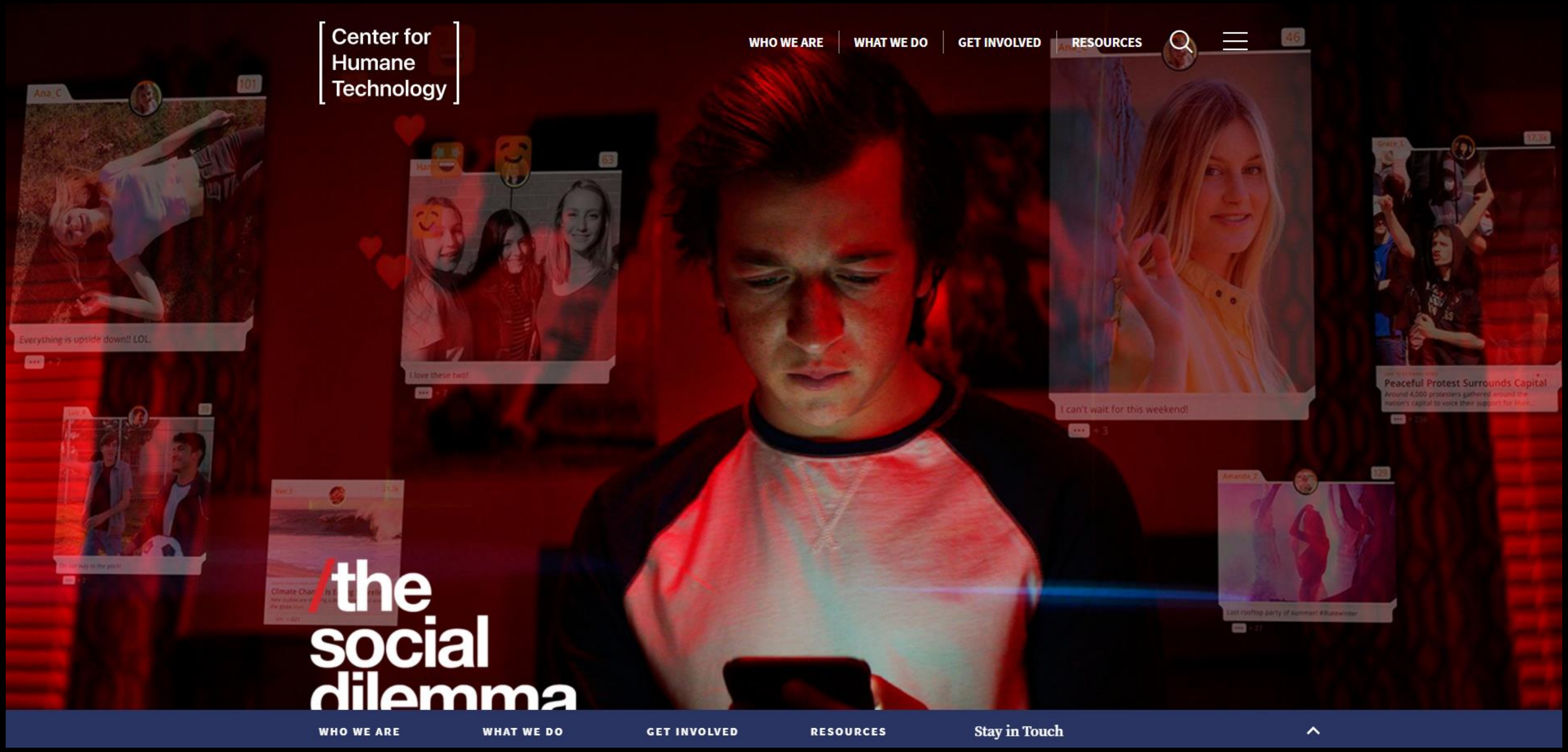
SMIL

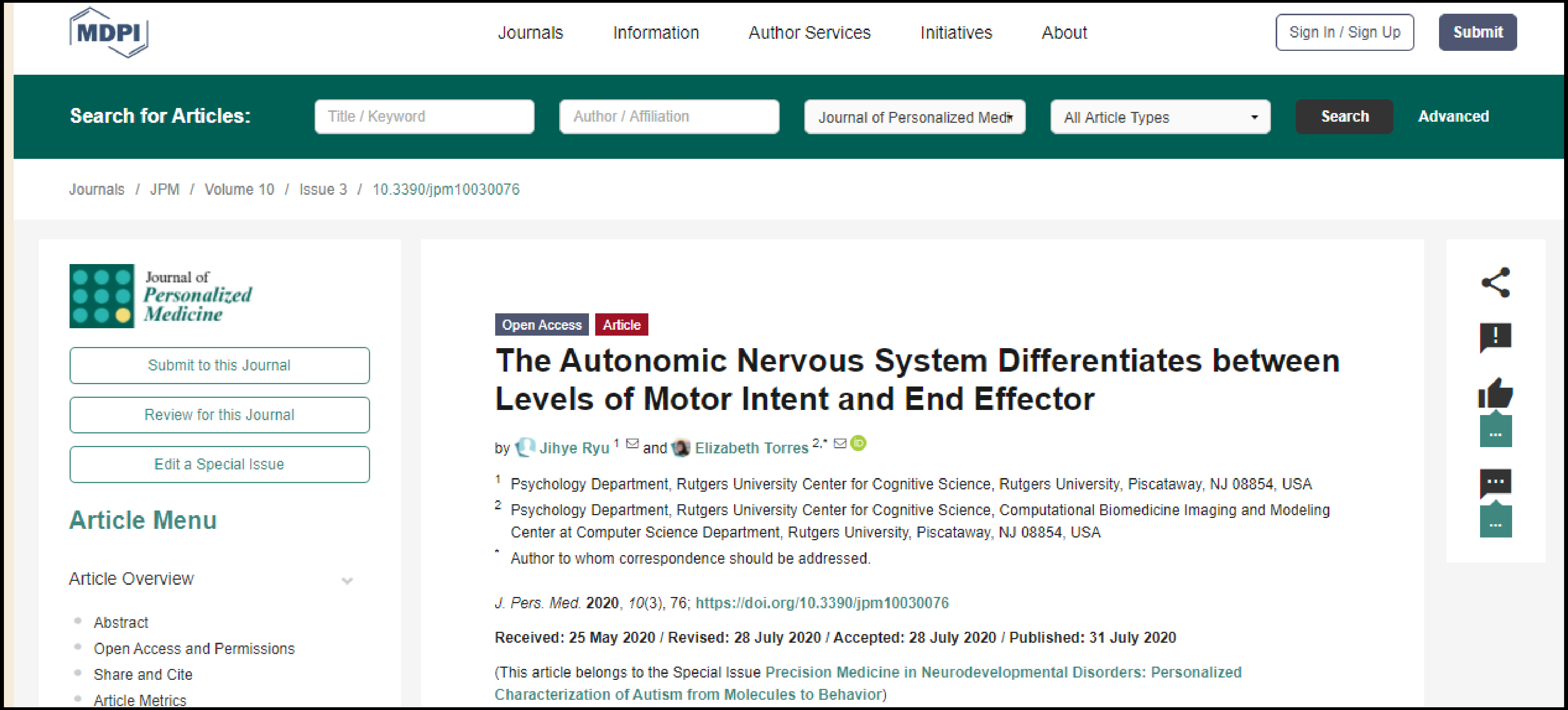
Connecting the Brain to the Body
from Molecules to Complex Social Behaviors

Some Info on the Social Dilemma

- https://www.humanetech.com/discussion-guide-for-technologists



NEXT CLASS: SEPARATING INTENT IN AUTONOMIC SIGNALS FROM INTENT IN KINEMATICS SIGNALS



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Open Access Article

The Autonomic Nervous System Differentiates between Levels of Motor Intent and End Effector

by Jihye Ryu [1] and Elizabeth Torres [2,*]

[1] Psychology Department, Rutgers University Center for Cognitive Science, Rutgers University, Piscataway, NJ 08854, USA

[2] Psychology Department, Rutgers University Center for Cognitive Science, Computational Biomedicine Imaging and Modeling Center at Computer Science Department, Rutgers University, Piscataway, NJ 08854, USA

[*] Author to whom correspondence should be addressed.

