Opportunities for computing to improve measurement of behavior in ASD

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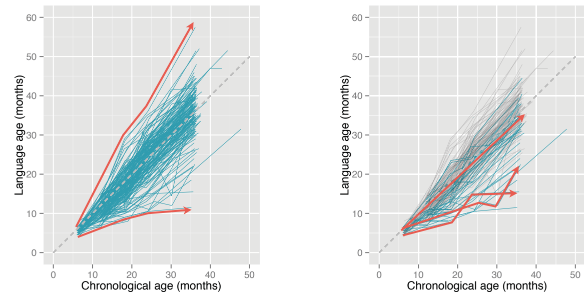
The challenge: Measuring development in ASD



The challenge: Measuring response to treatment in ASD

No gold-standard instruments: **289 unique tools** identified in a recent review, **61% used just once**

10% of tools include **direct observation** of specific skills

Strong reliance on **checklists** & **parent reports**

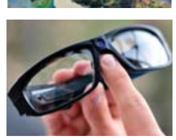
Bolte, E. E., & Diehl, J. J. (2013). Measurement tools and target symptoms/skills used to assess treatment response for individuals with autism spectrum disorder. Journal of Autism and Developmental Disorders, 43(11), 2491-2501.

Need **dense**, **continuous**, and **objective** measures of behavior that are **sensitive to change** and can ultimately be deployed in a range of **natural settings**

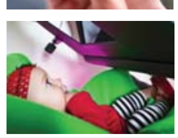
Research Vision: Computational Behavioral Science

We can transform how we **measure**, **analyze**, and **understand** behavior by leveraging advances in:

sensing technology
wearables
computational analysis methods



Computational Behavioral Science: A few examples*

Automated detection of **eye contact** in point-of-view videos

Detection & classification of **challenging behaviors** from body-worn accelerometers

Quantifying caregiver-infant **proximity** using depth cameras

**This interdisciplinary research was done in collaboration with colleagues at Georgia Tech, the Marcus Autism Center, Newcastle University, University of Washington, & University of Miami. Please see the acknowledgments slide*

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Challenges in measuring socially-directed gaze



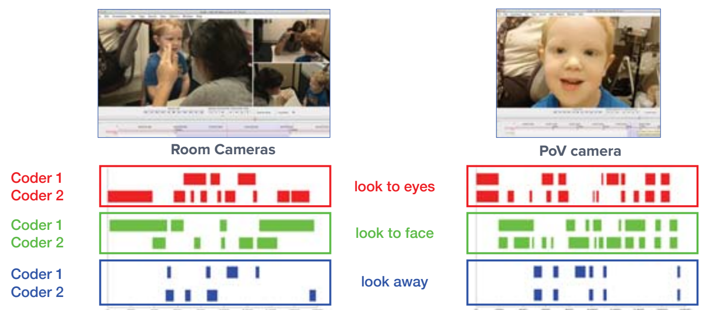
Reliance on environment-mounted cameras

Gaze to face as a proxy for gaze to eyes

Eye contact: a new lens on an old phenomenon


Pivothead Kudu
point-of-view (PoV) camera

Comparing agreement between human coders



19 36-month-olds (9 ASD/10 non-ASD); 90-sec clip (snack, song, facial expressions)

Comparing agreement between human coders


Room Cameras


PoV camera

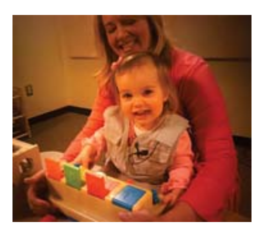
Inter-rater agreement on **looks to eyes** (weighted kappa)
higher for PoV camera (0.69) compared to room cameras (0.44)

Edmunds, S., Li, Y., Rozga, A., Ibanez, L., Karp, E., Rehg, J., & Stone, W. (2014). A novel, ecologically valid approach to measure eye-to-eye gaze in young children during naturalistic social interactions. Presented at the SRCD Special Topic Meeting: Developmental Methodology, September 11-13, San Diego CA.

