

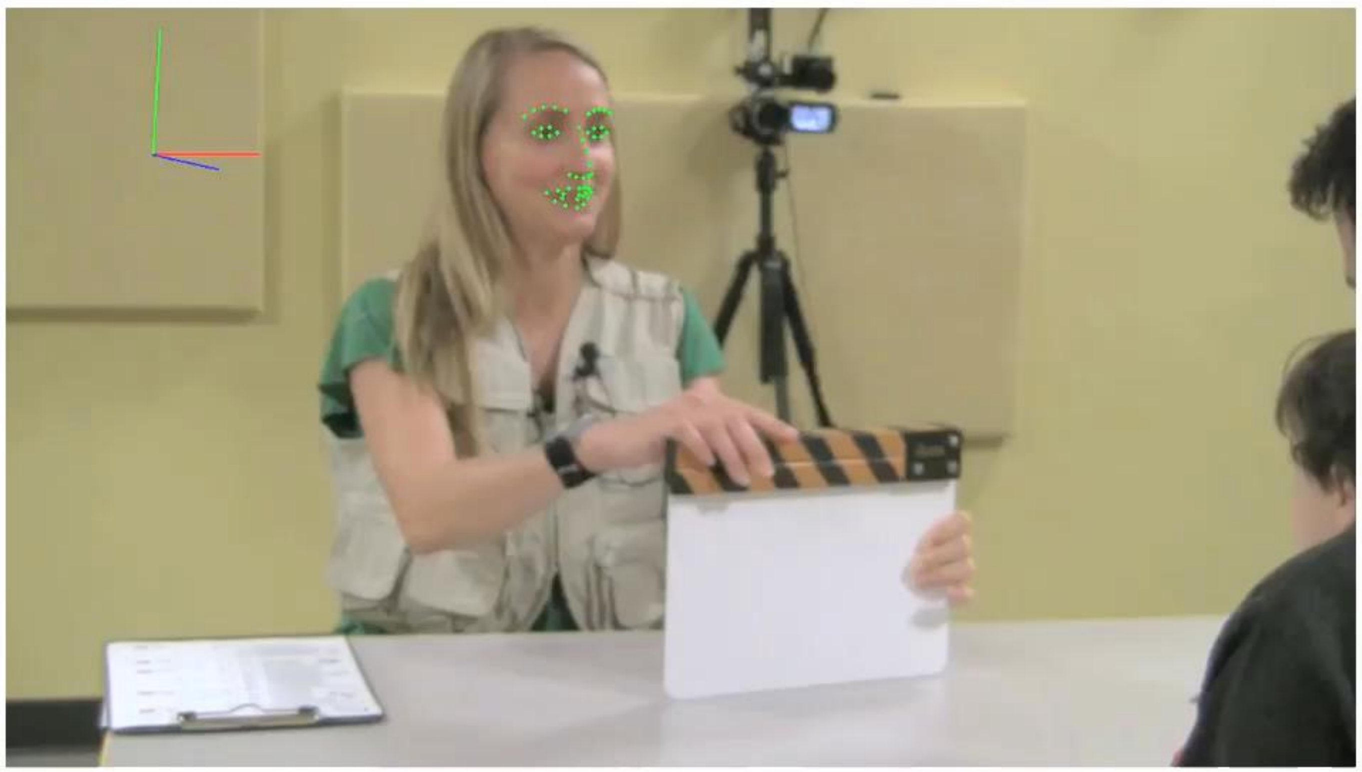
Basic Approach

- Facial feature analysis
  - Establish “face coordinate system” via landmarks
  - Local/global feature analysis to predict expression



Littlewort et. al.
Face & Gesture 2011

Facial Expression Tracking

IntraFace SDK by Fernando De la Torre (CMU)

Results produced by Yaser Sheikh (CMU)

http://www.humansensing.cs.cmu.edu/intraface/

Summary

- Face detection is a mature technology
- AdaBoost is a simple and powerful classification technology
- Facial tracking is becoming mature enough to be useful by nonexperts
- Usable expression recognition is sure to follow

Introduction to Behavior Imaging (part 2)

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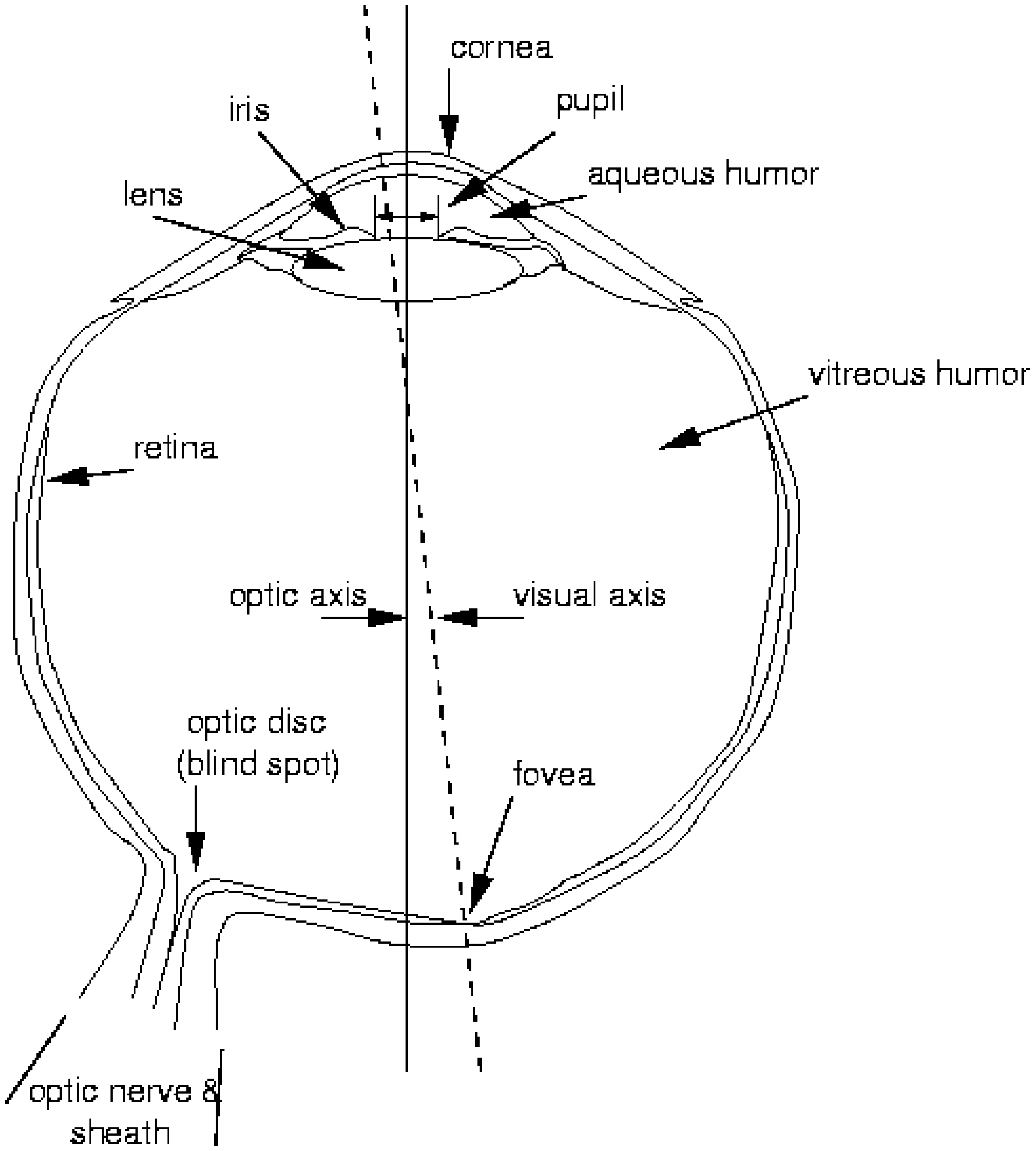
Estimating Attention via Eye Tracking

- Physiology of the eye
- Commercial gaze tracking and applications
- Wearable gaze tracking
- Example: Activities of daily living

Basic Physiology of the Eye

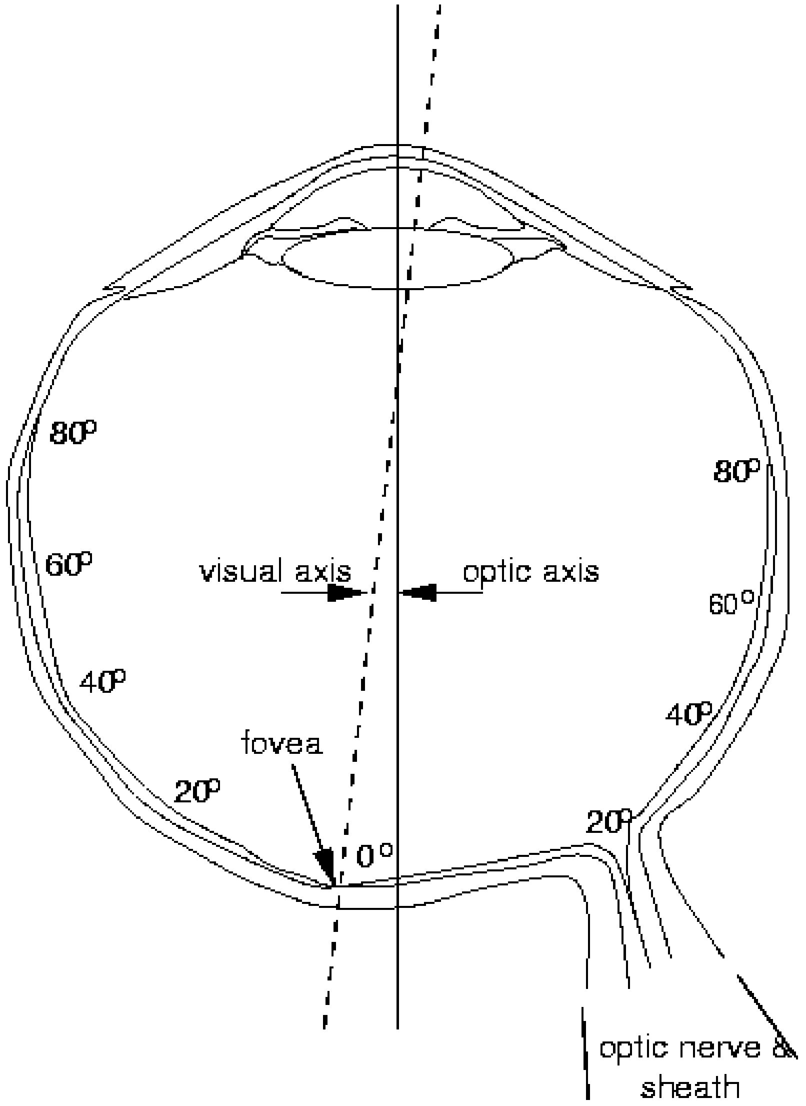


The Eye—

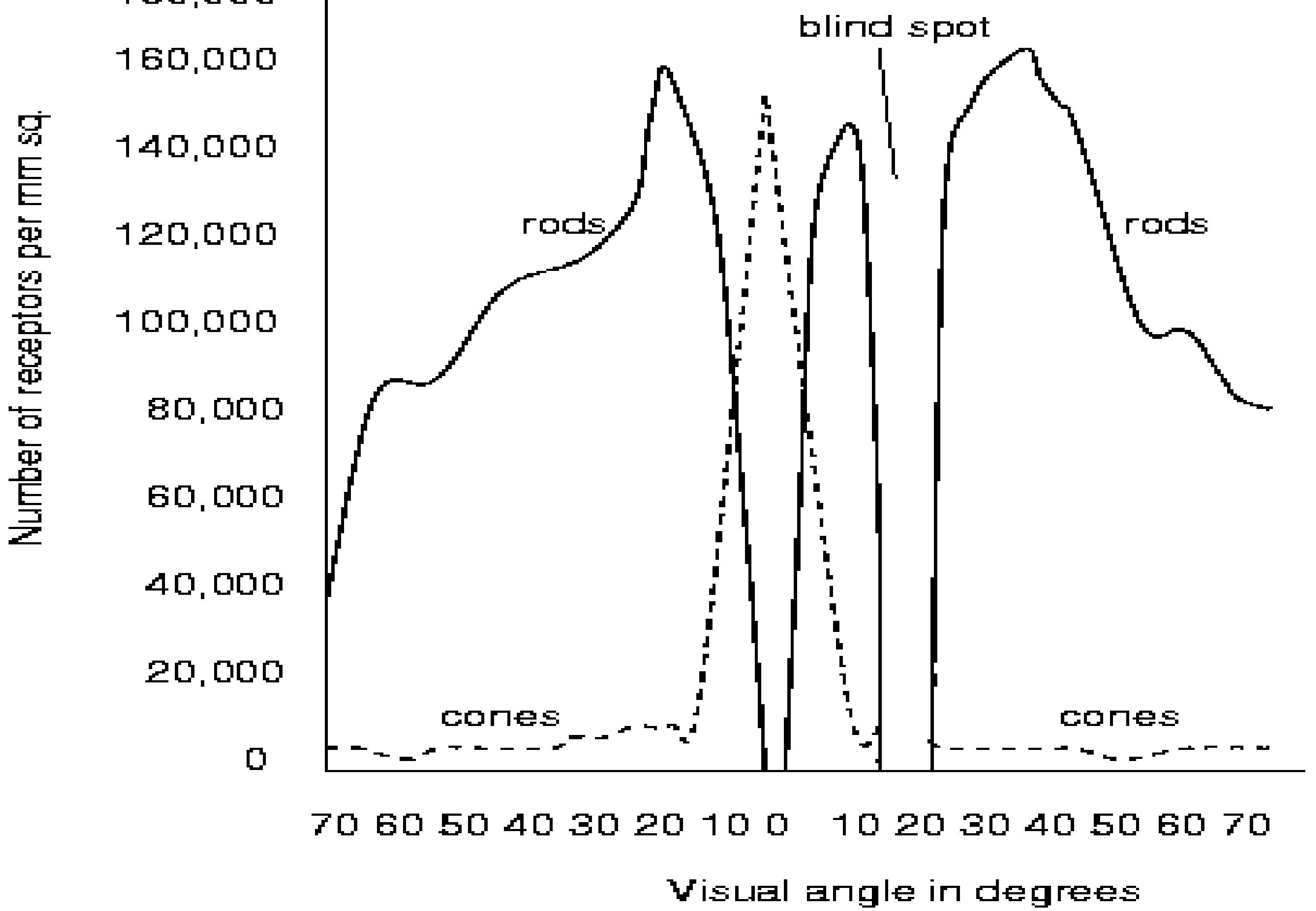
"the world's worst camera"

– suffers from numerous optical imperfections...
– ...endowed with several compensatory mechanisms

Spatial Vision—visual angle and receptor distribution



Retinotopic receptor distribution

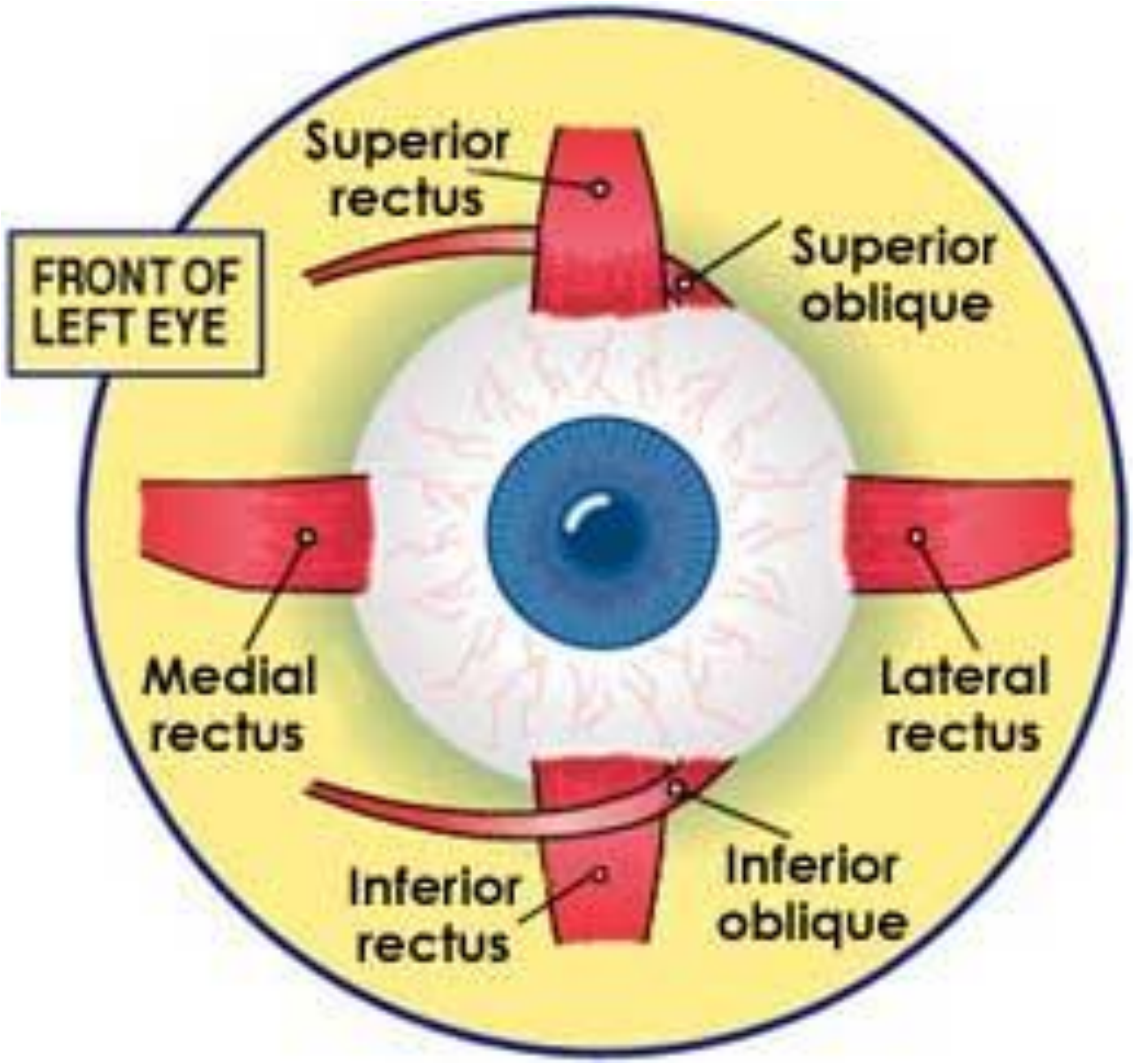


Foveal Vision

Photographic Simulation of Variable Retinal Spatial Resolution

Courtesy of Stuart Anstis

Muscles of the Eye



We must move our eyes to see

Saccades

- Rapid eye movements used to reposition fovea
- Voluntary and reflexive
- Range in duration from 10ms - 100ms
- Effectively blind during transition
- *ballistic* (pre-programmed)
- *stereotyped* (reproducible)

Smooth Pursuit

- Involved when visually tracking a moving target
- Depending on range of target motion, eyes are capable of matching target velocity
- Pursuit movements are an example of a control system with built-in negative feedback

Fixations

- Possibly the most important type of eye movement for attentional applications
  – 90% viewing time is devoted to fixations
  – duration: 150ms - 600ms
- Not technically eye movements in their own right, rather characterized by miniature eye movements:
  – tremor, drift, microsaccades

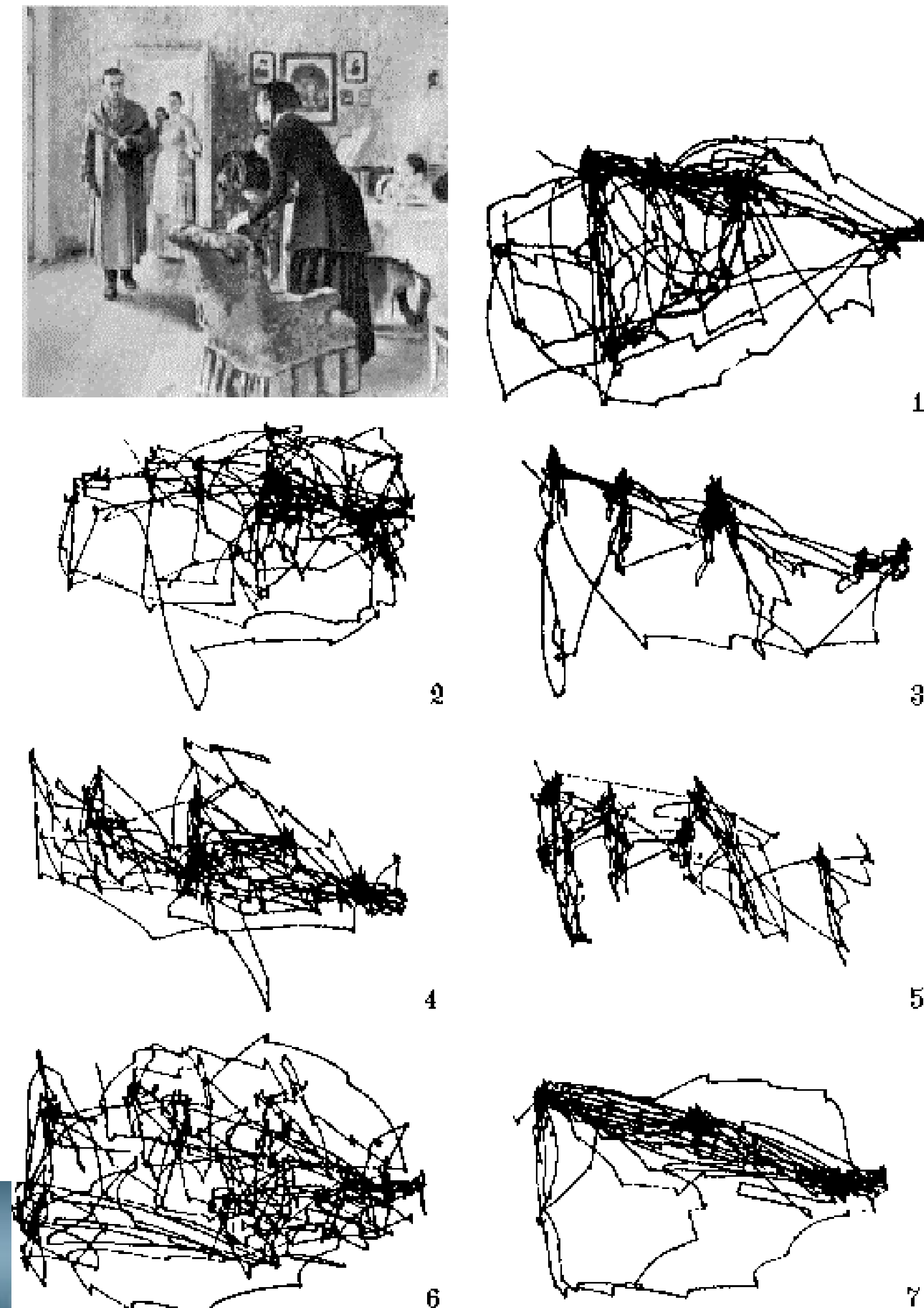
A Life in Fixations

- 60*2.5=150 eye fixations/minute
- 60*150=9000 eye fixations/hour
- 16*9000=144000 eye fixations/day
- 144000 is an average number of visual details processed per day