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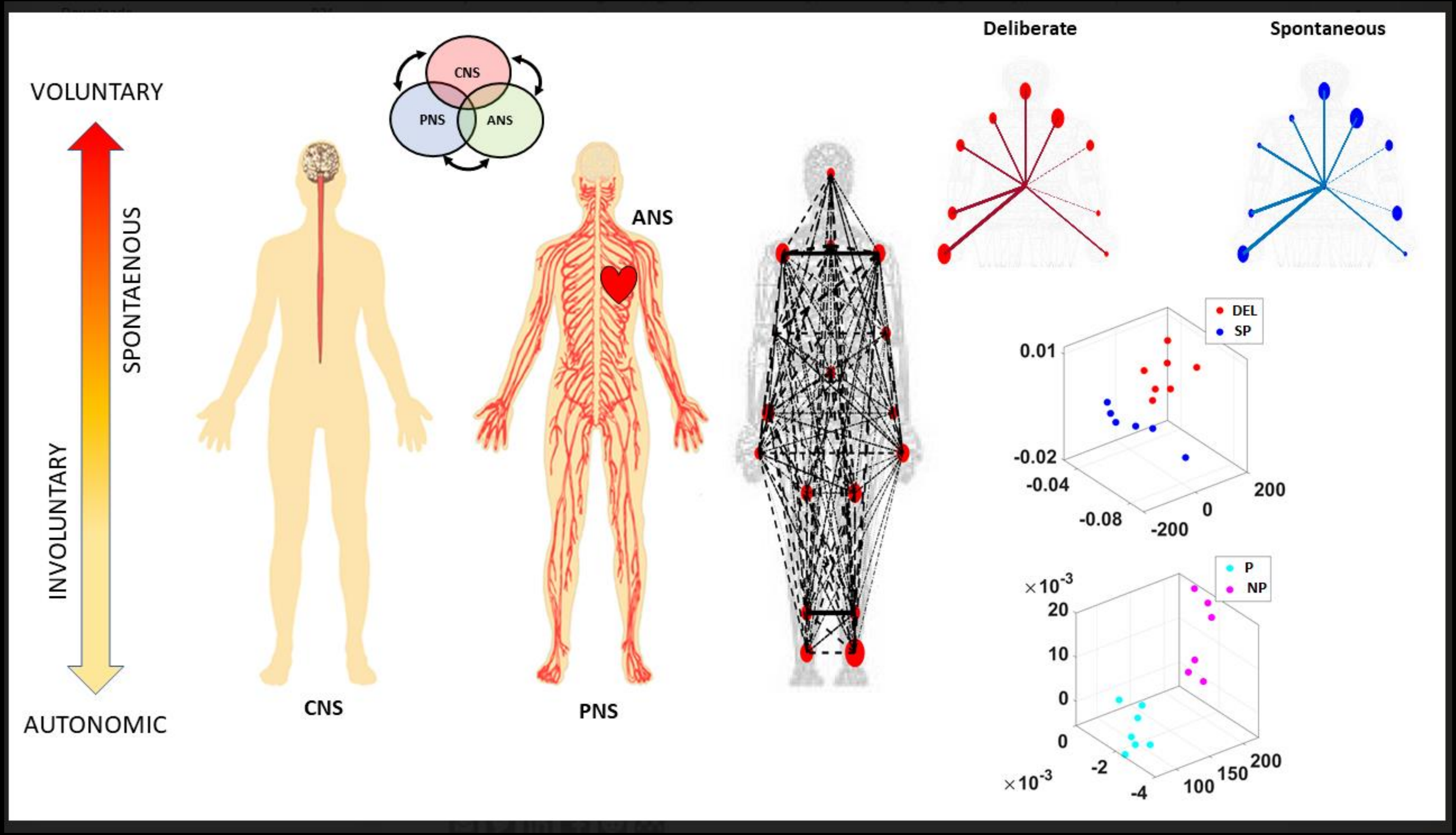