Automated detection of eye contact in PoV video

Key insight:

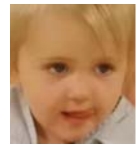
Detect child's gaze direction relative to camera (proxy for examiner's eyes)



Challenges in automated detection of eye contact

Eyes are not sufficient

Challenges in automated detection of eye contact



Eyes are not sufficient

Dependency between head pose and gaze

Pipeline for automated detection of eye contact

In **each frame** of the PoV video

Pipeline for automated detection of eye contact

We **detect** the child's **face**

(*OMRON OKAO Vision Library)*

Pipeline for automated detection of eye contact

We then **localize facial landmarks** and **estimate** the **head pose**

(IntraFace; De la Torre et al., CMU)

Pipeline for automated detection of eye contact

Using **human coded examples** of eye contact, we train a **classifier** to predict eye contact **in each frame**

We use temporal smoothing & merge frame-level results to predict **eye contact events**

For more details, see: Ye, Z., Li, Y., Liu, Y., Bridges, C., Rozga, A., & Rehg, J. "Detecting bids for eye contact using a wearable camera." Proceedings of the 11th IEEE International Conference on Automatic Face and Gesture Recognition (FG 2015).

Automated detection of eye contact: A video example

[video removed]

Ye, Z., Li, Y., Liu, Y., Bridges, C., Rozga, A., & Rehg, J. "Detecting bids for eye contact using a wearable camera." Proceedings of the 11th IEEE International Conference on Automatic Face and Gesture Recognition (FG 2015).

Dataset for evaluation of automated detection of eye contact

12 child-adult interactions

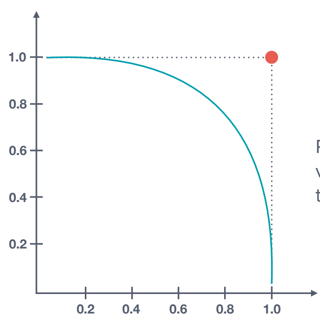
Toddlers 18-28 months of age

3-5 minute, semi-structured table-top play interaction

Full data (200+ sessions) available via the **Multimodal Dyadic Behavior Dataset** (cbi.gatech.edu/mmdb)

Precision-Recall curve explained

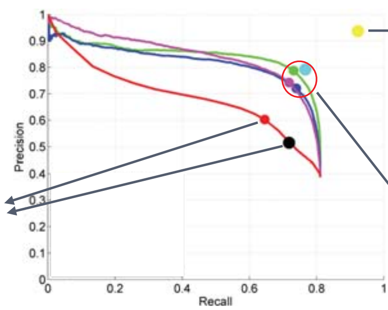
Precision
Proportion of true positives among the automatically detected events



Precision and recall vary with the classifier threshold(s)

Recall (sensitivity)
Proportion of behaviors correctly detected as such

Accuracy of automated eye contact detection



average across 5 human coders

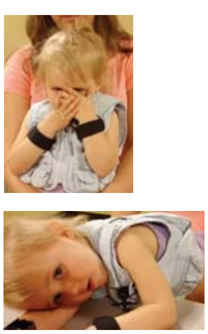
baseline methods (state of the art)

Our method, frame level detection

Recall: 76.6%
Precision: 79.2%

Ye, Z., Li, Y., Liu, Y., Bridges, C., Rozga, A., & Rehg, J. "Detecting bids for eye contact using a wearable camera." Proceedings of the 11th IEEE International Conference on Automatic Face and Gesture Recognition (FG 2015).

When does automated detection miss eye contacts?