Eye Movements are Task-Dependent

Eye movements as indicators of cognitive processes (Yarbus):

- trace 1: examine at will
- trace 2: estimate wealth
- trace 3: estimate ages
- trace 4: guess previous activity
- trace 5: remember clothing
- trace 6: remember position
- trace 7: time since last visit



Estimating Attention via Eye Tracking

- Physiology of the eye
- Commercial gaze tracking and applications
- Wearable gaze tracking
- Example: Activities of daily living

The Tobii T120 Eye tracker
Cost: ≈ €28,000
Minutes to learn to operate
Years to become an expert

Image credit: Tobii.com

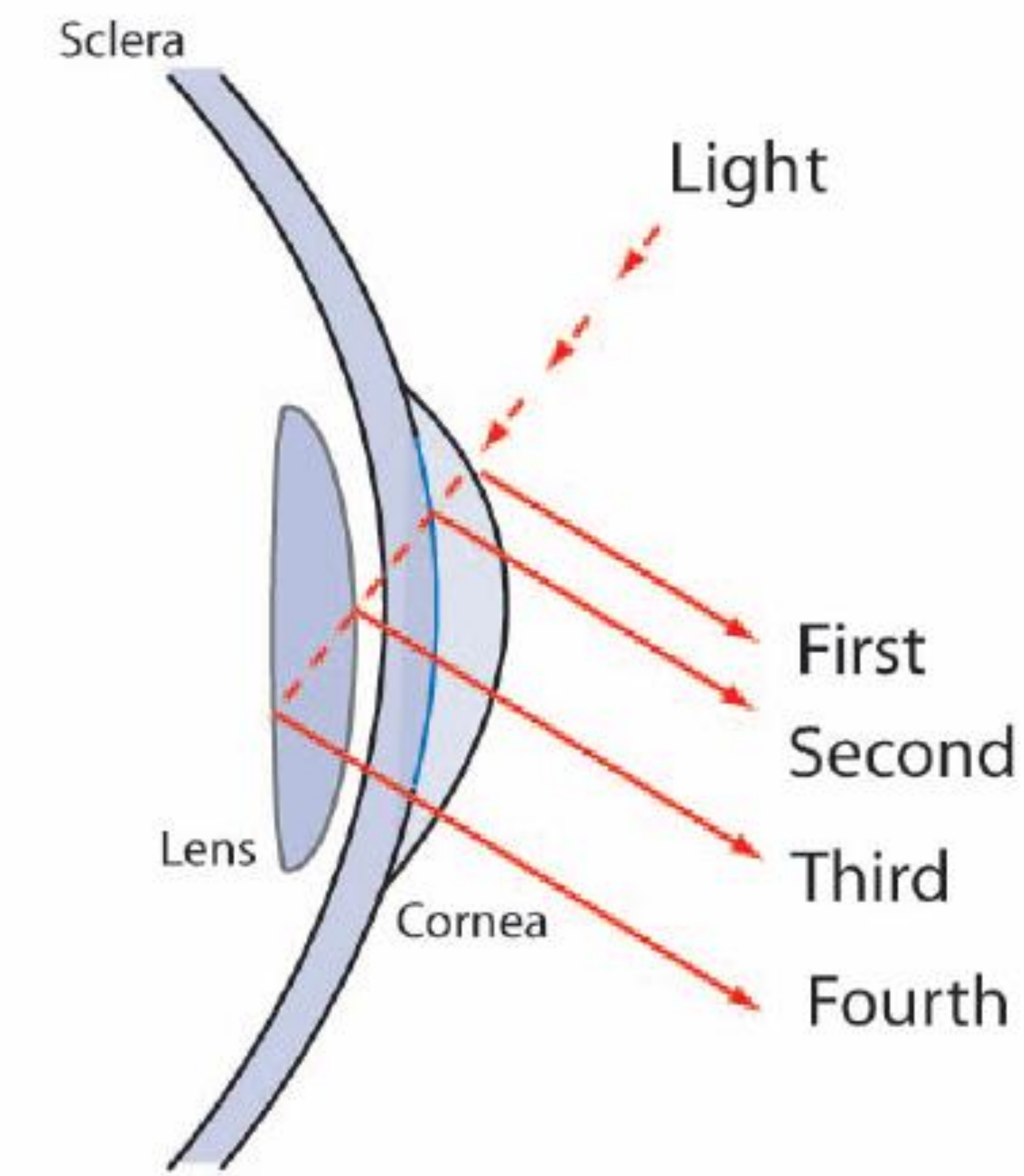
Commercial Uses of Eye Tracking

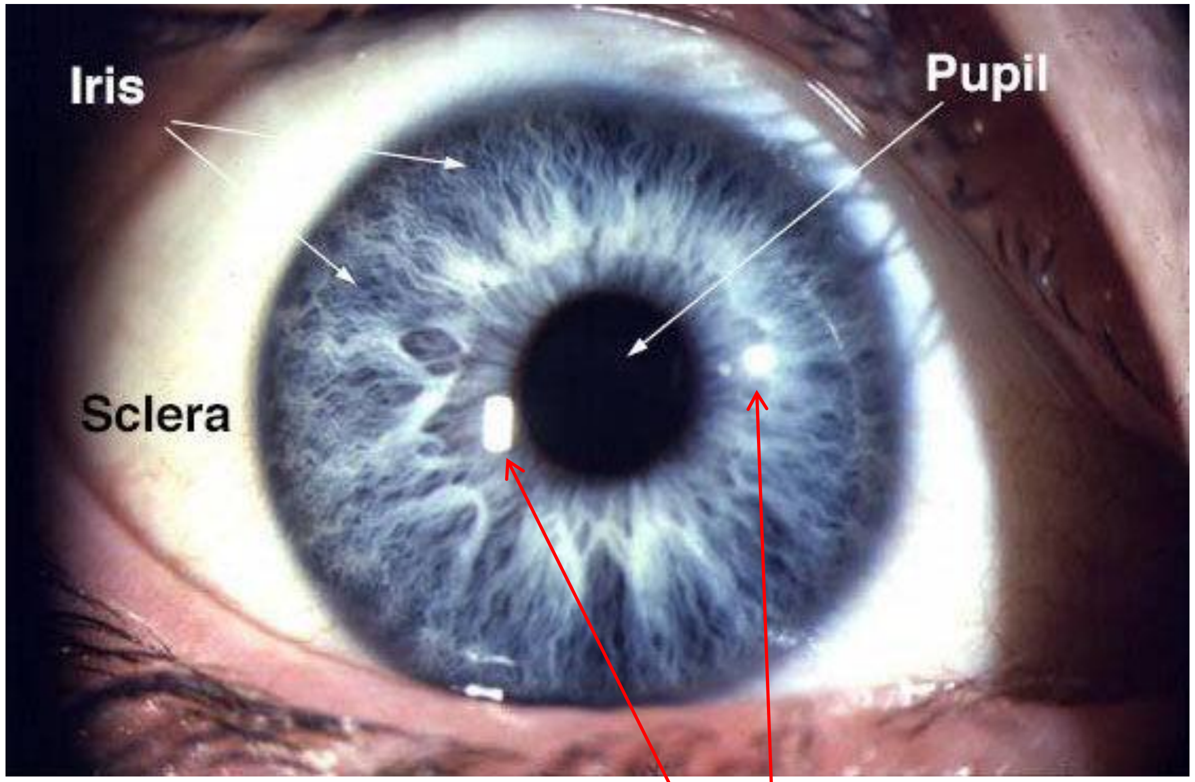
Do users notice branding within 5s ?

Commercial Uses of Eye Tracking

“Heat Map”

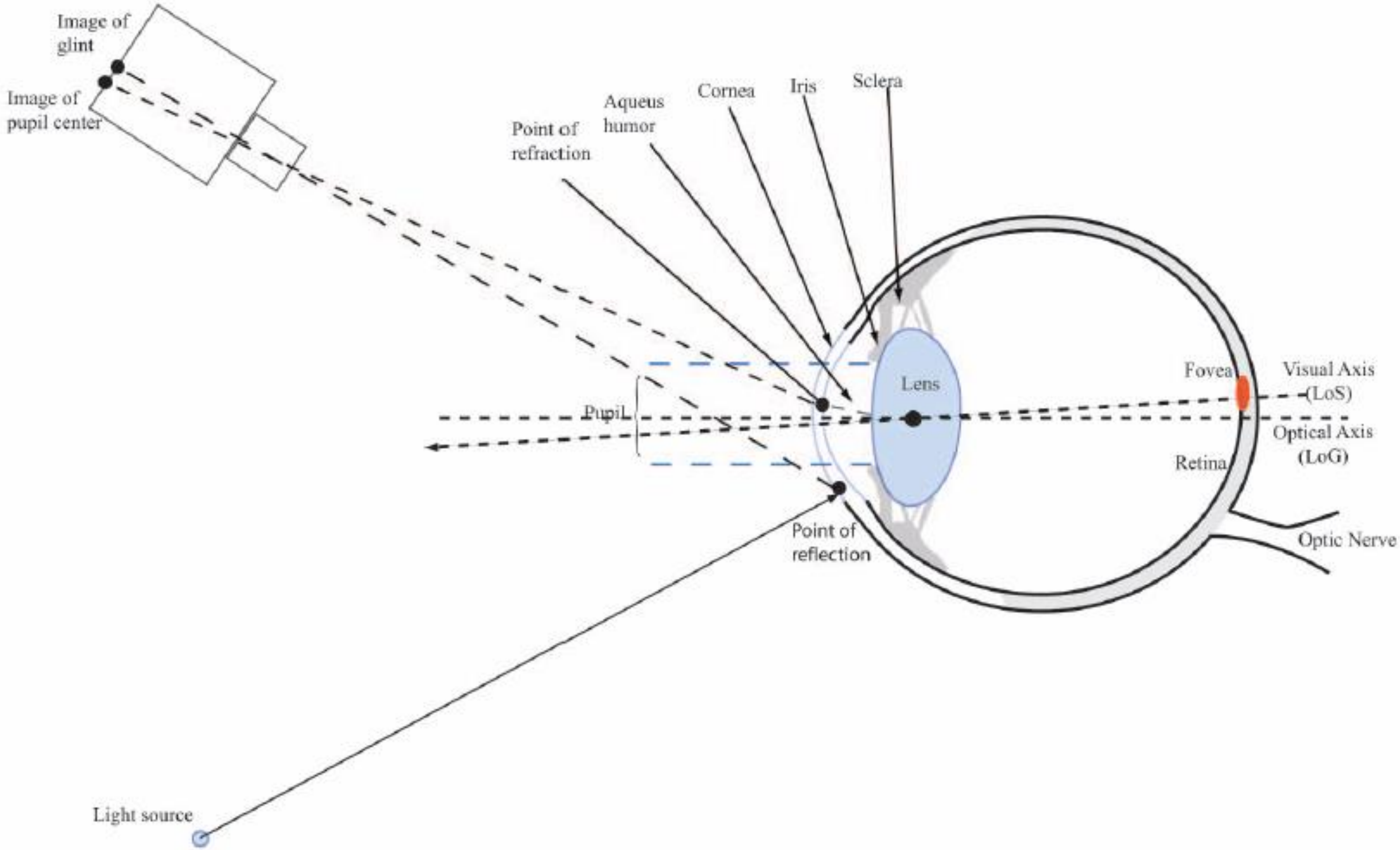
Purkinje Images





"glint"
(1st Purkinje)

Imaging the Eye

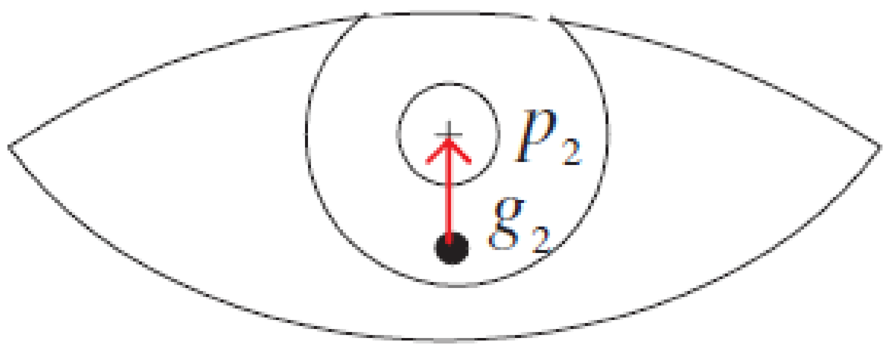


Pupil Center Corneal Reflection (PCCR)

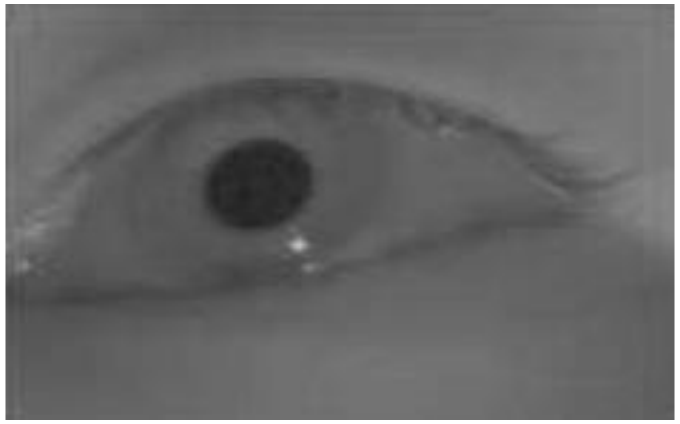
- Uses geometric relation between pupil and glint to compute Point of Regard (POR)
- Very common noninvasive approach
- Basis for many commercial products (e.g. Tobii)
- Comprehensive theory developed in 2006
- Simplest geometry:
  - Spherical cornea, single camera, single light source

Steps in PCCR

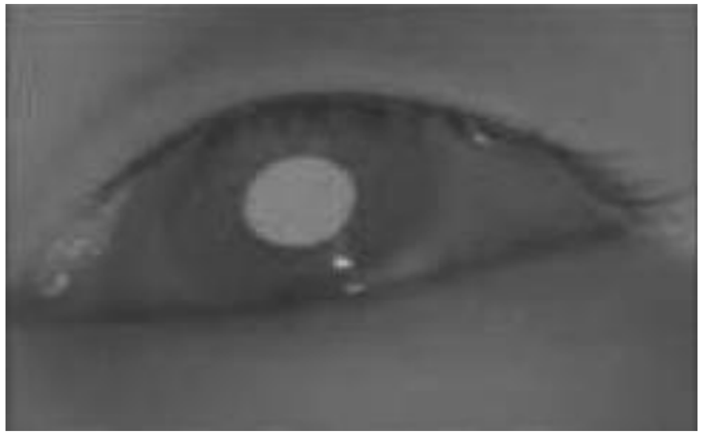
- Extract pupil-glint vector
  – Detect pupil center
  – Detect glint center(s)



Pupil Detection



Dark pupil
(off-axis IR)



Bright pupil
(on-axis IR)

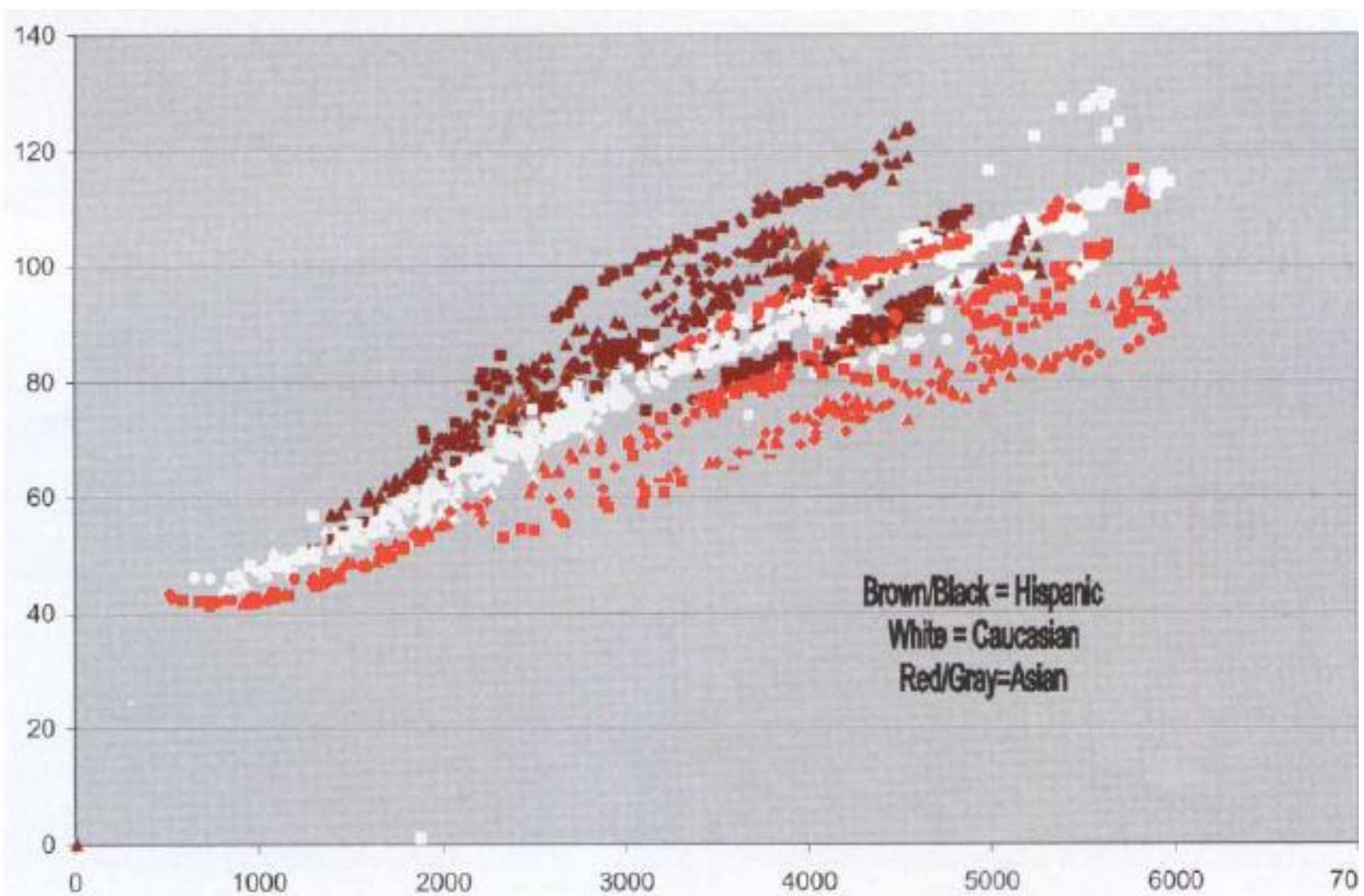
"red eye"

- Issues
  - Bright eye makes it easy to detect pupils (non-Asian)
  - Dark eye makes it easier to detect glints
- Modern systems (e.g. Tobii) do both