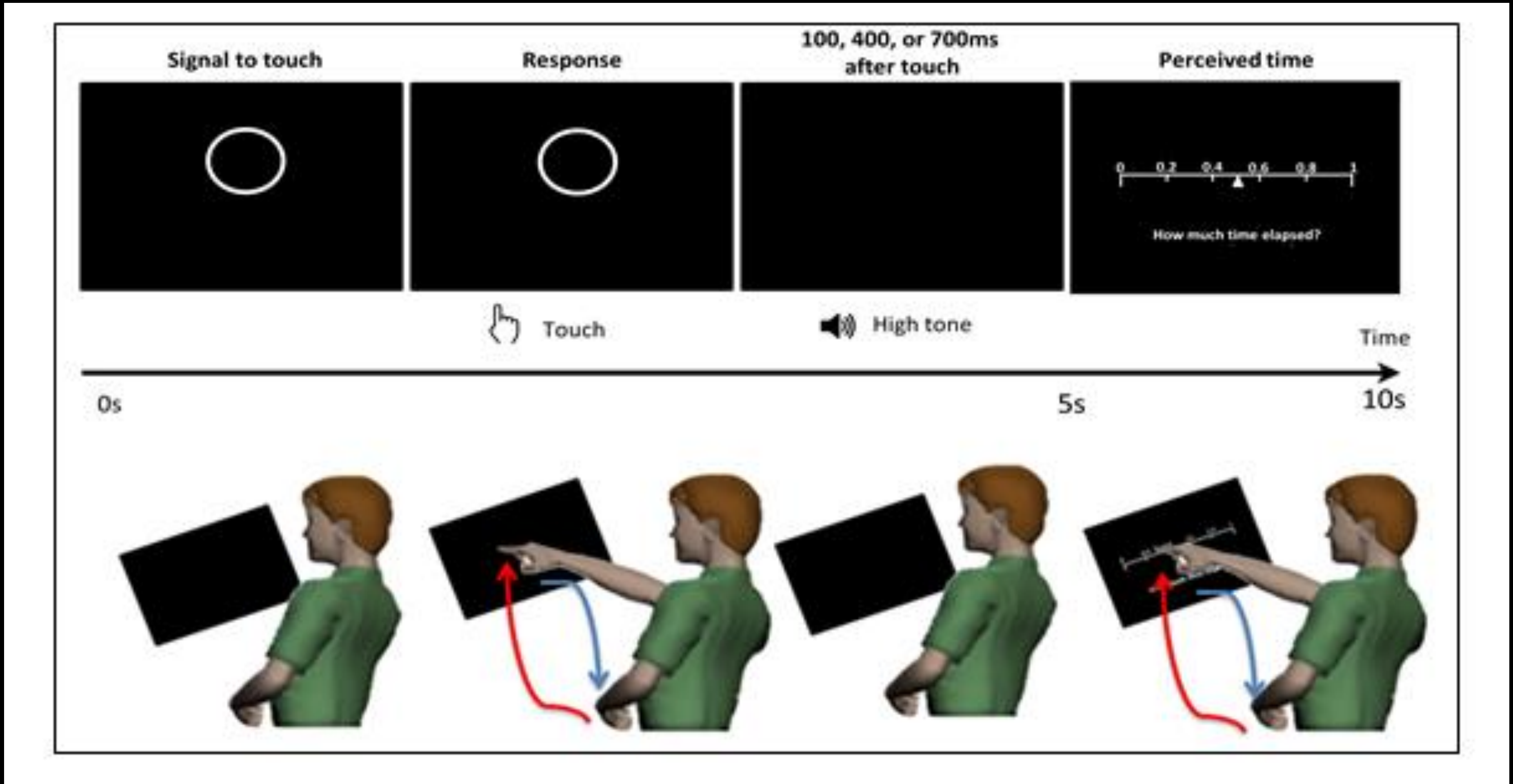
https://www.mdpi.com/2075-4426/10/3/76