Our method **does not detect the child's face** in 17% of frames that contain eye contact (based on human coding)

Face detection method was trained on images of adult faces captured by stationary cameras

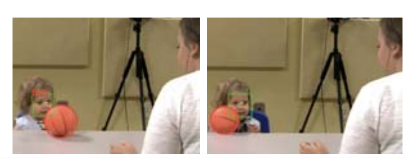
Challenges introduced by **motion blur**, **occlusions**, **head rotations**

Automated detection of eye contact: Next steps

Capturing & detecting eye contact in a clinical setting, sensitivity to change (pilot at Marcus with Dr. Caitlin Delfs)

[video removed]

Detecting gaze to objects & gaze shifts from objects to face



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Detection & classification of **problem behaviors** from body-worn accelerometers

Quantifying mother-infant proximity using depth cameras

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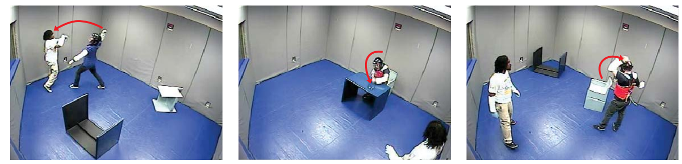
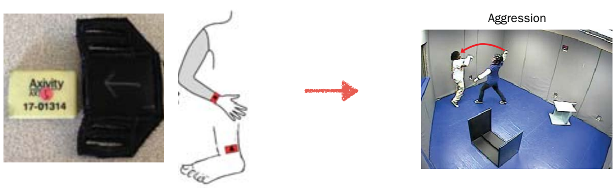
Challenges in measuring problem behaviors



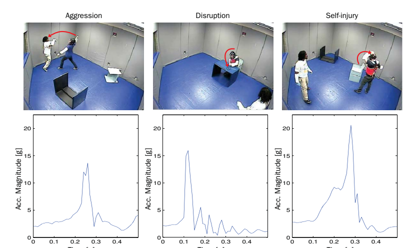
Live scoring is clinical best practice, but is time- and resource-intensive
Parent & teacher reports do not capture precise, time-based frequencies
No measures of severity, a key potential treatment target & outcome variable

Detecting problem behaviors using wearable accelerometers



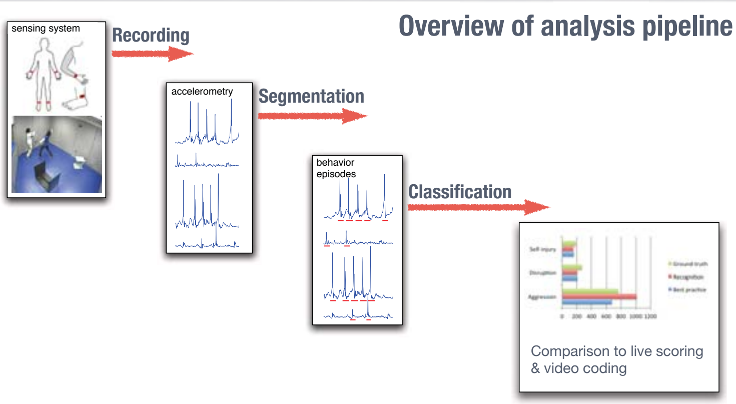
Problem behaviors involve **intensive movements** that can be **captured** with body-worn **accelerometers**

Classifying problem behaviors using wearable accelerometers



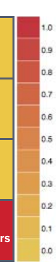
Different classes of problem behavior leave **unique "signatures"** in the accelerometry streams (e.g., **signal energy**, **orientation change**)

Overview of analysis pipeline



Confusion matrix explained

	Other	Agg.	Dis.	Self Inj.
Other	# behaviors	0	0	0
Aggression	0	# behaviors	0	0
Disruption	0	0	# behaviors	0
Self Injury	0	0	0	# behaviors

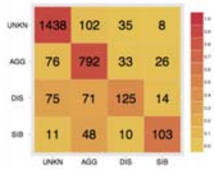


Actual: behaviors in each class identified by video coding

Agreement (%)

Predicted: Behaviors in each class identified by the classifier

Accuracy of automated measurement compared to manual coding from video



Mock (simulated) data from 5 Marcus staff
1214 problem behavior events

Average accuracy across limbs: 80%

Mock data model applied to data from 3 individuals with ASD

Average accuracy across limbs: 69-88%

Ploetz, P., Hammerla, N., Rozga, A., Reavis, A., Call, N., & Abowd, G. Automatic assessment of problem behavior in individuals with developmental disabilities. Proceedings of the 2012 ACM Conference on Ubiquitous Computing, UbiComp, 2012, pp. 391-400.