Variations in Bright Eye Response

Within individuals

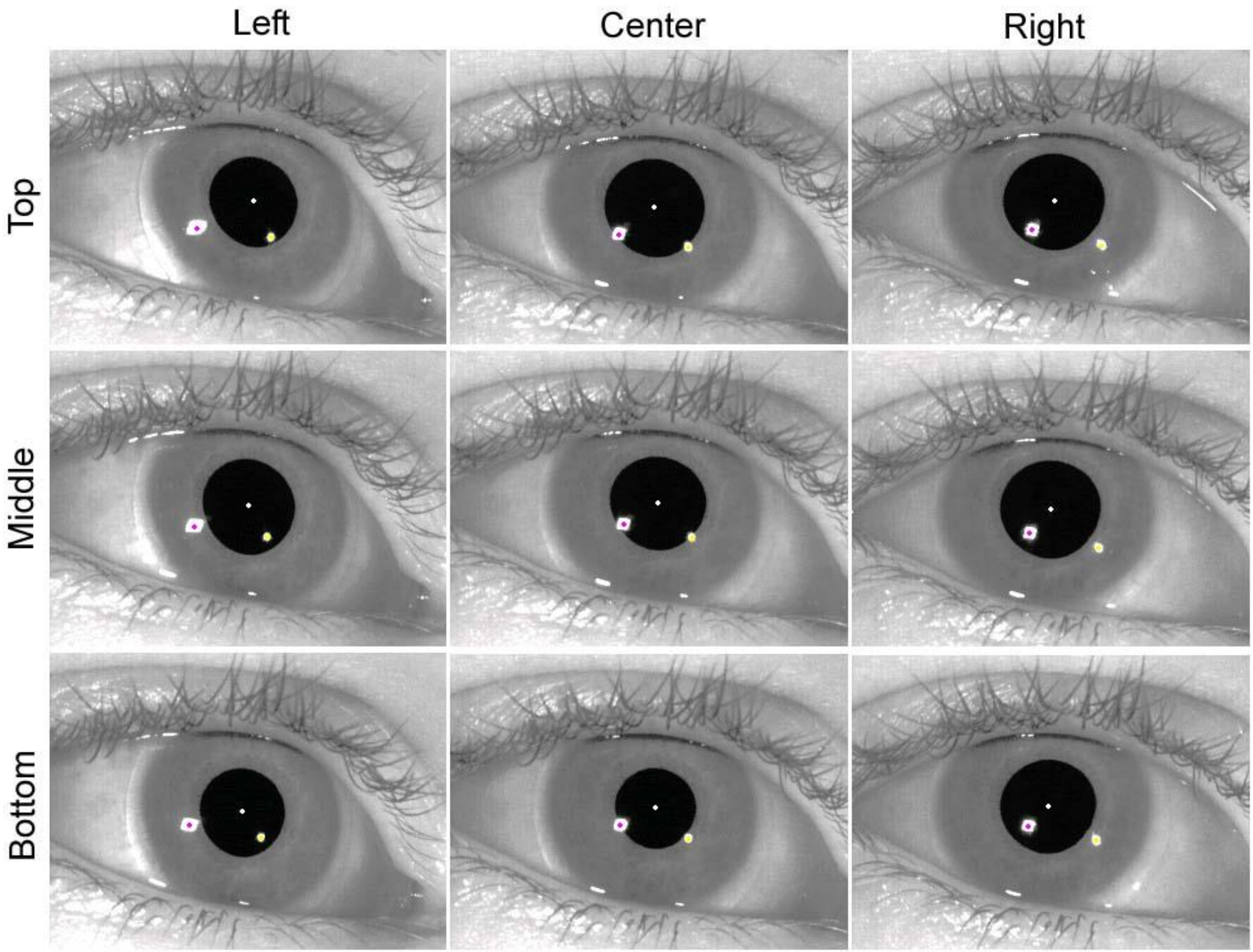
Pupil intensity



Pupil size

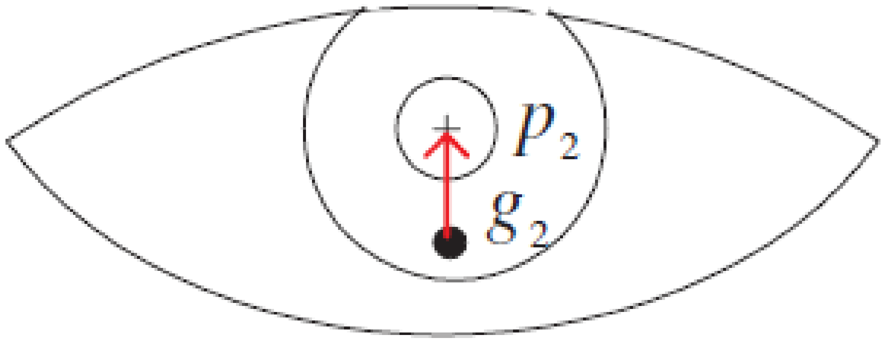
Across individuals

Geometry of Corneal Reflections



Steps in PCCR

- Extract pupil-glint vector
  - Detect pupil center
  - Detect glint center(s)



- Calibrate gaze-specific mapping function
  - Parametric models: linear, homography, polynomial, etc.
  - General function approximators: neural network, gaussian processes, etc.

Estimating Attention via Eye Tracking

- Physiology of the eye
- Commercial gaze tracking and applications
- Wearable cameras, gaze, and egocentric vision
- Example: Activities of daily living

“There is nothing more powerful than an idea whose time has come” – Victor Hugo

GoPro

Google Glass

Looxcie

Tobii

SMI

Pivothead

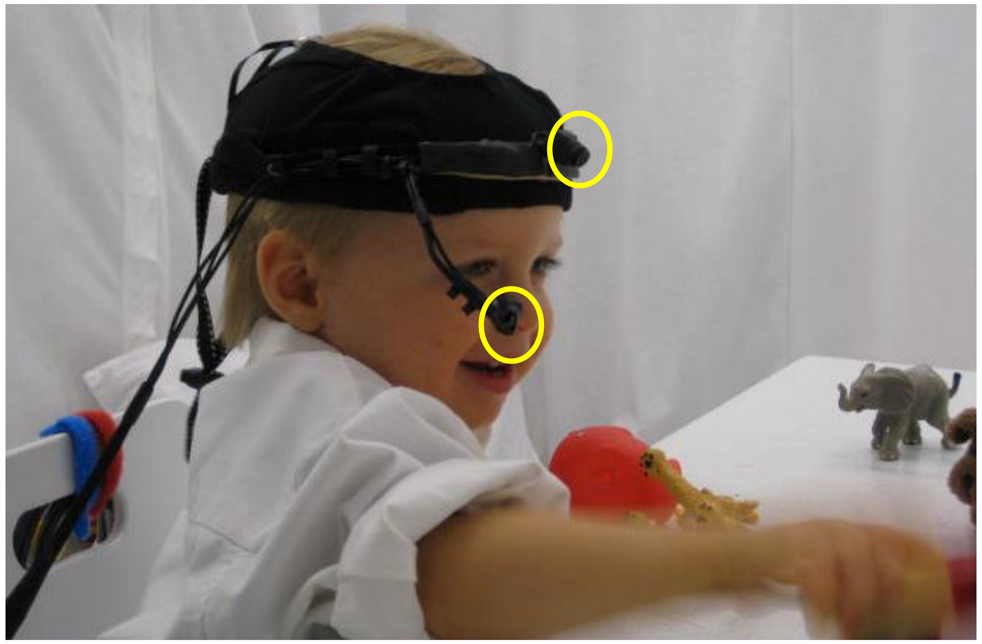

SQUEEZE

Gaze on relevant objects

- During the task = 82%
- Before the task = 48%

Benefits of Wearable Eye Tracker

- Enable naturalistic movement and mobility
- Direct measurement of both scene image and point of gaze
- Limitations:
  - Expensive ($24K)
  - May not be safe for kids
  - Power-hungry

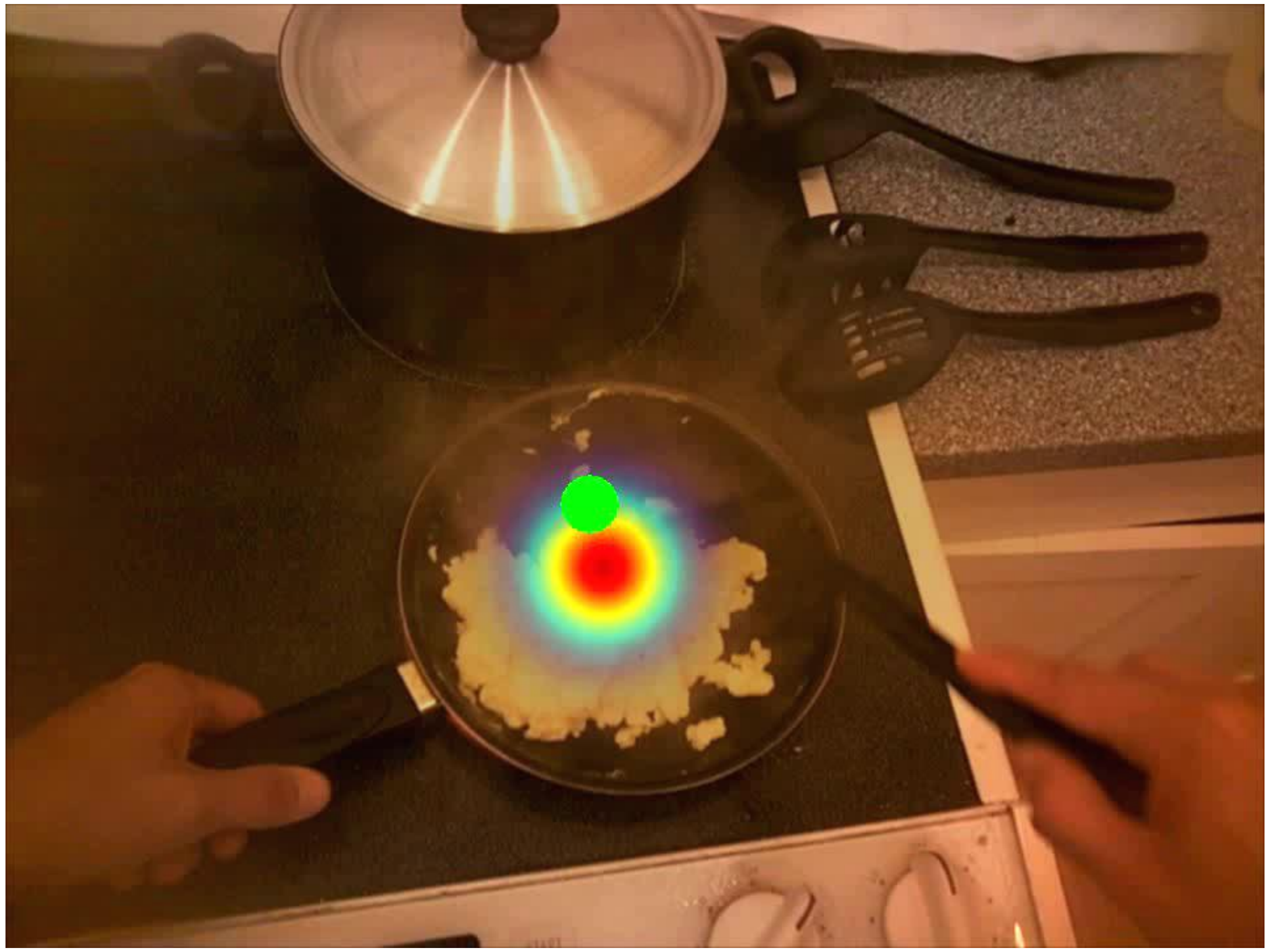


Positive Science & UI

Predicting Gaze in Egocentric Setting

Input Egocentric Video

Gaze Prediction

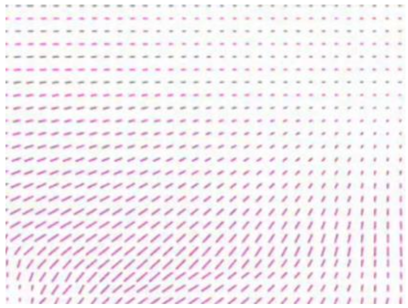


Li, Fathi, & Rehg ICCV 13

Egocentric Cues
Eye, Head and Hand Coordination

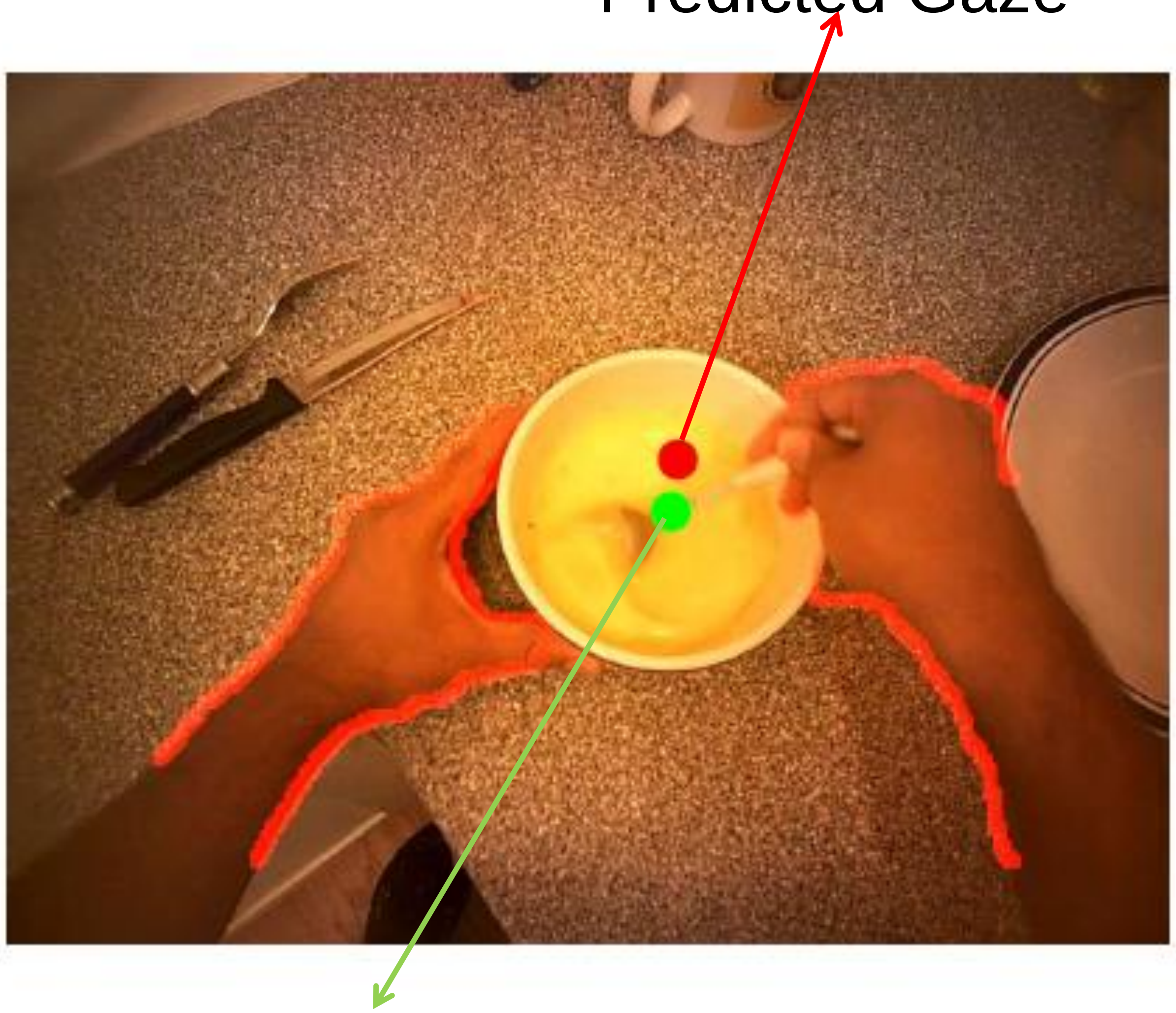
Center Prior
(Head Orientation)

Head Motion



Hand Location

Predicted Gaze



Human Gaze

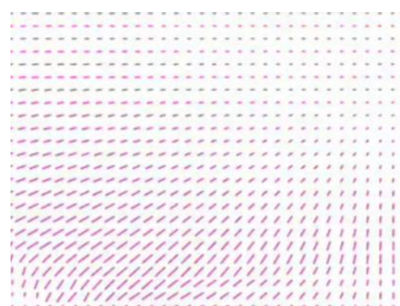
We don't use low-level image features or high-level task information

Egocentric Cues

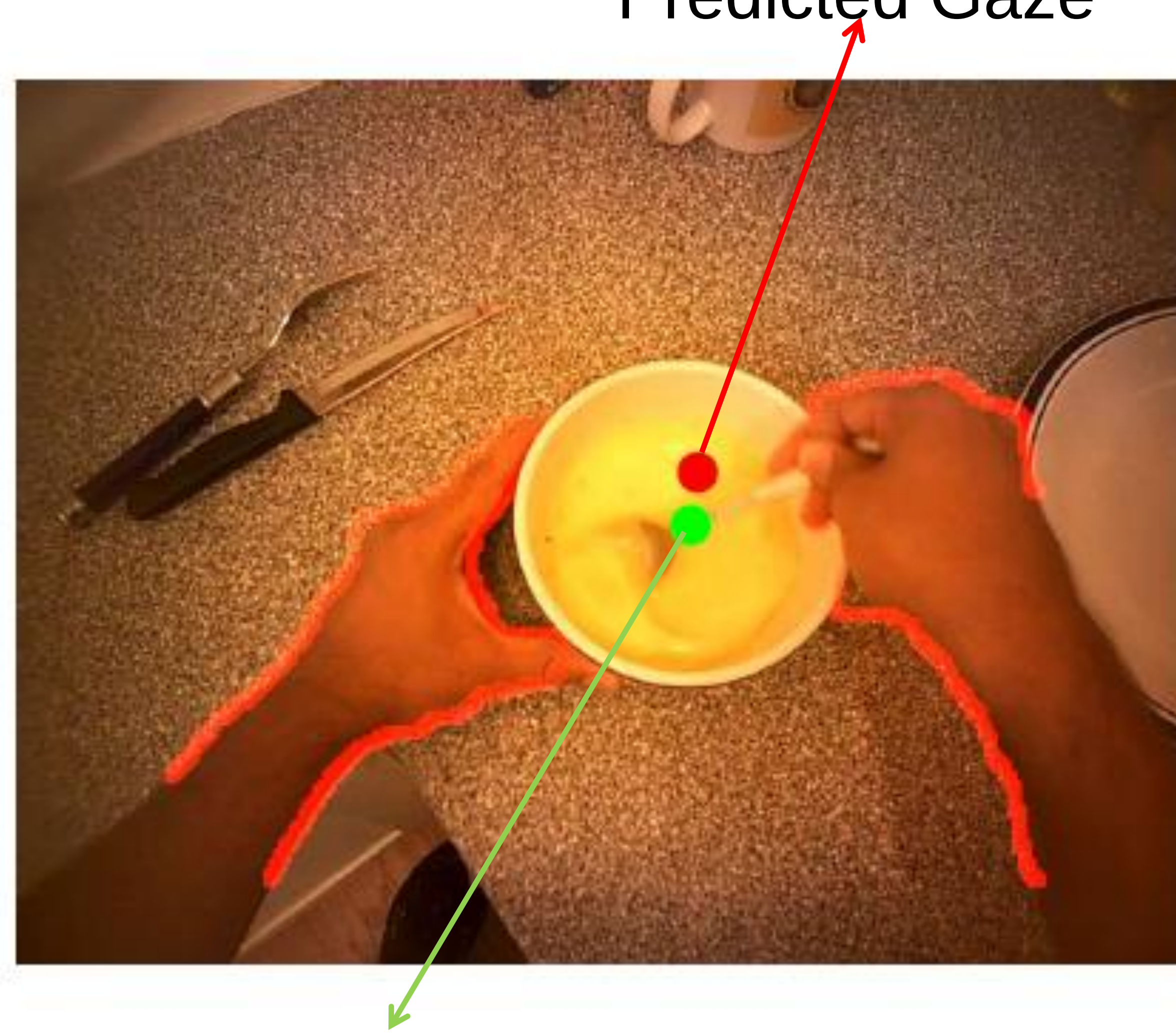
Eye, Head and Hand Coordination

Center Prior (Head Orientation)

Head Motion



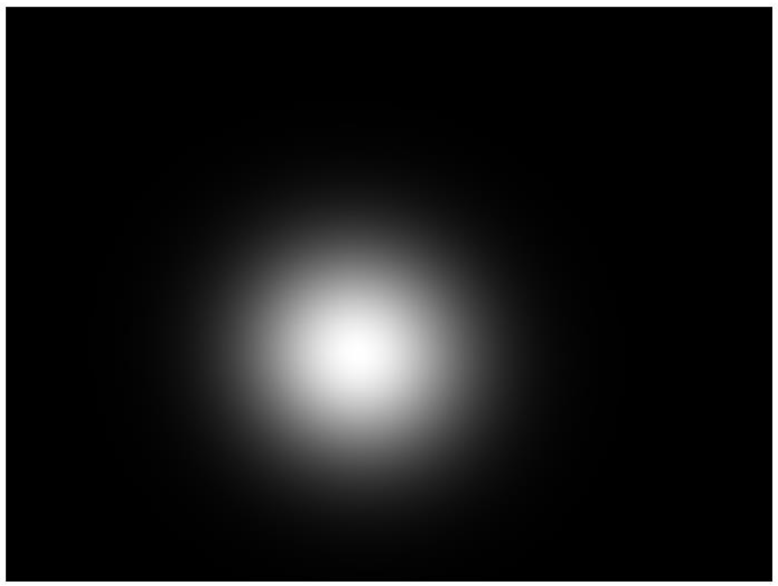
Hand Location



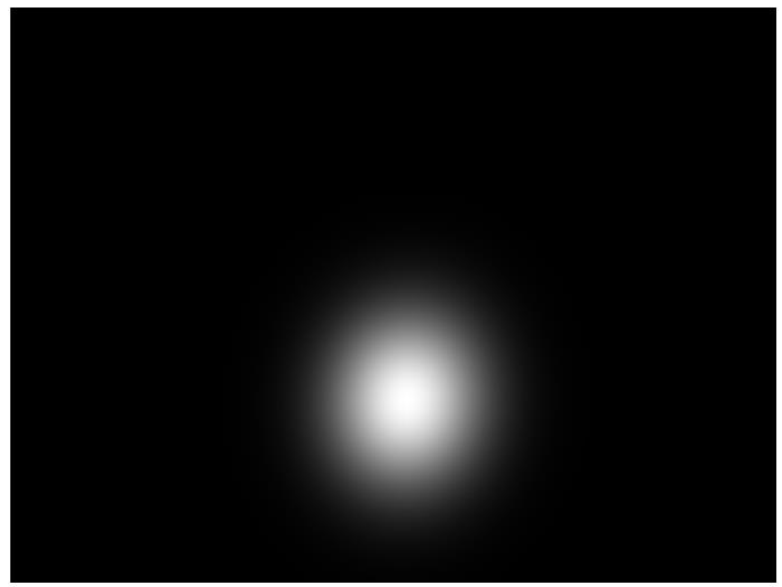
We don't use low-level image features or high-level task information