GRAPHICAL ABSTRACT



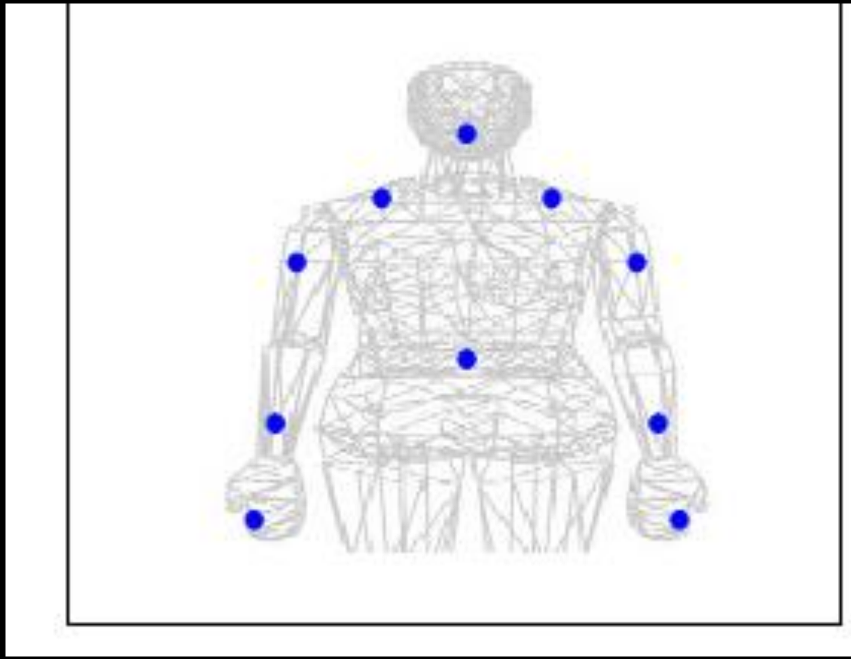
Dr. Jihye Ryu

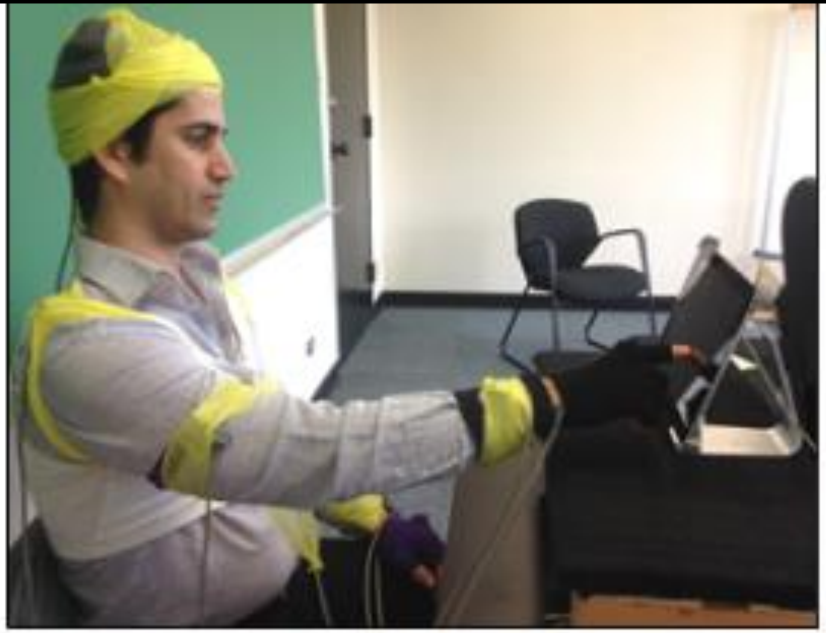