Automated measurement of problem behaviors

Objective, direct measure of **frequency** of problem behavior types

New clinically-relevant dimension: **intensity** as a measure of **severity**

Next steps:

model adaptation & personalization
sensitivity to pre/post change
comparison to parent report measures
feasibility of in-home deployment by caregivers

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From qualitative ratings to quantitative insight

Strange Situation observation → Expert ratings → Attachment classifications

Rating scale: Proximity- and Contact-Seeking Behavior

"…the **intensity** and **persistence** of the baby's efforts to **gain** (or to regain) **contact** with - or, more weakly, **proximity** to - a person."

4. Obvious desire to achieve physical contact, but with ineffective effort or lack of initiative OR active effort to gain proximity without persisting to toward contact

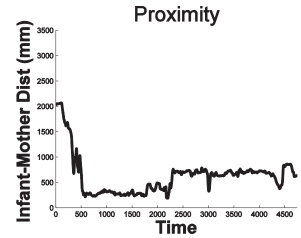
*"(b)…**begins to approach** the adult but **goes only part of the distance**, and either with or without a further signal **waits** for the adult, who **completes the pick-up**"*

*"(d)…makes **repeated full approaches** either **without completing contact** or with only **momentary contact**"*

2. Minimal effort to achieve physical contact or proximity

"seems to be making a ***full approach****, but* ***changes direction*** *to* ***approach something else****, or* ***passes beyond the adult*** *- for example, to go out the door, to the door, or to explore something beyond the adult,* ***without pause*** *for any kind of interaction en route"*

From qualitative ratings to quantitative insight



Infant approach behavior and mother-infant proximity are key

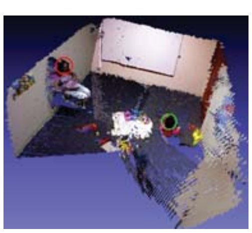
Deriving measures of approach & proximity from video

We **capture** the interaction using color+depth (kinect) cameras

Deriving measures of approach & proximity from video

We **track** mom and infant in 2D (semi-automated/interactive tracking)

Deriving measures of approach & proximity from video

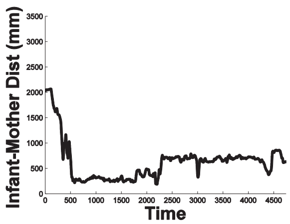


We **fuse** data from multiple kinects, and **track mother** and **infant** in **3D**

A video example of automated 3D tracking

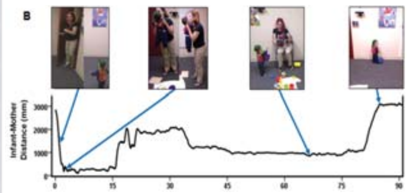
[video removed]

Deriving measures of approach & proximity from video



We calculate **mother-infant distance** over time

Proximity measure captures individual differences in approach and exploration



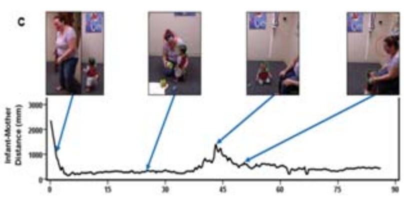
Baby B approaches mom, who picks him up

Stays near mom for a while

Resumes exploration & play

Emily B. Prince, Katherine Martin, Devon Gangi, Rongfang Jia, Daniel Messinger, Arri Ciptadi, Agata Rozga, and Jim Rehg (2015). Automated measurement of dyadic interaction predicts expert ratings of attachment in the Strange Situation. Poster presented at the Annual Meeting of the Association for Psychological Science, May 21-25, New York, NY.