Center Prior

Egocentric Gaze Tracking



GTEA Gaze Dataset



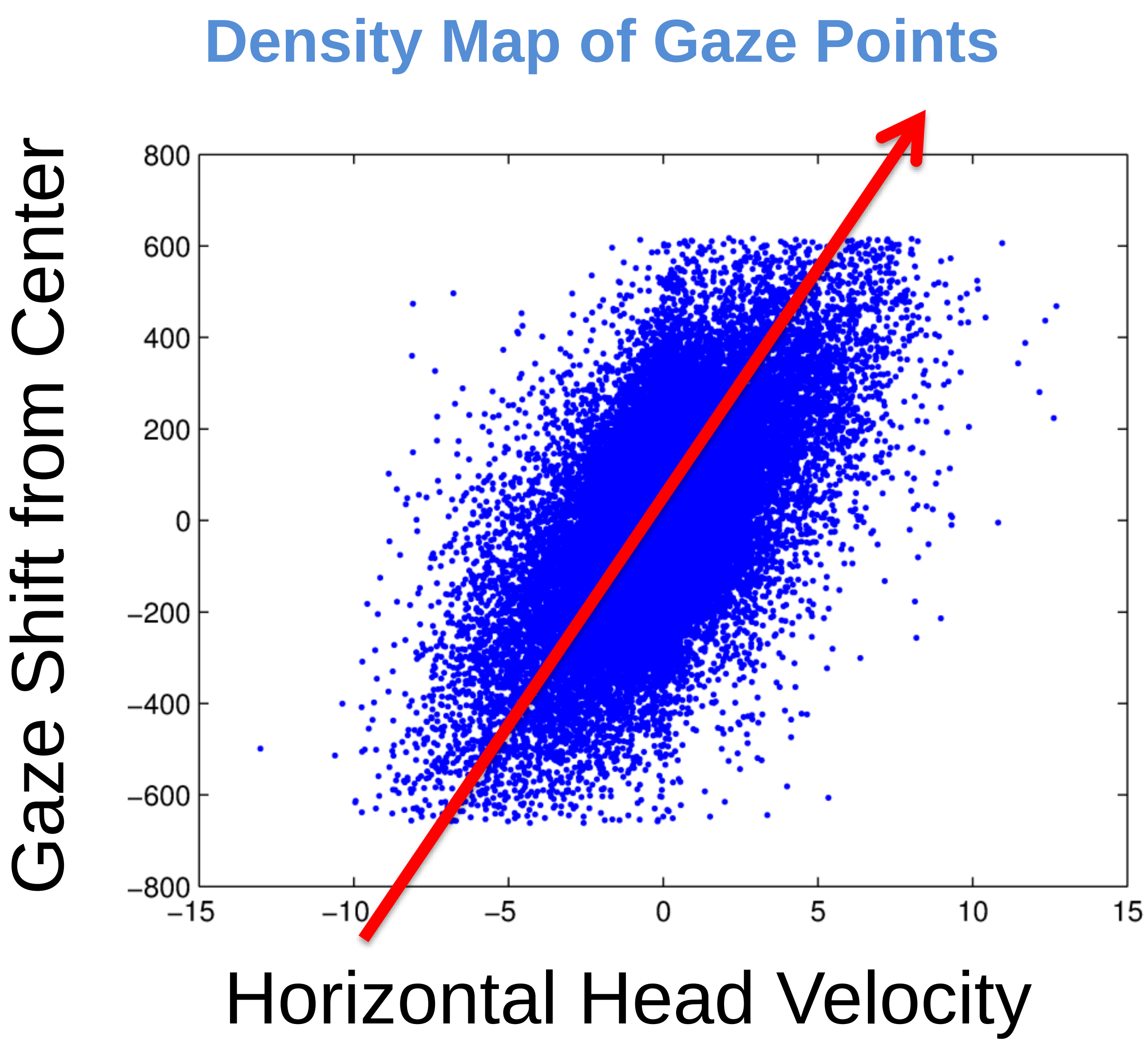
GTEA Gaze+ Dataset

Monitor based Gaze

MIT Dataset
Judd et al., ICCV 2009

Eye-Head Coordination: Head Motion

Eye-Head Coordination: Head Motion



- **Strong correlation** between **gaze shift** and **head velocity** in horizontal direction

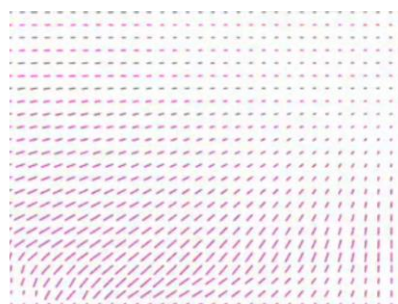
- Gaze point shifts towards the **same** direction (left/right) of one's head movement

Yamada et al., Advances in Image and Video Technology, 2012.

Egocentric Cues
Eye, Head and Hand Coordination

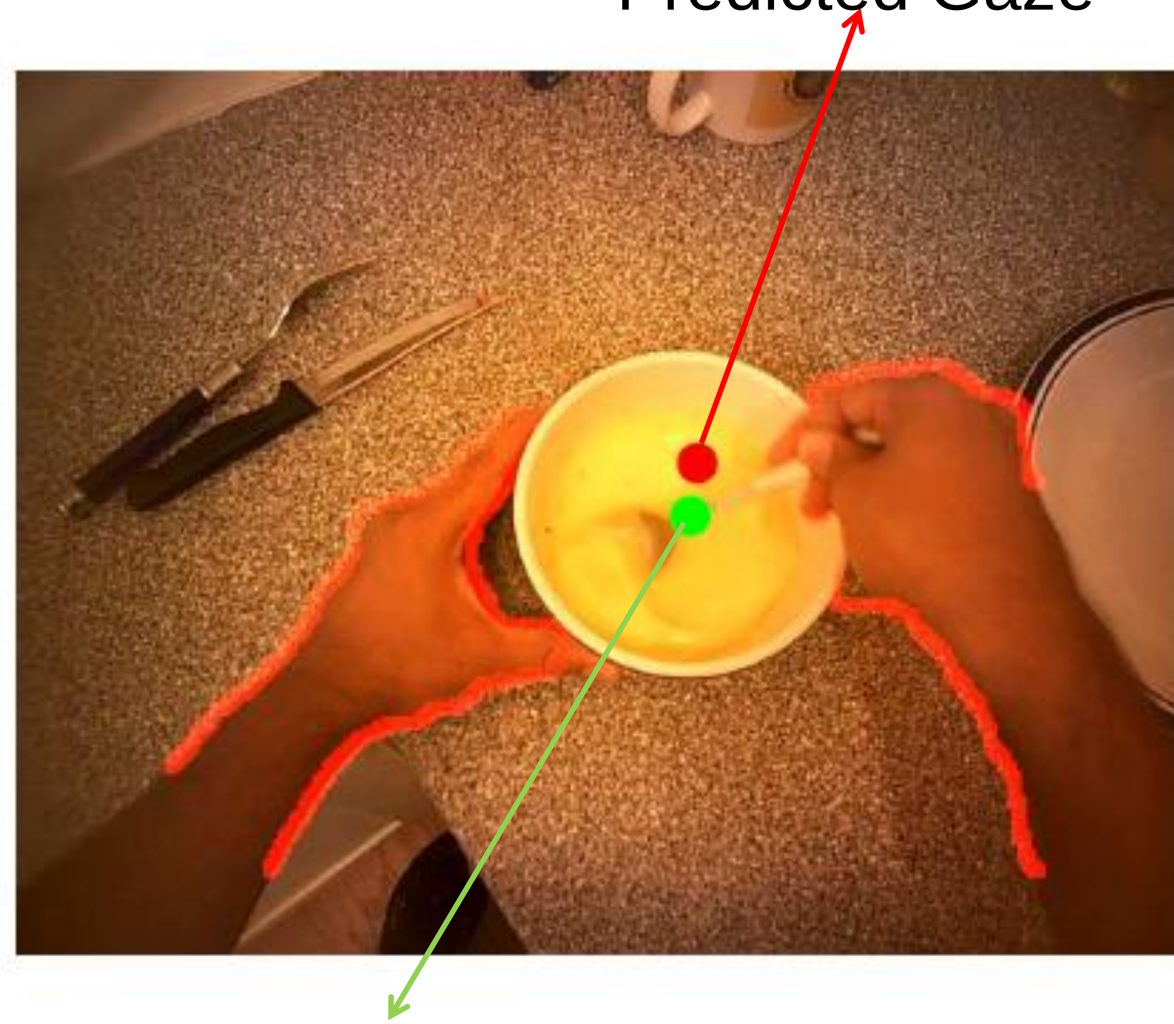
Center Prior
(Head Orientation)

Head Motion



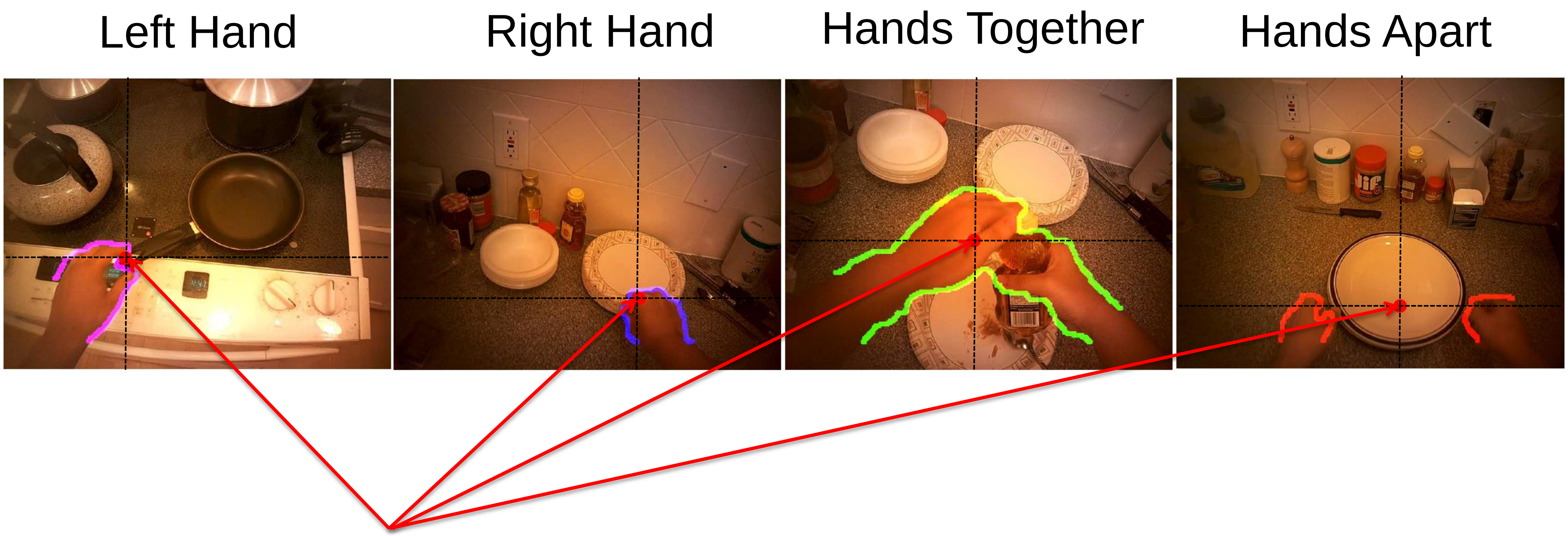
Hand Location

Predicted Gaze



Human Gaze

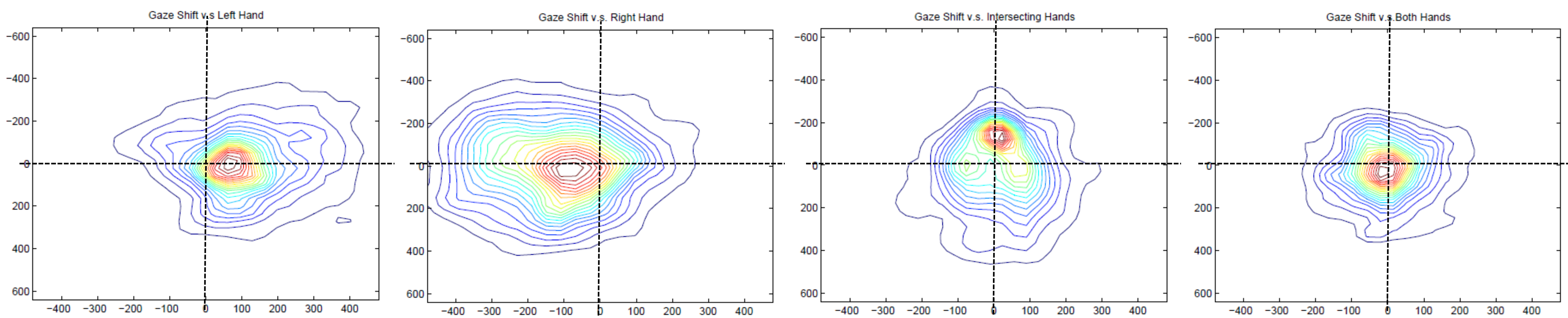
Eye-Hand Coordination



Manipulation Point: a control point where the person is most likely to manipulate an object

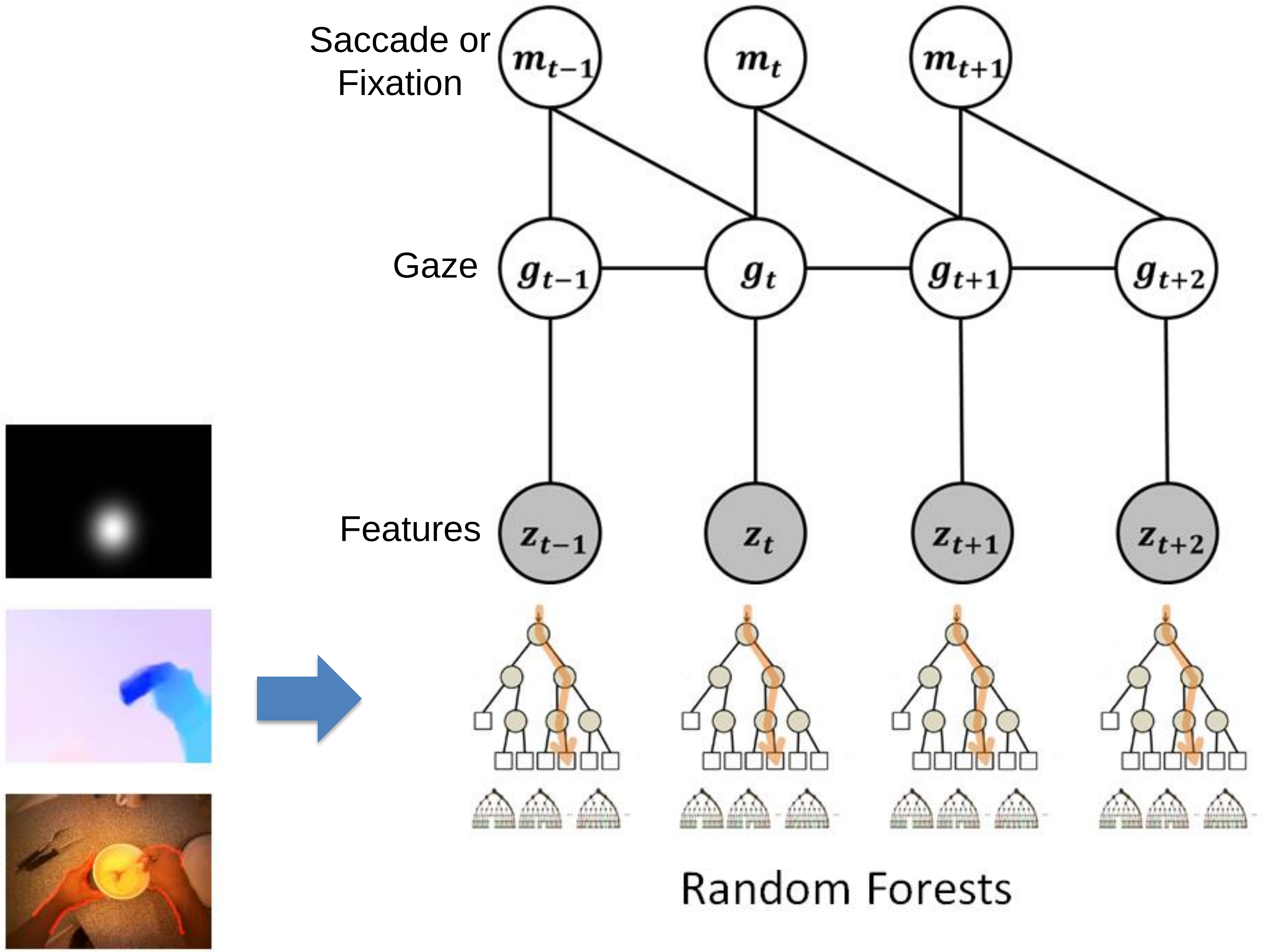
Eye-Hand Coordination

Left Hand | Right Hand | Hands Together | Hands Apart



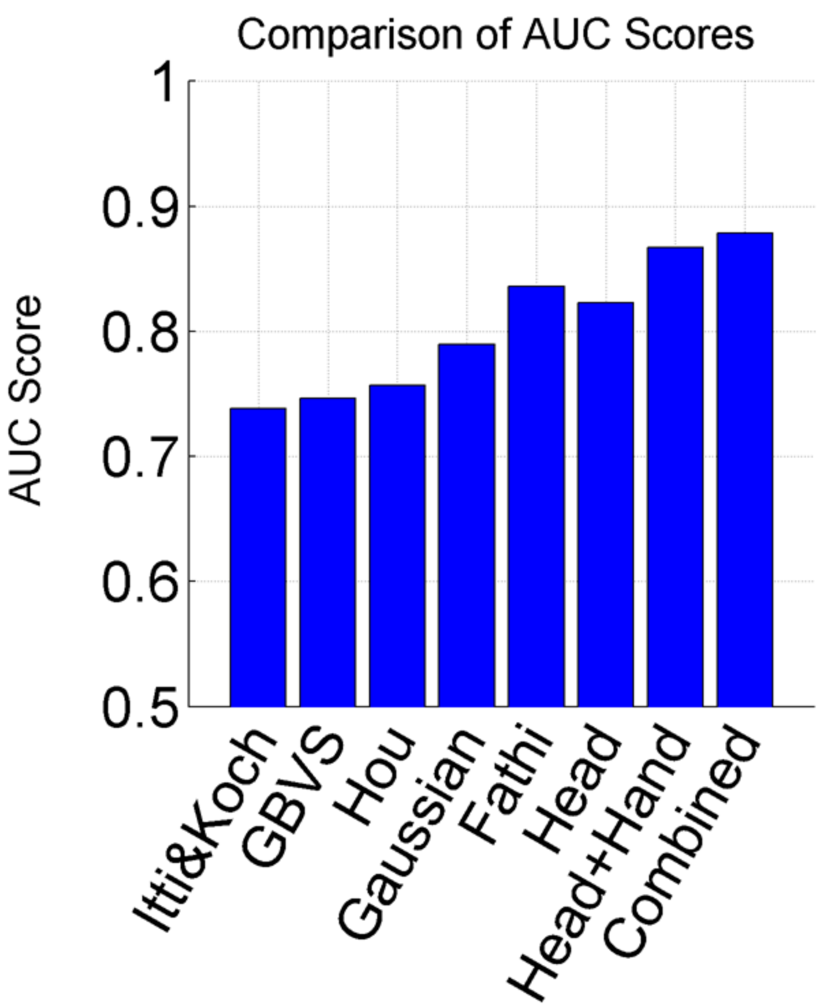
Density map of Gaze offset relative to the manipulation point