EXPERIMENTAL ASSAY



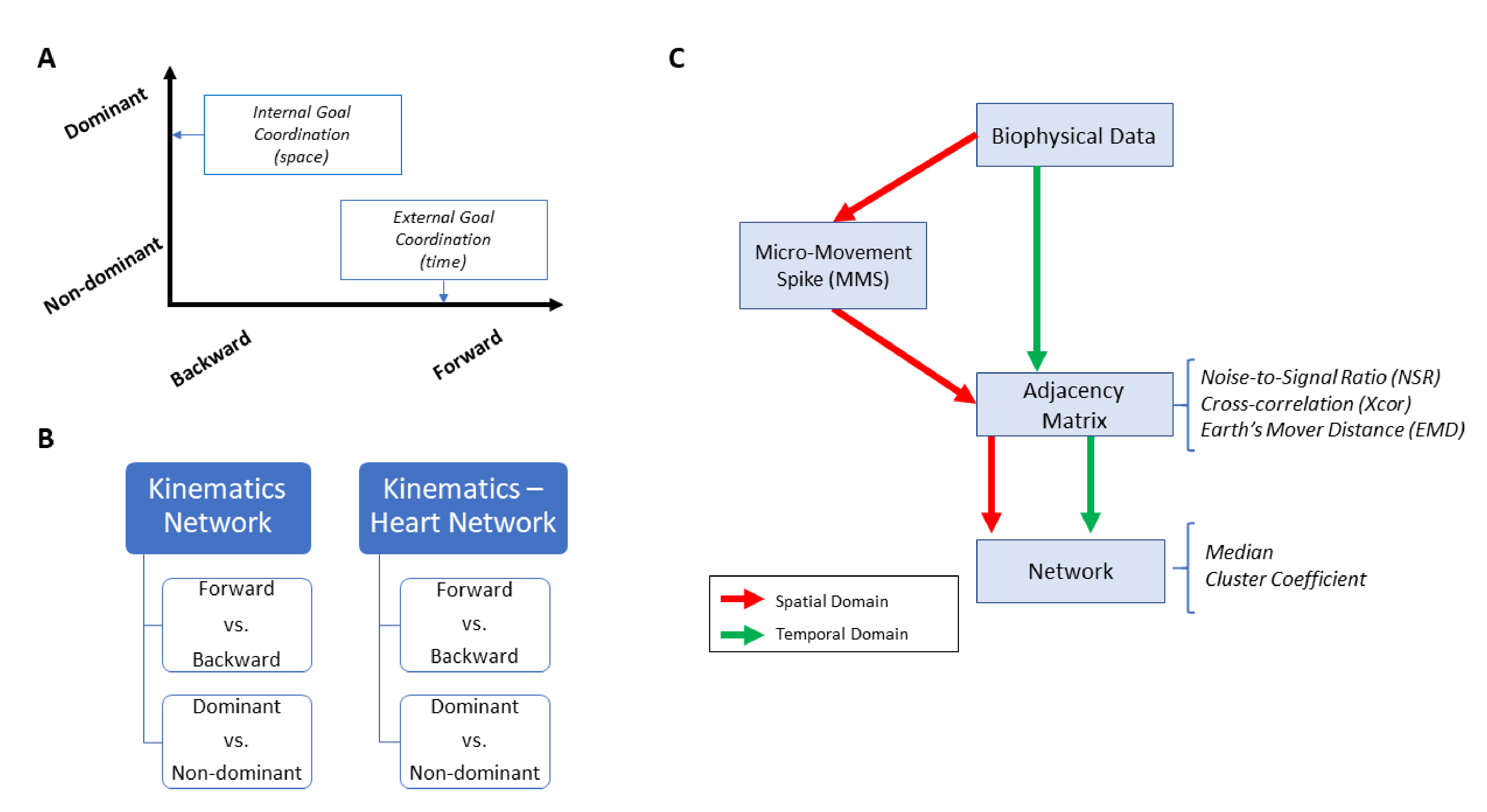
INSTRUMENTATION