Proximity measure captures individual differences in approach and exploration



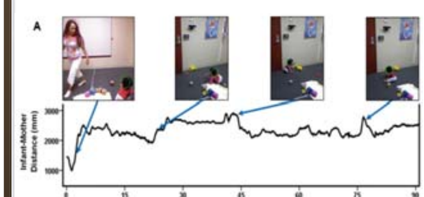
Baby C approaches mom

Stays near mom throughout (little variability)

Follows mom to the chair, does not resume play

Emily B. Prince, Katherine Martin, Devon Gangi, Rongfang Jia, Daniel Messinger, Arri Ciptadi, Agata Rozga, and Jim Rehg (2015). Automated measurement of dyadic interaction predicts expert ratings of attachment in the Strange Situation. Poster presented at the Annual Meeting of the Association for Psychological Science, May 21-25, New York, NY.

Proximity measure captures individual differences in approach and exploration



Baby A does not approach mom

Maintains her distance throughout, exploring the room

Emily B. Prince, Katherine Martin, Devon Gangi, Rongfang Jia, Daniel Messinger, Arri Ciptadi, Agata Rozga, and Jim Rehg (2015). Automated measurement of dyadic interaction predicts expert ratings of attachment in the Strange Situation. Poster presented at the Annual Meeting of the Association for Psychological Science, May 21-25, New York, NY.

Proximity measure correlates with expert ratings

	Proximity Seeking	Contact Maintenance	Resistance	Avoidance
Average Mother-Infant Distance in Reunion 1	-.54*	-.68**	-.53*	.46*
Average Mother-Infant Distance in Reunion 2	-.47*	-.82**	-.67**	.46*

Emily B. Prince, Katherine Martin, Devon Gangi, Rongfang Jia, Daniel Messinger, Arri Ciptadi, Agata Rozga, and Jim Rehg (2015). Automated measurement of dyadic interaction predicts expert ratings of attachment in the Strange Situation. Poster presented at the Annual Meeting of the Association for Psychological Science, May 21-25, New York, NY.

From proximity measures to objective characterization of interactions

Differentiate “infant approach mom” from “mom approach infant”

Latency & speed of approach

Infant response to mom approach/move away

Infant initiation of contact vs. initiation of exploration

Time spent in contact/proximity

Not specific to measuring attachment!

CBS: What's the next frontier?

What we measure: capture & quantify **novel** behaviors, qualitative dimensions (intensity, variability, latency, timing)

Where we measure it: moving **outside the lab** & into the world

How often we measure it: possibility of **large scale**, dense measurements

Collaborators

Georgia Tech:
Dr. Jim Rehg
Dr. Gregory Abowd
Arridhana Ciptadi
Eunji Chong
Yin Li
Yun Liu
Zhefan Ye

University of Washington
Dr. Wendy Stone
Dr. Lisa Ibanez
Sarah Edmunds
Elizabeth Karp

Marcus Autism Center
Dr. Nathan Call
Dr. Caitlin Delfs
Ally Coleman
Andrea Reavis
Hannah Robinson

Newcastle University
Dr. Thomas Ploetz
Dr. Aftab Khan
Dr. Nils Hammerla

University of Miami:
Dr. Daniel Messinger
Devon Gangi
Rongfang Jia
Katherine Martin
Whit Mattson
Emily Prince
Katherine Zambrana

Computational Behavioral Science

Modeling, Analysis, and Visualization of Social and Communicative Behavior

Project website: cbi.gatech.edu

Multimodal Dyadic Behavior Dataset (MMDB): cbi.gatech.edu/mmdb

Child Study Lab: childstudy.gatech.edu

Georgia Tech
Child Study Lab
NSF
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Questions? Comments?