Temporal Model

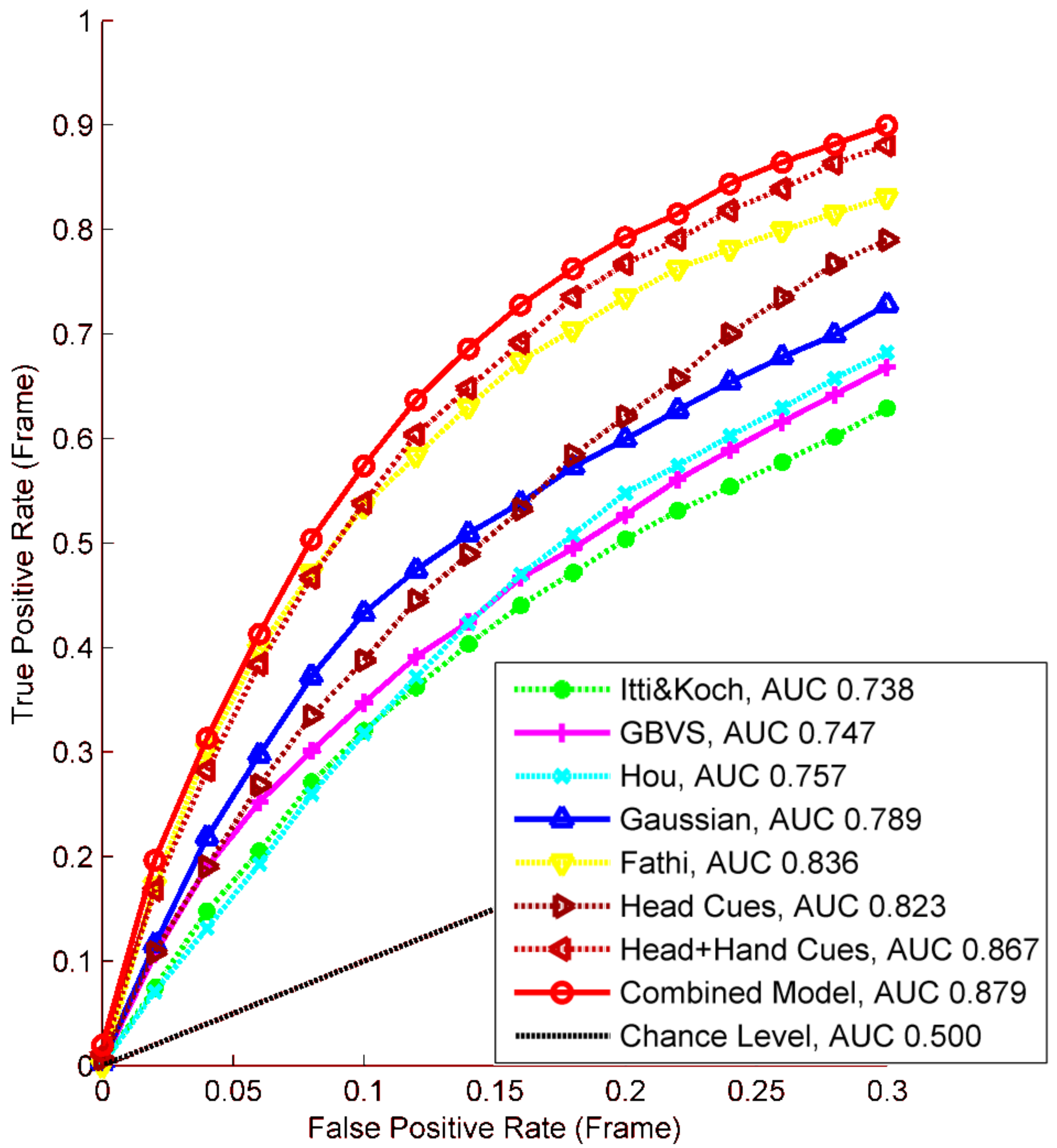


Gaze Prediction

Results: Gaze Prediction



ROC Curve



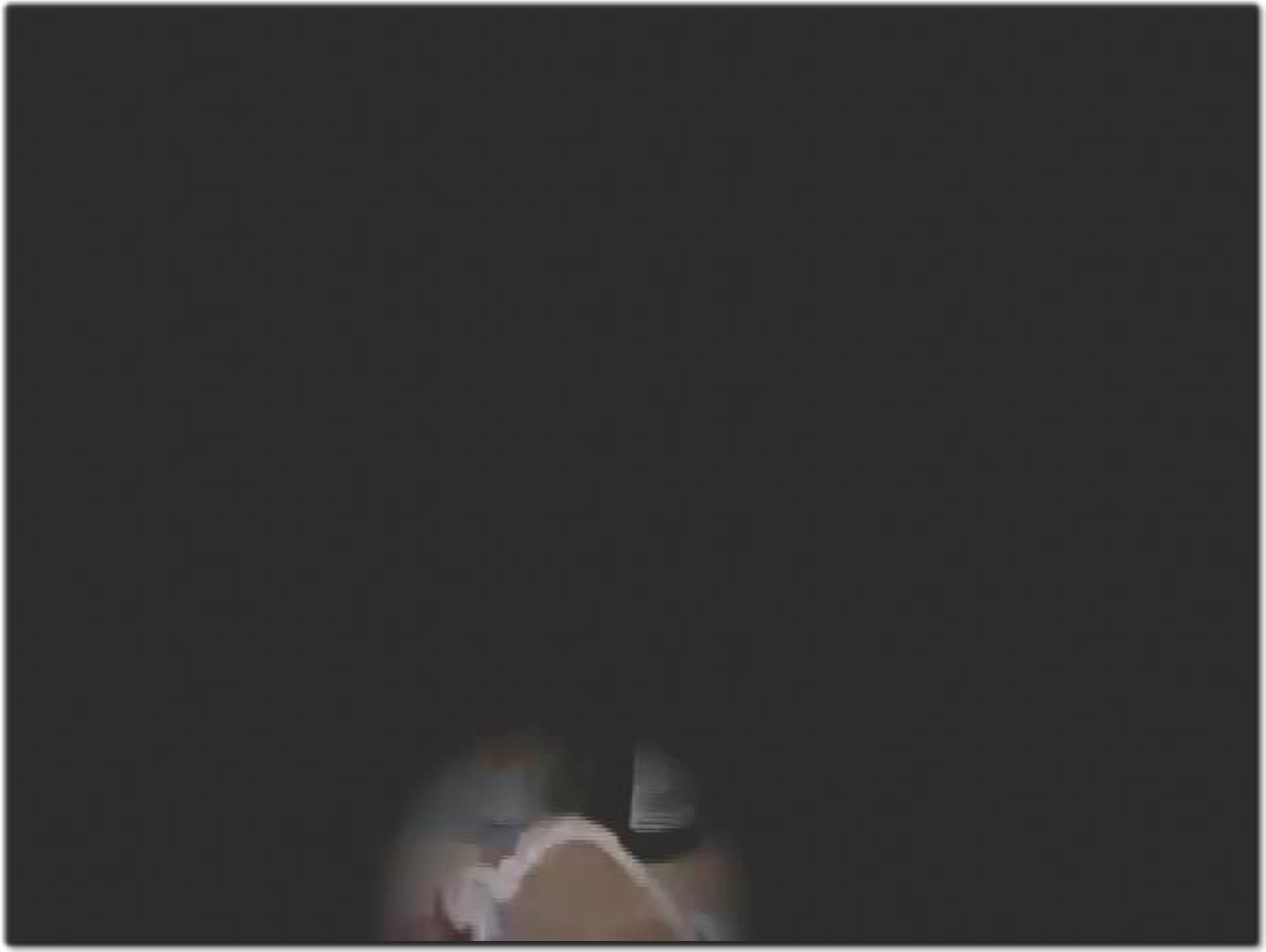
GTEA Gaze+ Dataset

- 6 Subjects
- 7 Activities (Making Pizza, Hamburger, Breakfast, Greek Salad, etc.)
- Each activity takes around 10 min, Around 100 actions in each activity

Estimating Attention via Eye Tracking

- Physiology of the eye
- Commercial gaze tracking and applications
- Wearable cameras, gaze, and egocentric vision
- Example: Activities of daily living

Is gaze useful for recognizing activities?

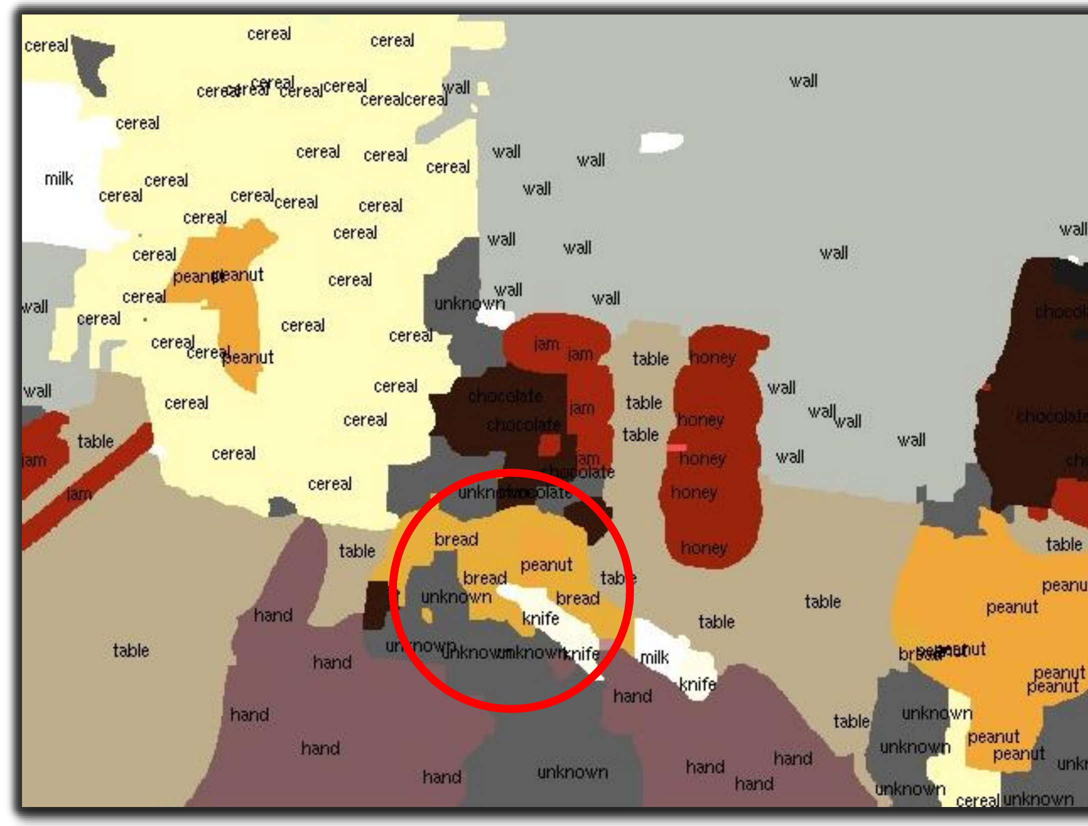


Object-based Features

Detector response of objects in a small circle around gaze point

Object detection and segmentation results

Spread peanut-butter on bread



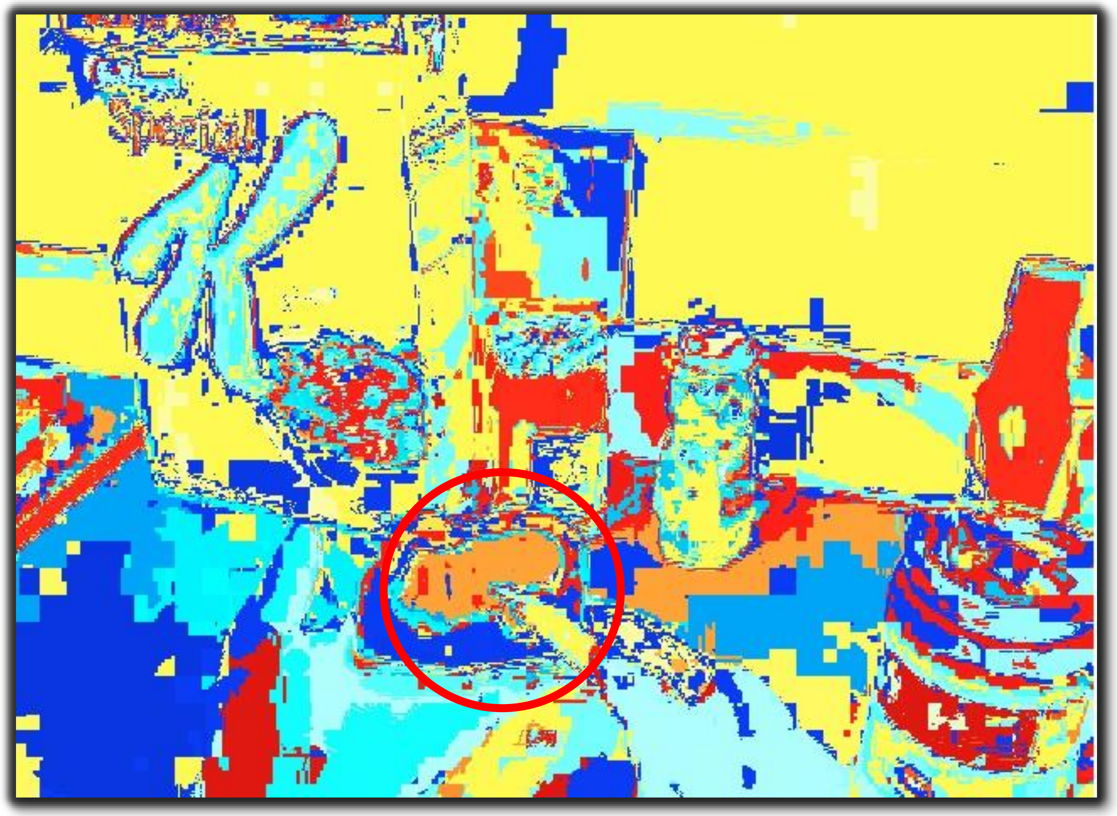
Knife, Bread, Peanut around gaze point

Appearance Features

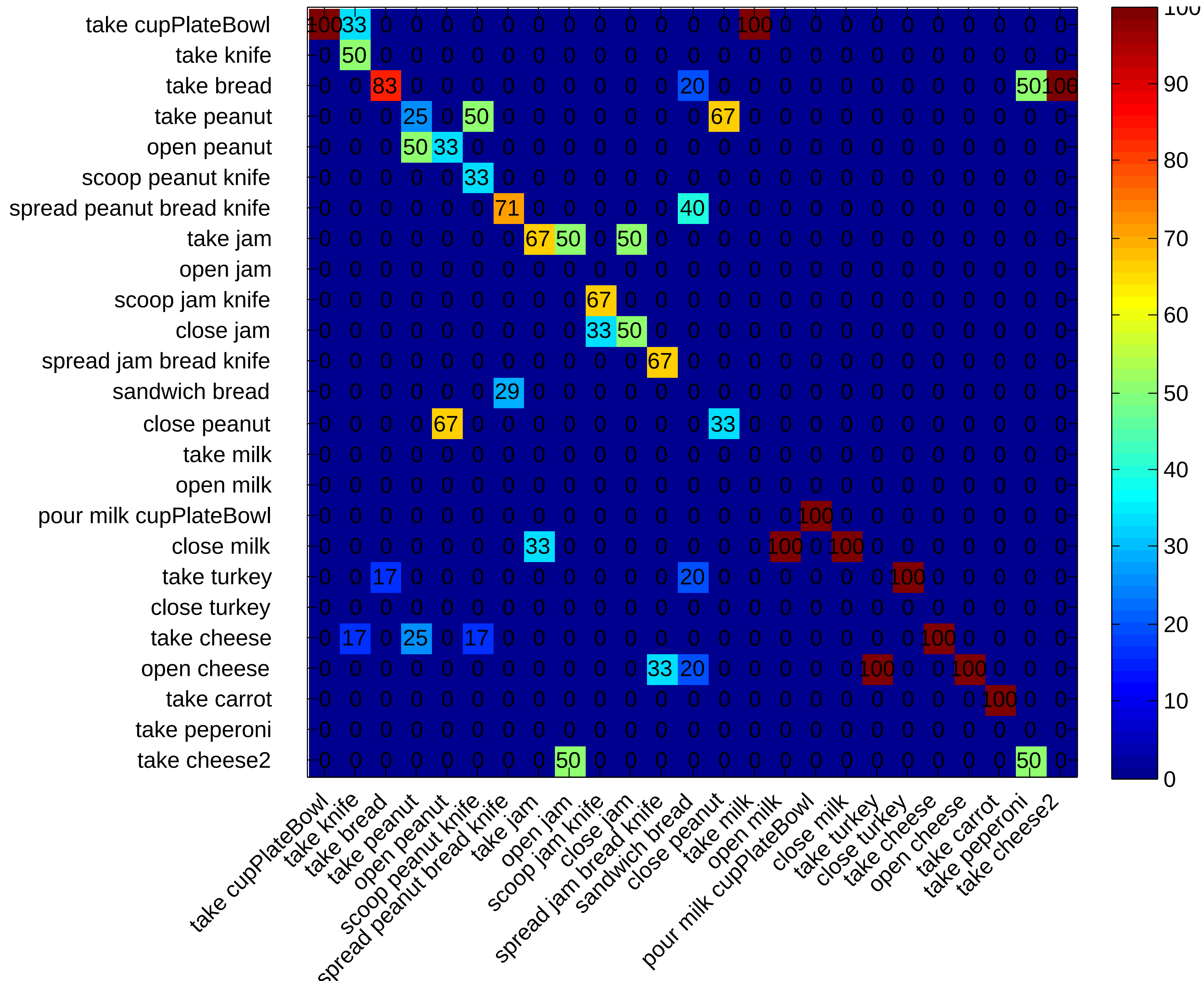
Histogram of color and texture in a small circle around gaze point

Spread peanut-butter on bread

Color/texture bins assigned to pixels



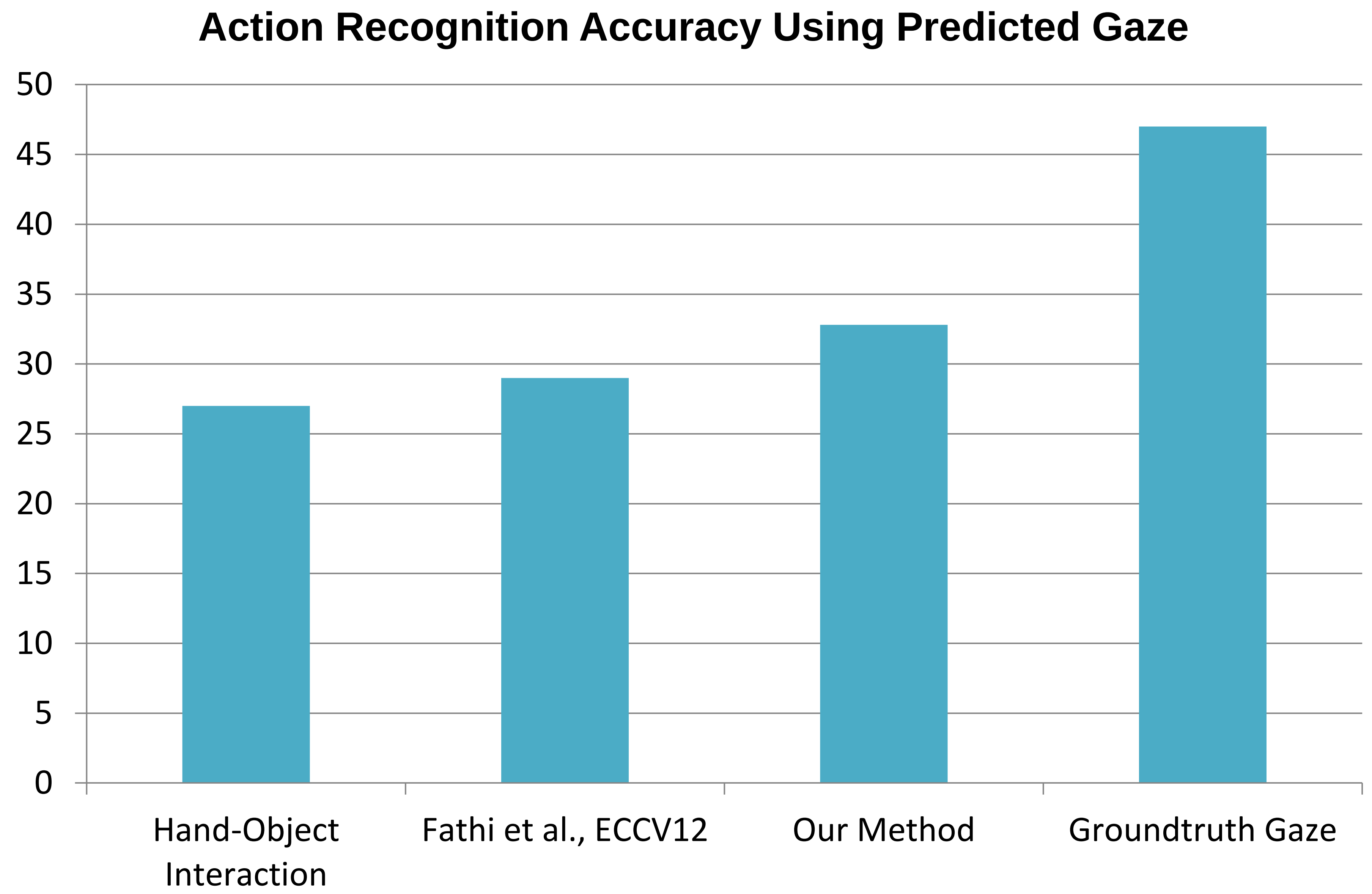
Action Recognition Given Gaze



We get from 27% using foreground to **47%** using gaze

Bag of STIP features: 12%

Bag of SIFT features: 19%



Average accuracy for 25 action classes

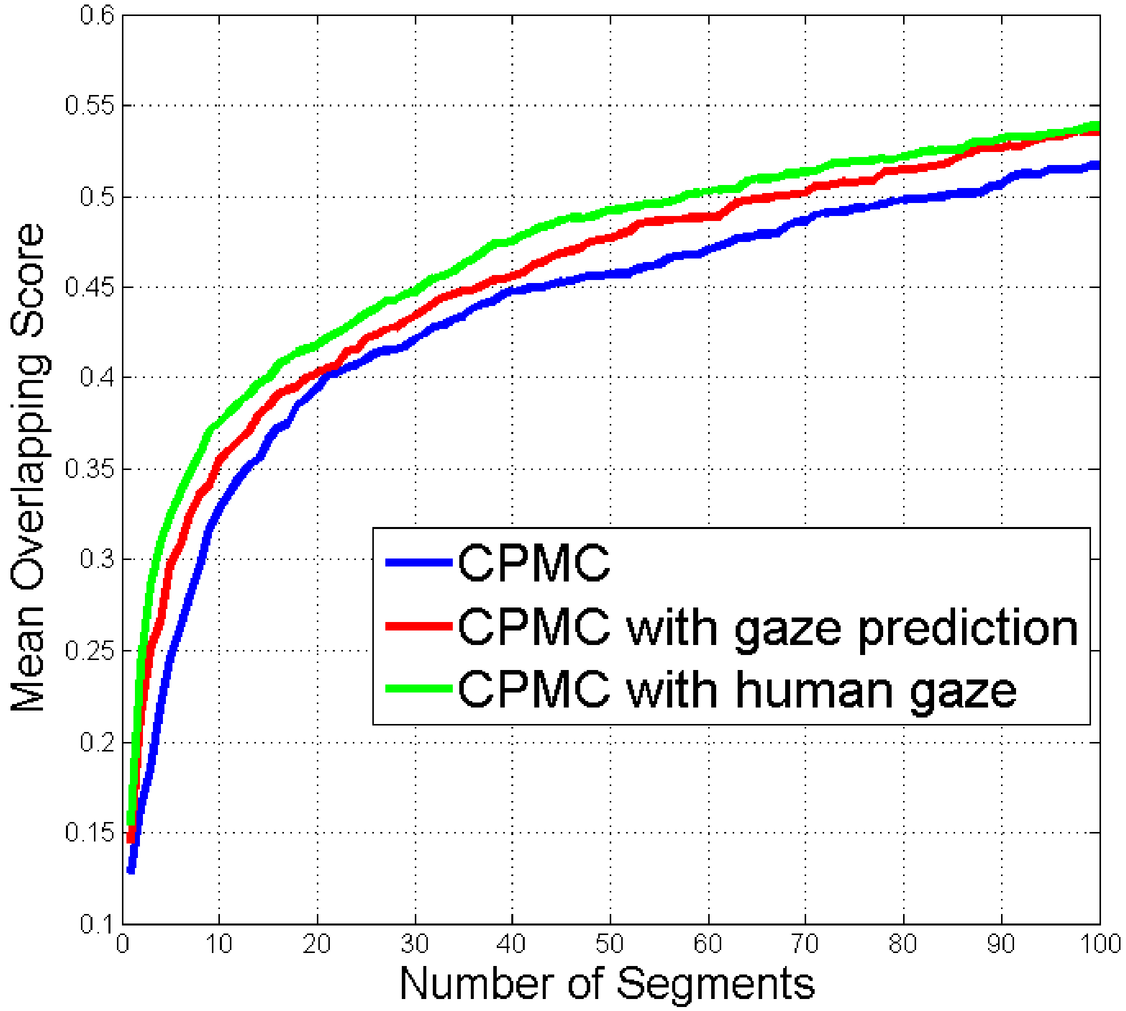
- Features from hand-object interaction: 27%
- Features around ground truth gaze: 47%
- Features around predicted gaze (Fathi, Li, Rehg, ECCV12): *29%*
- Features around predicted gaze (Egocentric Cues): ***32.8%***

Application to Object Segmentation

Gaze often falls on the foreground object

Foreground Object with 80 pixel margin

Results for Object Segmentation



- Foreground hypothesis generation
- *Ranking* the segments

Carreira and Sminchisescu
Constrained Parametric Min-Cut for Automatic Object Segmentation, CVPR 2010

Actions Change the State of Objects

Opening Coffee Jar

Fathi and Rehg

Modeling Actions through State Changes

CVPR 2013

Detected State-Specific Region

Detected State-Specific Region

Detected State-Specific Region

Detected State-Specific Region

Summary

- Classical gaze tracking uses the relationship between pupil center and glints (landmarks)
- This technology is now migrating into wearable platforms
- It is possible to make useful predictions about the subject's gaze by exploiting egocentric cues
- Egocentric vision is a powerful paradigm for sensing behaviors and every-day activities

Introduction to Behavior Imaging (part 3)

Jim Rehg
Georgia Tech

UBIHealth Winter School
January 13, 2014

Applications of Behavior Imaging

- Applications to autism
- Possible applications to smoking cessation

Applications of BI in Autism

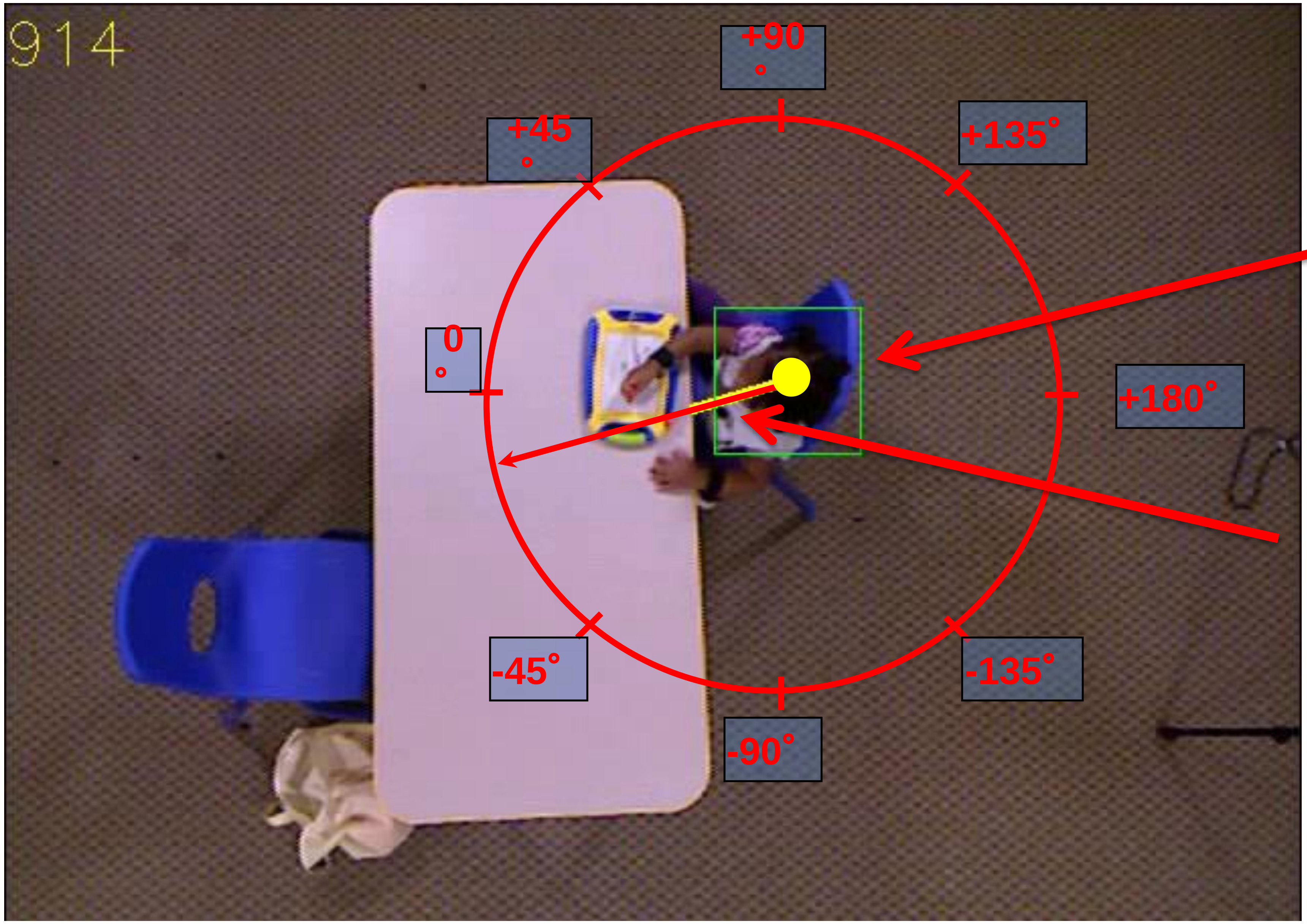
- Detecting response to name
- Detecting eye contact
- Recognizing gestures
- Predicting engagement in R-ABC

Response to Name Protocol

Overhead view using a Kinect camera

examiner

Frame #914

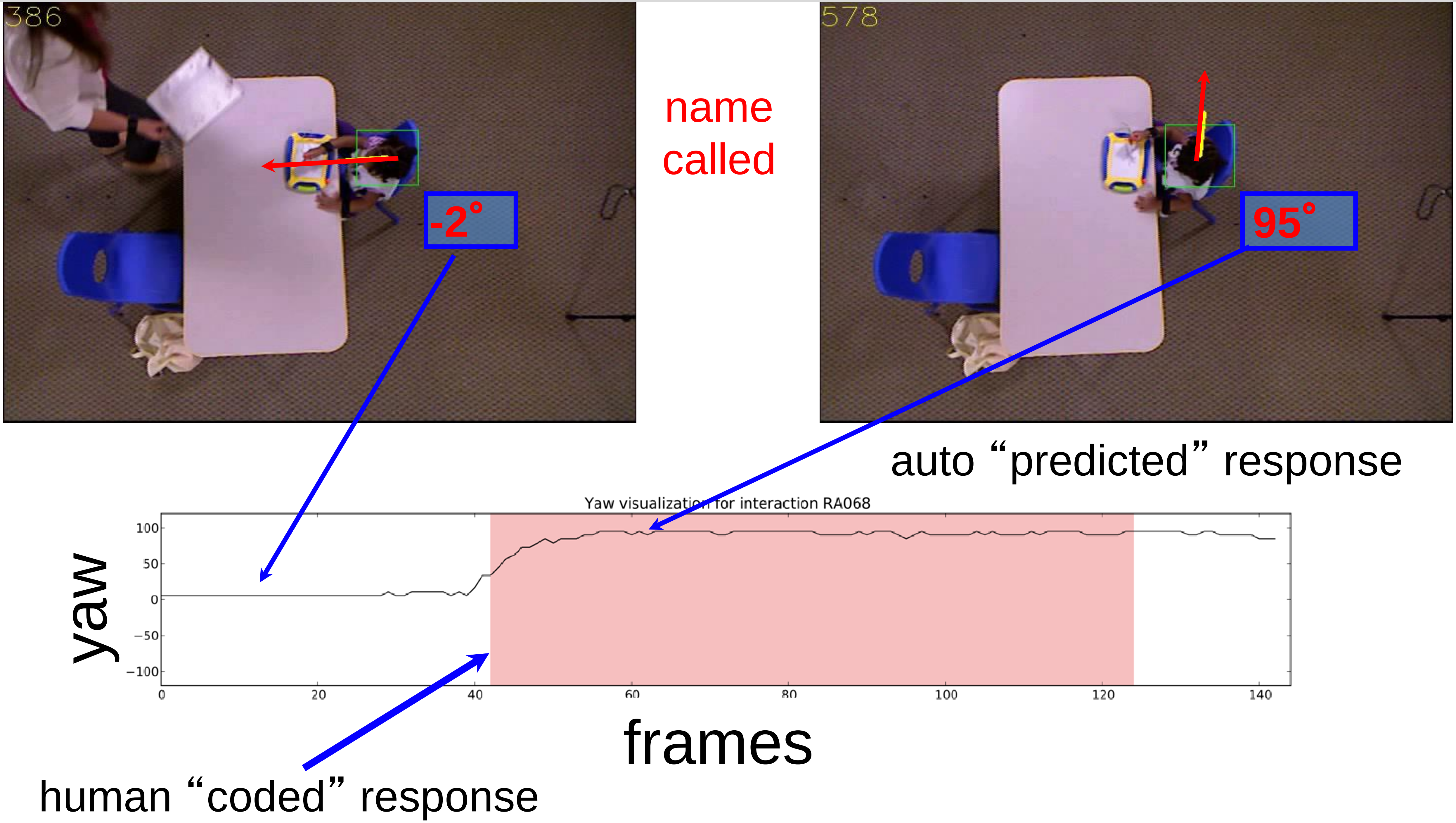


Child's head

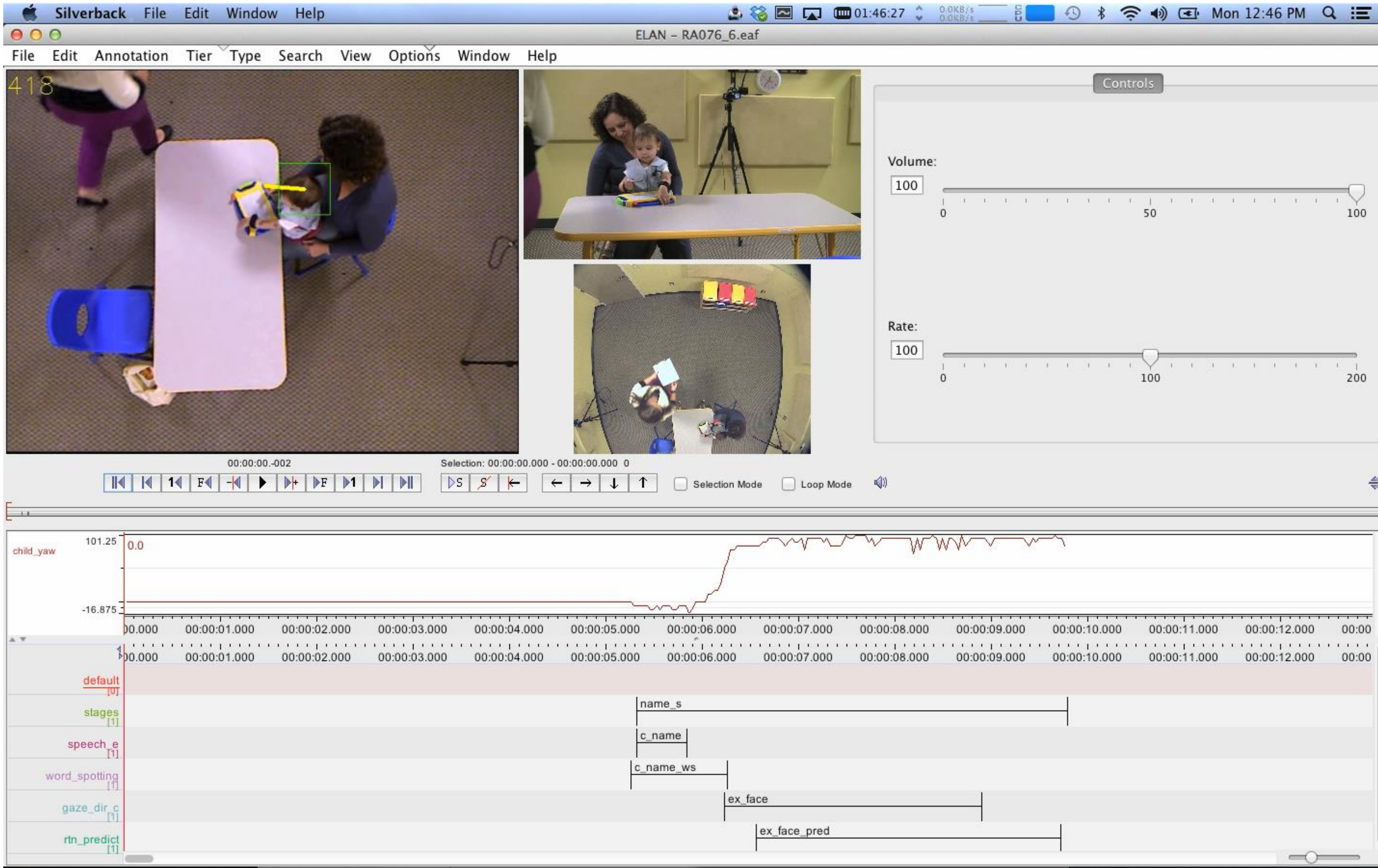
Head orientation
yaw
Gaze proxy

Bidwell et. al. (GT)

Predicting response to name



ELAN Visualization



Applications of BI in Autism

- Detecting response to name
- Detecting eye contact
- Recognizing gestures
- Predicting engagement in R-ABC

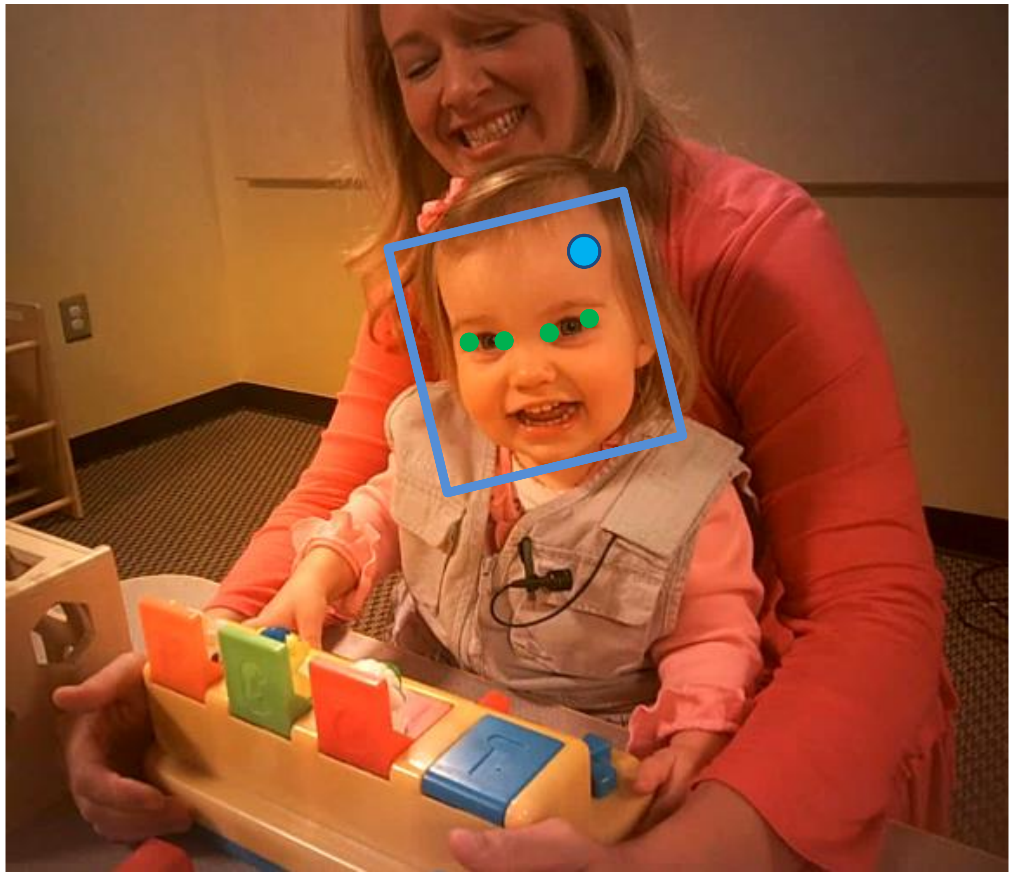
Egocentric Vision

Glasses capture:
- *What examiner sees*
- *Where examiner looks*

Gaze camera

Scene camera

Automatic Detection of Eye Contact



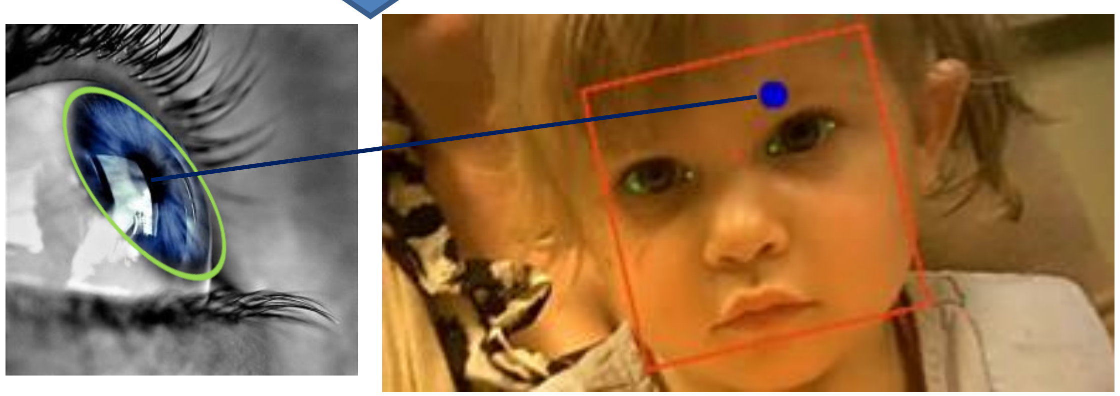
Key Idea #1
Detect child's face to interpret examiner's point of gaze

Key Idea #2
Detect child's gaze direction relative to camera (proxy for examiner)

Omron OKAO library

Technical Details

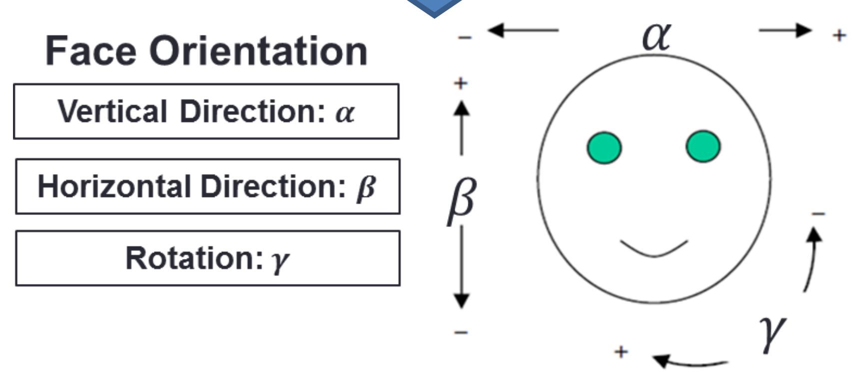
SMI Eye Tracking Glasses

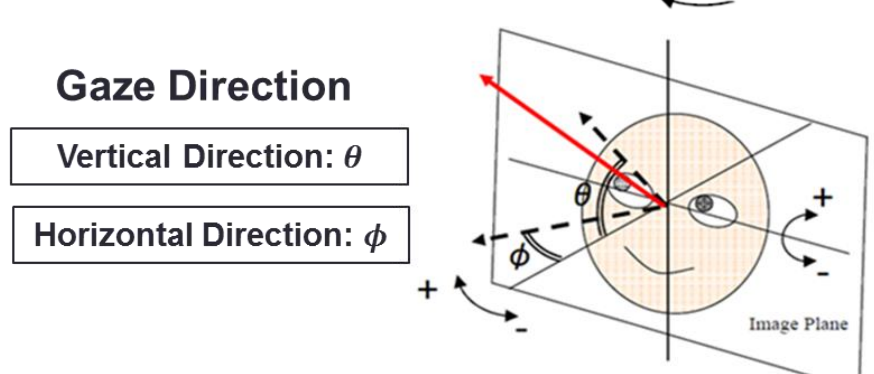


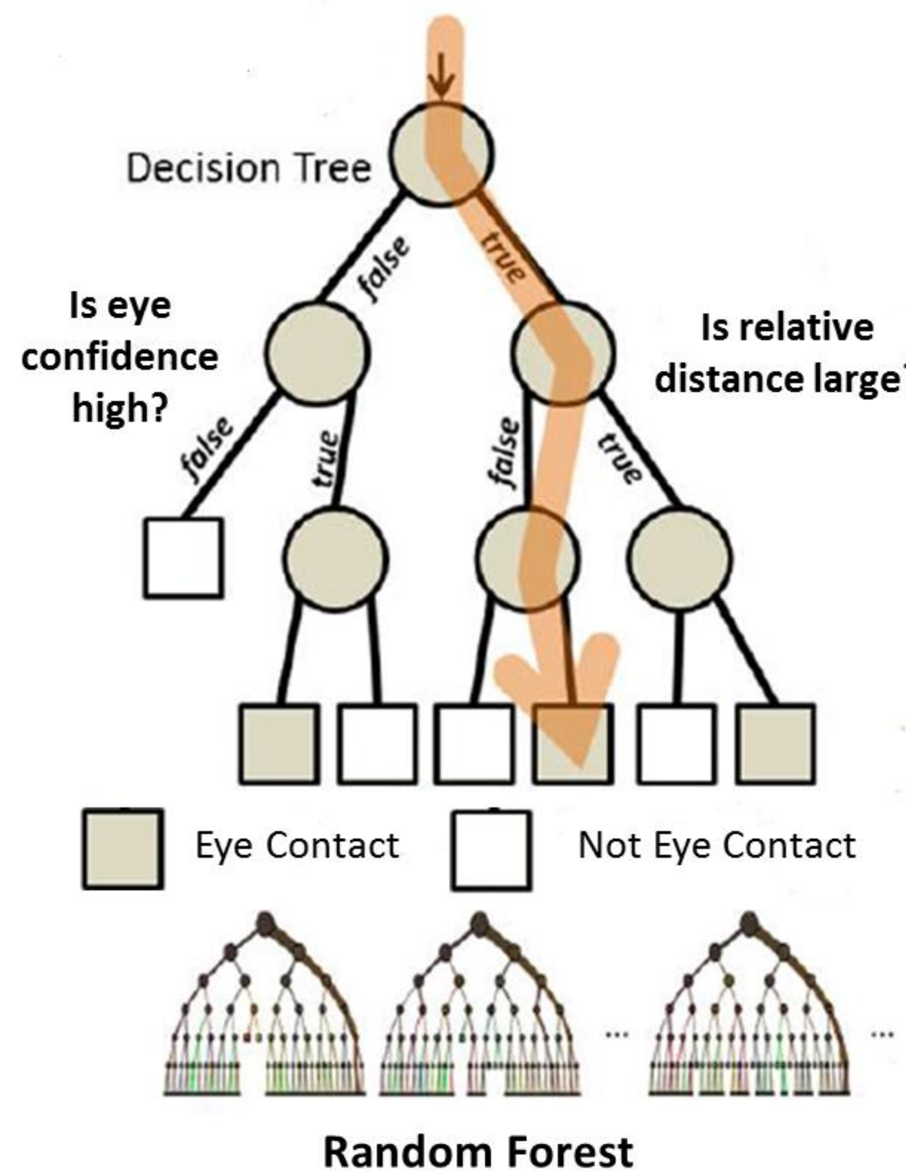
Features

Relative Location (Gaze - Eyes), Face orientation, Gaze Direction …

Omron OKAO Vision Library

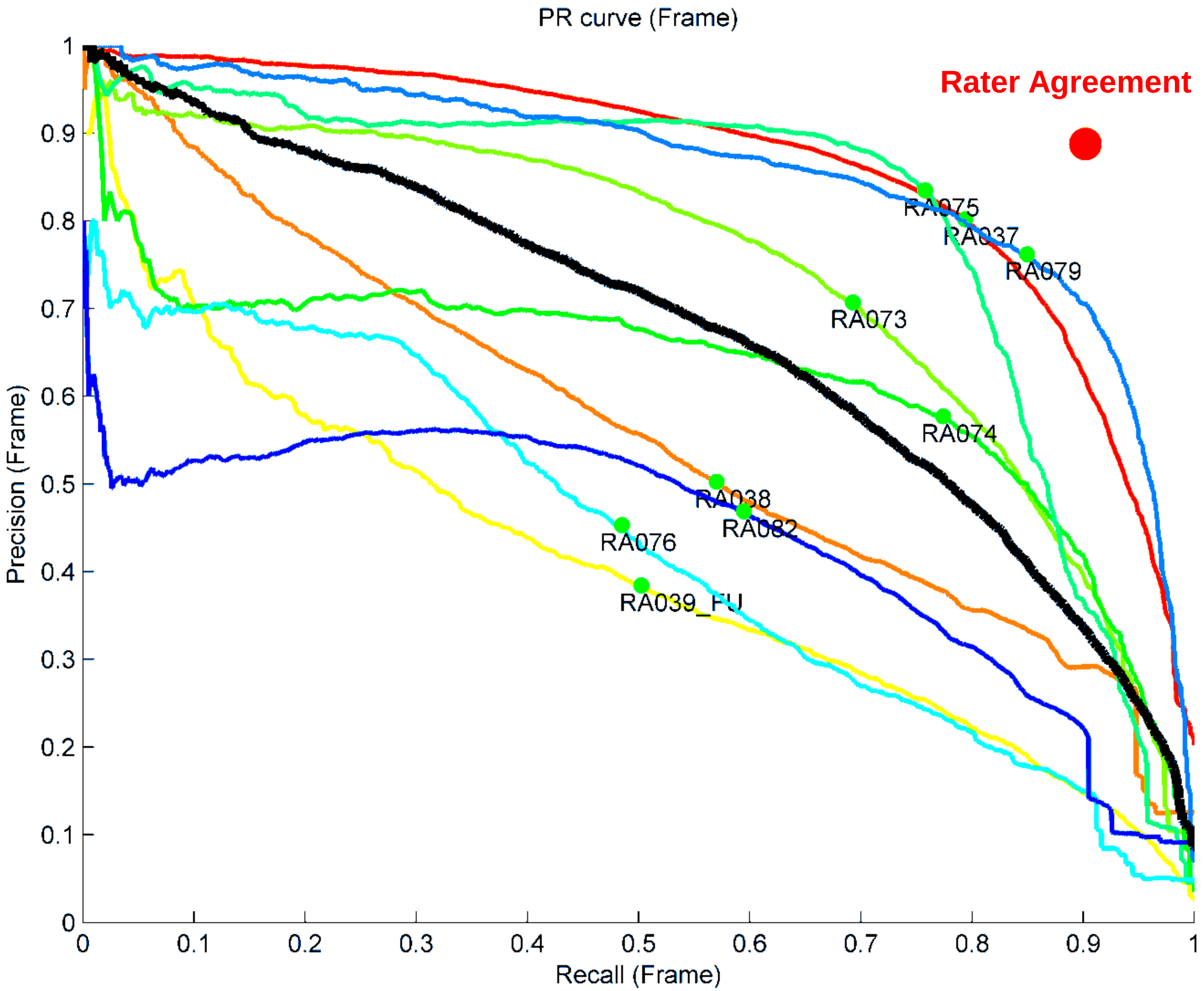






Results

Quantitative Results: Precision/Recall



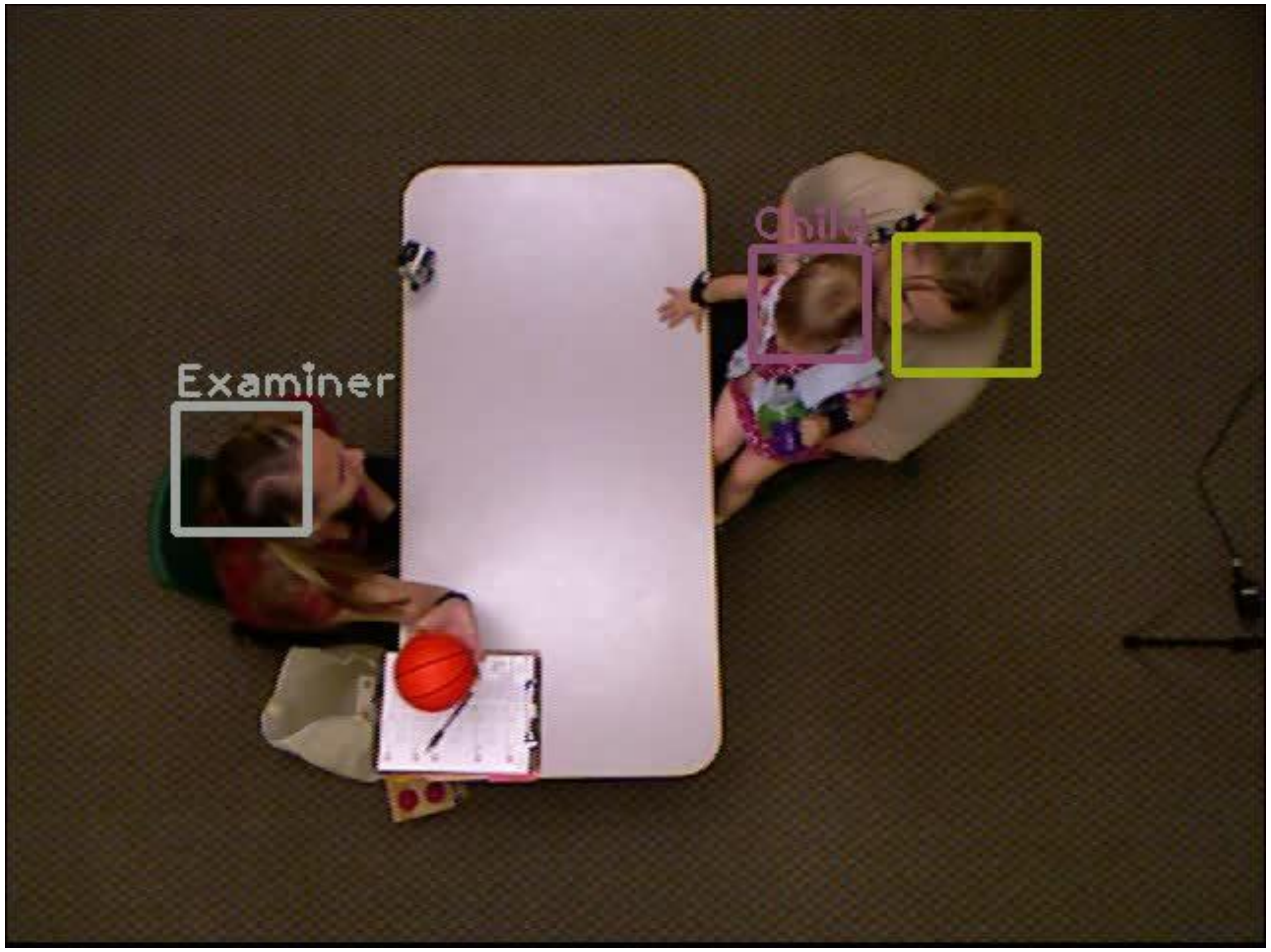
- Each curve stands for a session
- **Green dots:** best F1 scores for each session
- **Black curve:** average over all sessions

Applications of BI in Autism

- Detecting response to name
- Detecting eye contact
- Recognizing gestures
- Predicting engagement in R-ABC

Tracking by Detection:
Hierarchy of Template Ensembles

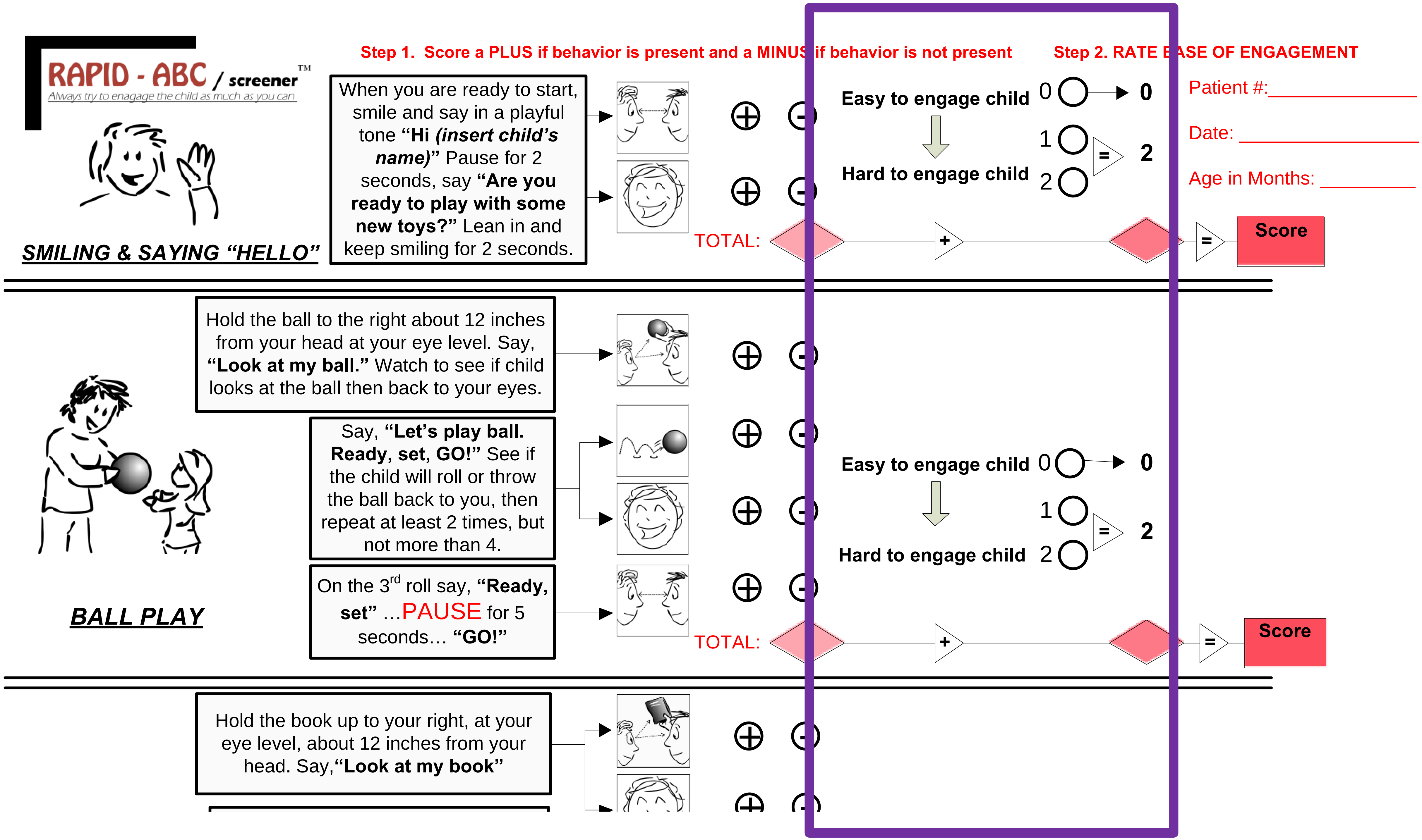
- Tracker exploits RGB plus depth from Kinect.
- Template Ensembles dynamically updated to model object appearance.
- Tracker Hierarchy decides the best tracking strategy for each tracker.
- Tracker is automatic, and there is no intervention needed to correct lost tracks.



Tracker subsystem publicly available (AVSS 2012).

Stan Sclaroff, Liliana Presti (Boston University)

Predicting Engagement

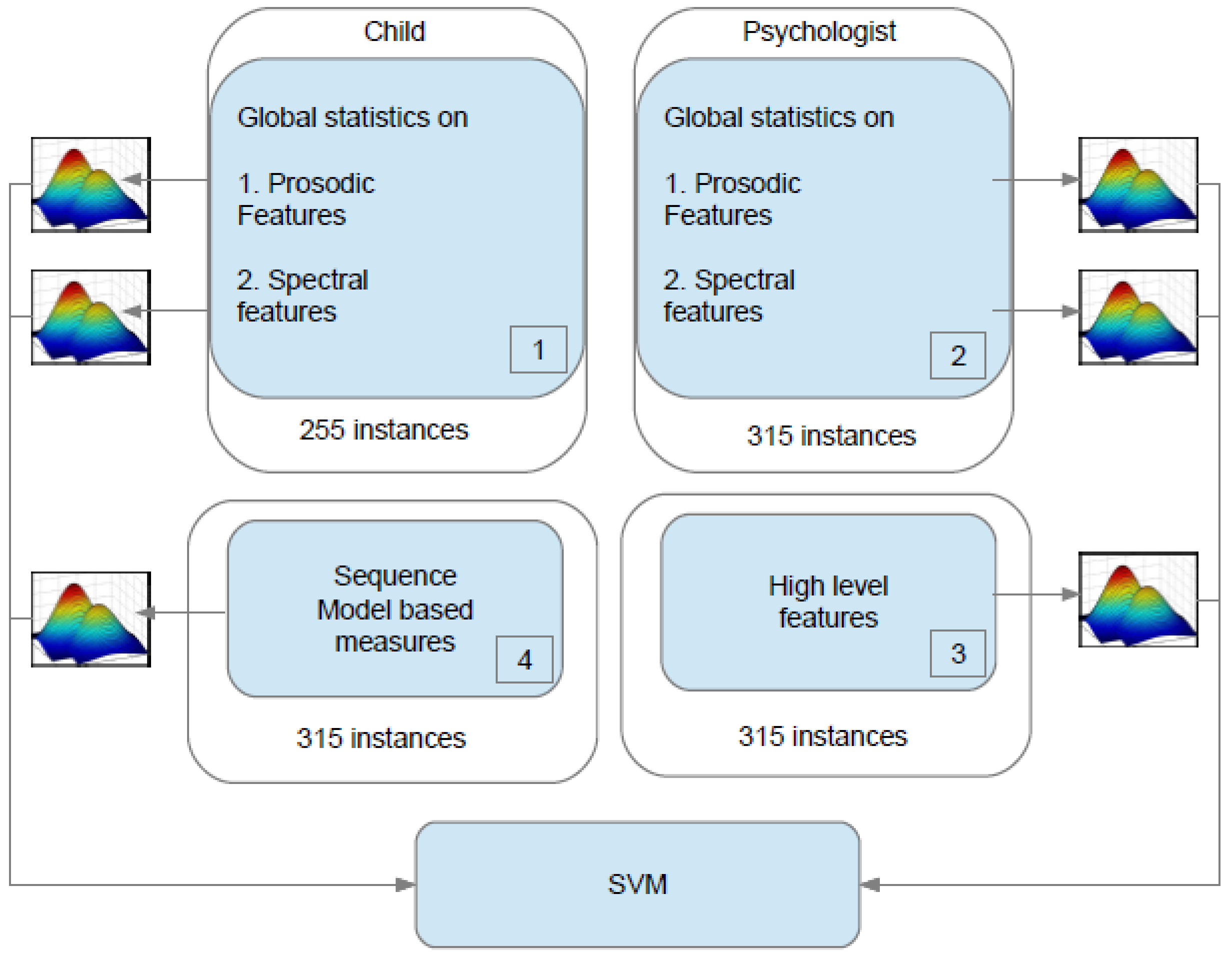


Three Approaches to Engagement

- Acoustic cues
  - Pitch, intensity, jitter, shimmer
  - Computed from child and examiner utterances
- Speech event cues (from diarization)
  - Duration and number of speech segments, patterning, etc.
- Physiological cues
  - EDA features (slope, peak amplitude, etc.)
  - Physiological linkage features (e.g. correlation)

Acoustic Features

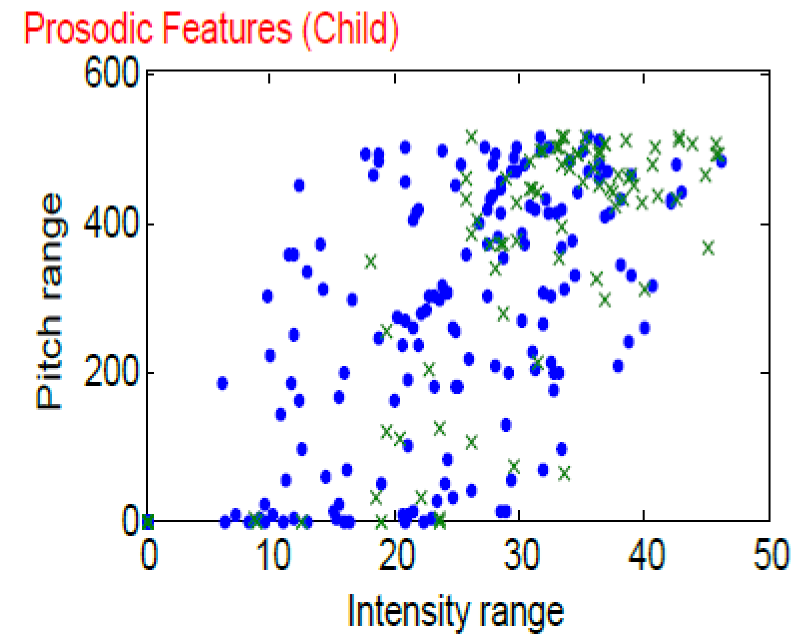
Classifier Architecture



Gupta et. al. Ubicomp 2012 (USC)

Feature Accuracy

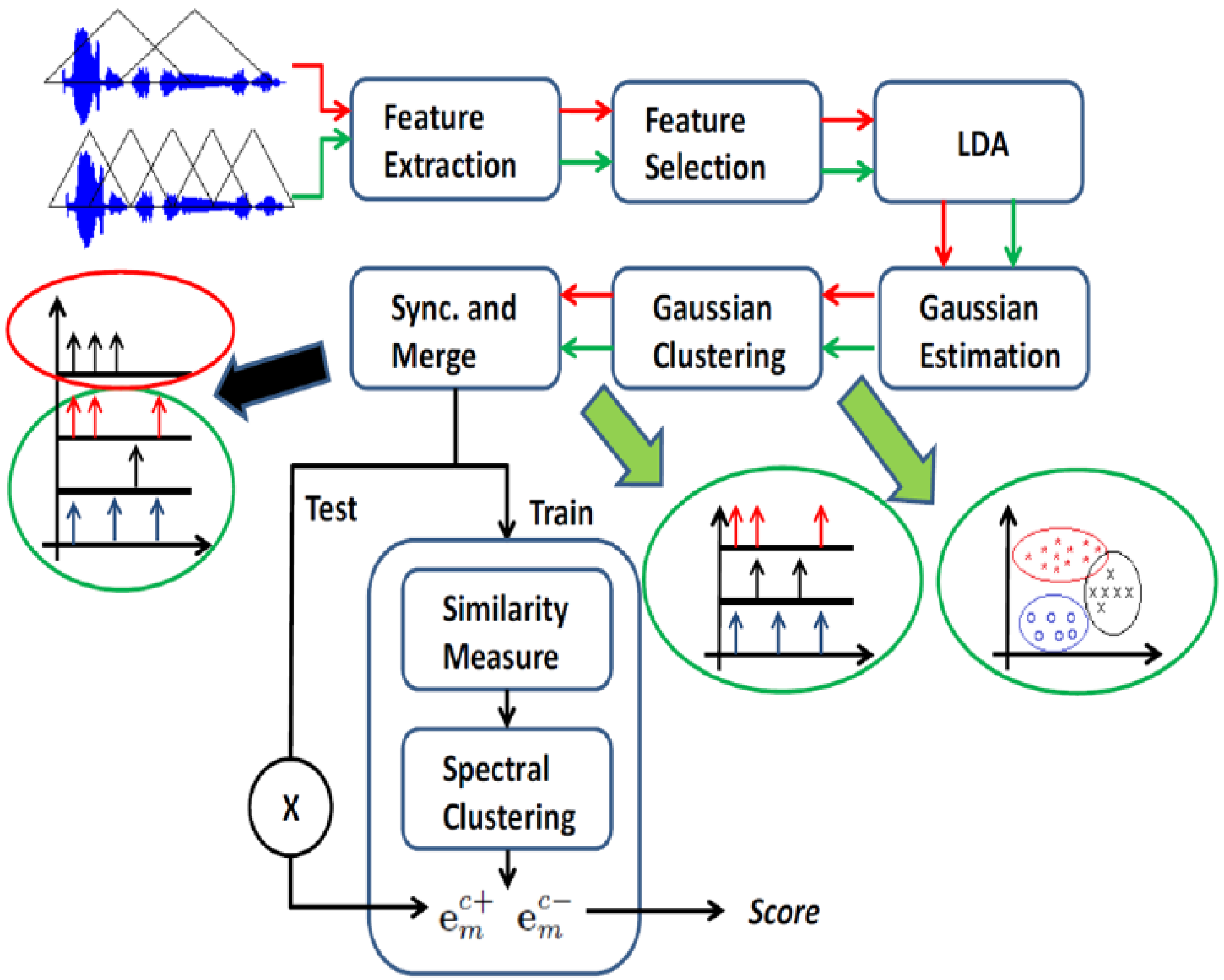
Prosodic Features	Child	59.01
	Psyc.	54.30
Spectral Features	Child	67.15
	Psyc.	65.17



Child's acoustic features better than examiner's

Event Features

Classifier Architecture



Top Features

Order	Feature	Type
1	Number of Child Speech Segments	Event
2	Number of E-to-C	Event
3	audSpec-Rfilt-sma-de[3]-upleveltime90	Spectral
4	mfcc-sma-de[7]-qregc1	Spectral
5	pcm-RMSenergy-sma-de-percentile1.0	Energy
6	Duration of cross-talk	Event
7	F3-percentile50	Formant
8	Number E-to-C / (number of E segments)	Event
9	mfcc-sma[2]-linregc1	Spectral
10	Bandwidth2-percentile25	Formant
11	F0-sma-qregc2	Prosodic

Rehg et. al. CVPR 2013 (GT & BU)

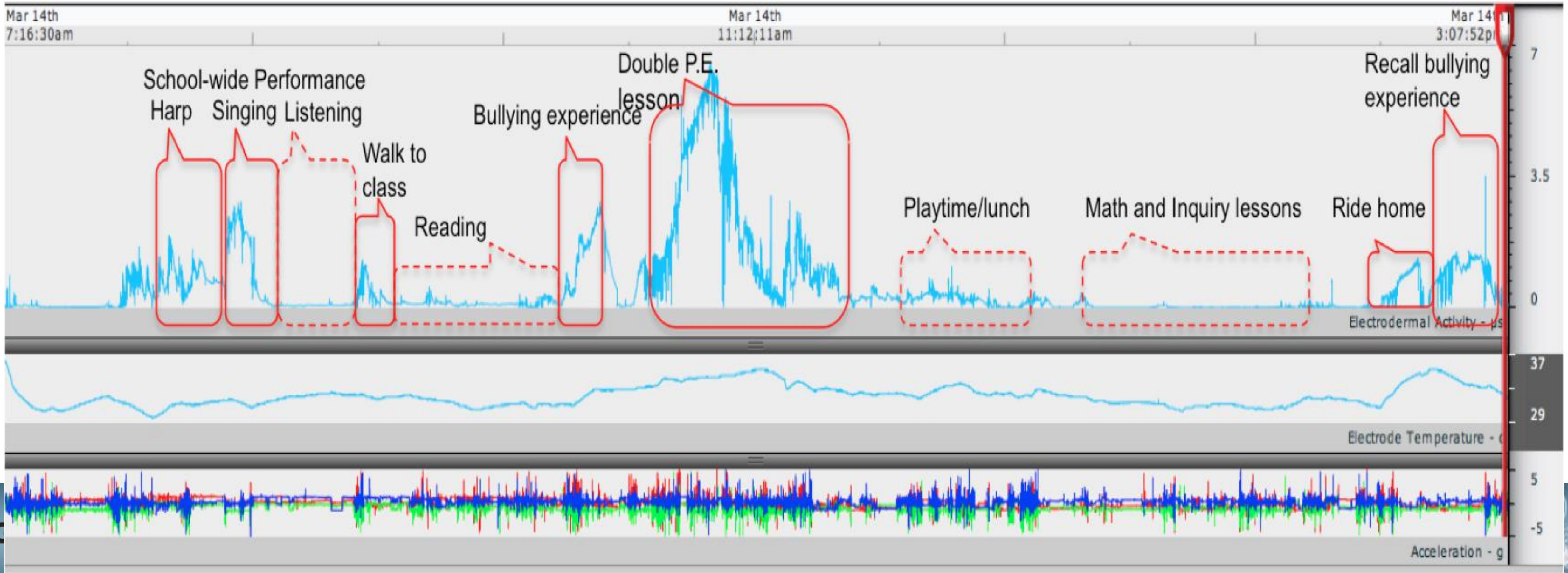
- Most informative event-based features:
  - Number of child speech segments
  - Number of examiner-to-child transitions

Affectiva Q Sensor

Picard and Goodwin

Q™ Sensor

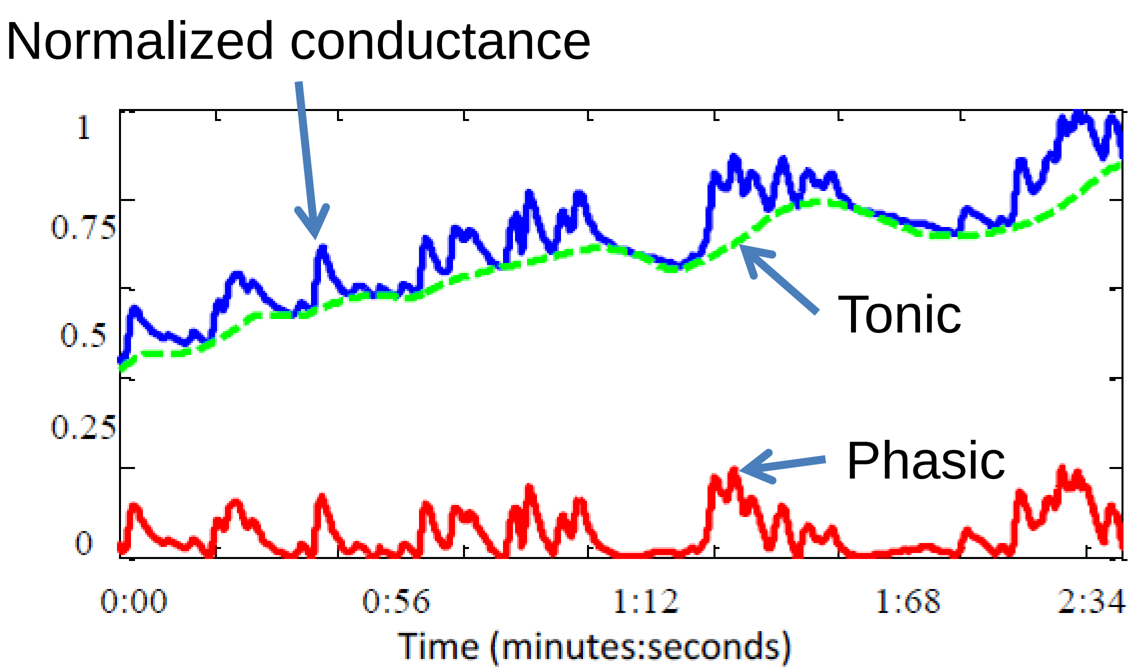
Electrodermal activity over a school day (6 year old girl)



Q Sensor Specs

- Modalities (sampled at 32 Hz)
  - Electrodermal activity
  - 3-axis accelerometry
  - Skin temperature
- Manually synchronized with video and audio
- Provides measurement of sympathetic nervous system activity (stress, arousal)
- No longer available commercially
  - (Hopefully) a temporary condition
  - Other vendors providing similar products (e.g. BodyMedia/Jawbone)

EDA Features



Riobo et. al. (GT & MIT)

Signal Features
- Tonic range
- Phasic maximum

Linkage Features
- Pearson cor. (tonic)
- Canonical cor. (phasic)

- Signal features (90% accuracy) and Linkage features (89%) were comparable
- Best combination yielded 97% accuracy

Summary of Engagement Prediction

- Examiner's behavior provides key features for engagement prediction
- Multi-modal features (acoustic, EDA, activity) are clearly informative about engagement
- Challenges
  - Going beyond "black box" prediction of ratings to identifying mid-level featueres (e.g. joint attention)
  - Single engagement rating is too coarse to capture complex behavior patterns

Summary

- Dyadic social interactions are a challenging domain for multimodal analysis
  - MMDB is a new large dataset of adult-child interactions
- Development and its derailments (e.g. autism) are a key context with potential for impact
- Technologies make automated assessments possible in lab settings

BI for Smoking Cessation

- Smoking as a public health concern
- Physiological sensors
- Possible applications

Smoking as Dependence: Confessions of a Smoker

- He smoked 22-40 cigars per day.

- "To cease smoking is the easiest thing I ever did. I ought to know because I've done it a thousand times."

- "As an example to others, and not that I care for moderation myself, it has always been my rule never to smoke when asleep* and never to refrain when awake." --70th birthday speech

- * "He always went to bed with a cigar in his mouth, and sometimes, mindful of my fire insurance, I went up and took it away, still burning, after he had fallen asleep." William Dean Howells.

Samuel Langhorne Clemens

Slide by Noboru Hiroi

“Nicotine is not Addictive”

THE WHOLE TRUTH? In 1994 seven tobacco CEOs—now being investigated for perjury—swore before Congress that nicotine is not addictive

Slide by Noboru Hiroi

Nicotine is an Addictive Substance

- Smokers prefer nicotine-containing cigarettes to de-nicotinized cigarettes.

- Smokers experience withdrawal when switching to light cigarettes.

- Nicotine replacement alleviates withdrawal symptoms.

How easily would you develop dependence?

32% **Nicotine**

23% **Heroin**

17% **Cocaine**

15% **Alcohol**

11% **Stimulants other than cocaine (d-amphetamine and methamphetamine)**

9% **Cannabis (marijuana, hashish, or both)**

9% **Anxiolytics/sedative and hypnotic drugs (secobarbital, diazepam, flurazepam, alprazolam, and triazolam)**

8% **Analgesics (morphine, propoxyphene, and codeine)**

% of individuals with dependence among extra-medical users.

n=8,098, 15-54 years old. **(Anthony et al., 1994)**

Slide by Noboru Hiroi

Actual Causes of Death

CW PHS
CENTER FOR WIRELESS & POPULATION HEALTH SYSTEMS

Year 2000: 2.4 Million deaths in US

Tobacco: 435,000 (18.1%)
Poor Diet and PI: 365,000 (15.2%)
Alcohol consumption: 85,000 (3.5%)
Microbial Agents: 75,000 (3.1%)
Toxic Agents: 55,000 (2.3%)
Motor Vehicle Crashes: 43,000 (1.8%)
Deaths from Firearms: 29,000 (1.2%)
Others: 37,000

Total: 1,124,000 (47%)

What about the other half?

Mokdad, JAMA 2004

The Exposome

CW PHS
CENTER FOR WIRELESS & POPULATION HEALTH SYSTEMS

At it's most complete, the exposome encompasses life-course environmental exposures (including lifestyle factors), from the prenatal period onwards.

-- Christopher Paul Wild

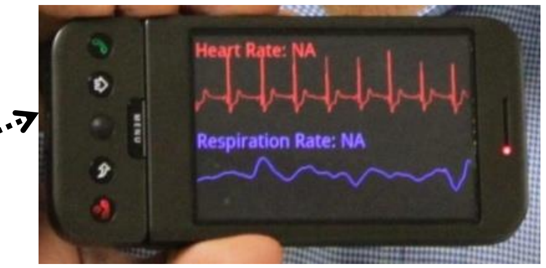






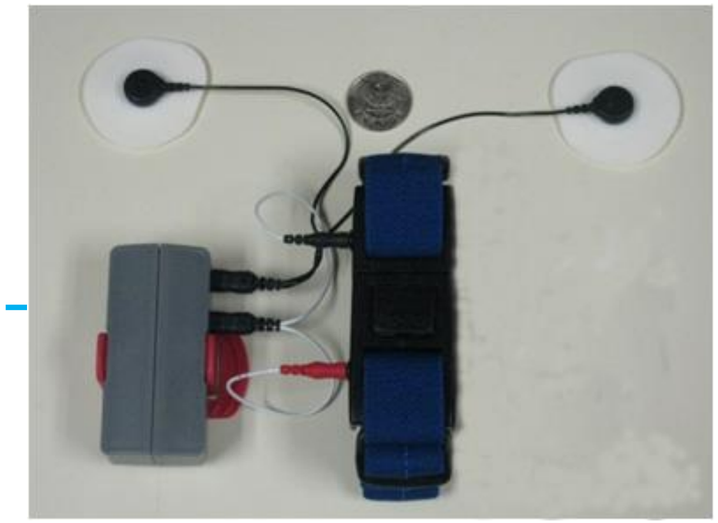

AutoSense Wearable Sensor Suite

Wireless



Android G1 Smart Phone

Armband sensors: Alcohol (WrisTAS), Temp, GSR, Accelerometer



Chestband sensors: ECG, Respiration, GSR, Accelerometer, Temp

Ten wireless sensors in two wearable units

Long lifetime (10+ days)

Used in 3 studies (n=60) for automated modeling of stress, conversation

Being used in 4 ongoing studies (n=85, 1-4 weeks of field wearing) for automated modeling of smoking, drinking, drug usage, and craving

(Ertin, et. al., ACM SenSys 2011)

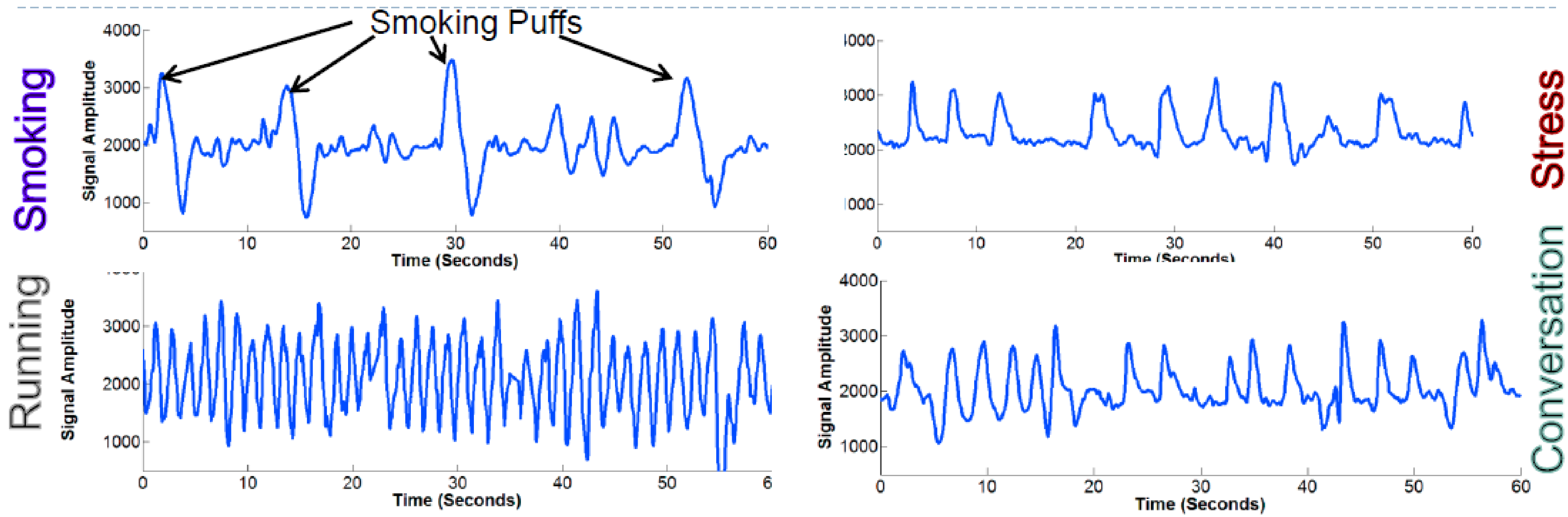
Detecting Smoking Events

- Existing devices can measure and display/store **CO** levels in a single breath exhaled through a mouthpiece
- CReSS can provide smoking topography
  - If subjects smokes through CReSS
- These devices require users to remember to use for each smoking
- They may also cause embarassment

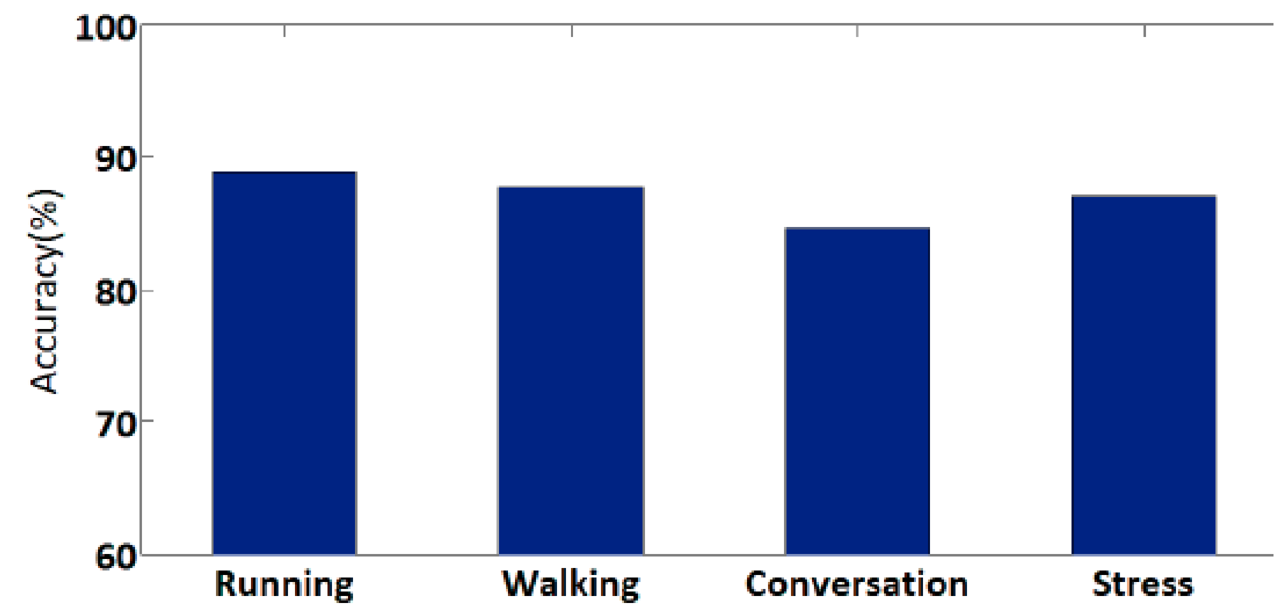
piCO+ and Micro+

CReSS Pocket

Detecting Smoking from Resipiration



- **Data:** 161 puffs from10 daily smokers
- **Evaluation:** Each puff is detected with 86.7% accuracy
- **Research:** Need to develop models for detecting entire smoking episodes
  - By leveraging smoking topography, and
  - By using other contexts (e.g., activity)



(Ali, et. al., *ACM IPSN*, 2012)

Applications in Smoking Cessation

- Identifying person-specific triggers for relapse
- Quantifying the effect of environmental stimuli on smoking behavior
- Supporting just-in-time interventions for more effective smoking cessation

Summary

- Reduction in smoking is a significant public health issue
- Physiological sensing can provide a detailed portrait of smoking-related behavior: smoking acts, conversation, and stress
- More work is needed to develop and test existing behavioral theories based on field data

Georgia Tech Collaborators

Computer Science

Dr. G. Abowd

Dr. M. Clements

Dr. A. Fathi

Y. Li

Psychology

Dr. A. Rozga

Dr. R. Arriaga

Conclusion

- Behavior imaging technology has great potential to revolutionize the measurement of behavior
- Applications range from child developmental disorders to health-related behaviors
- Join us in creating this new discipline!

Questions?