10 Polhemus sensors 240Hz Integrated in the Motion Monitor

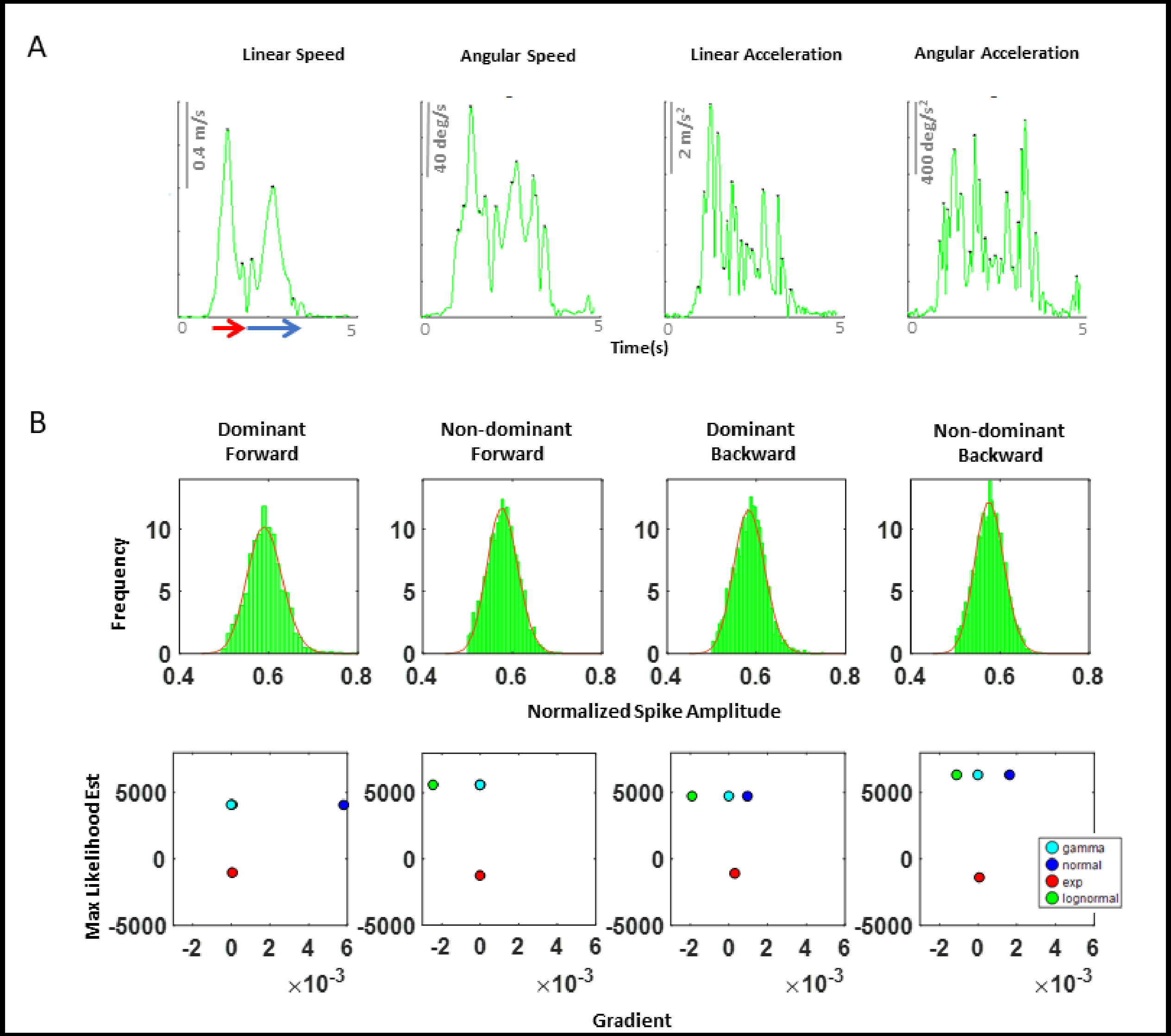




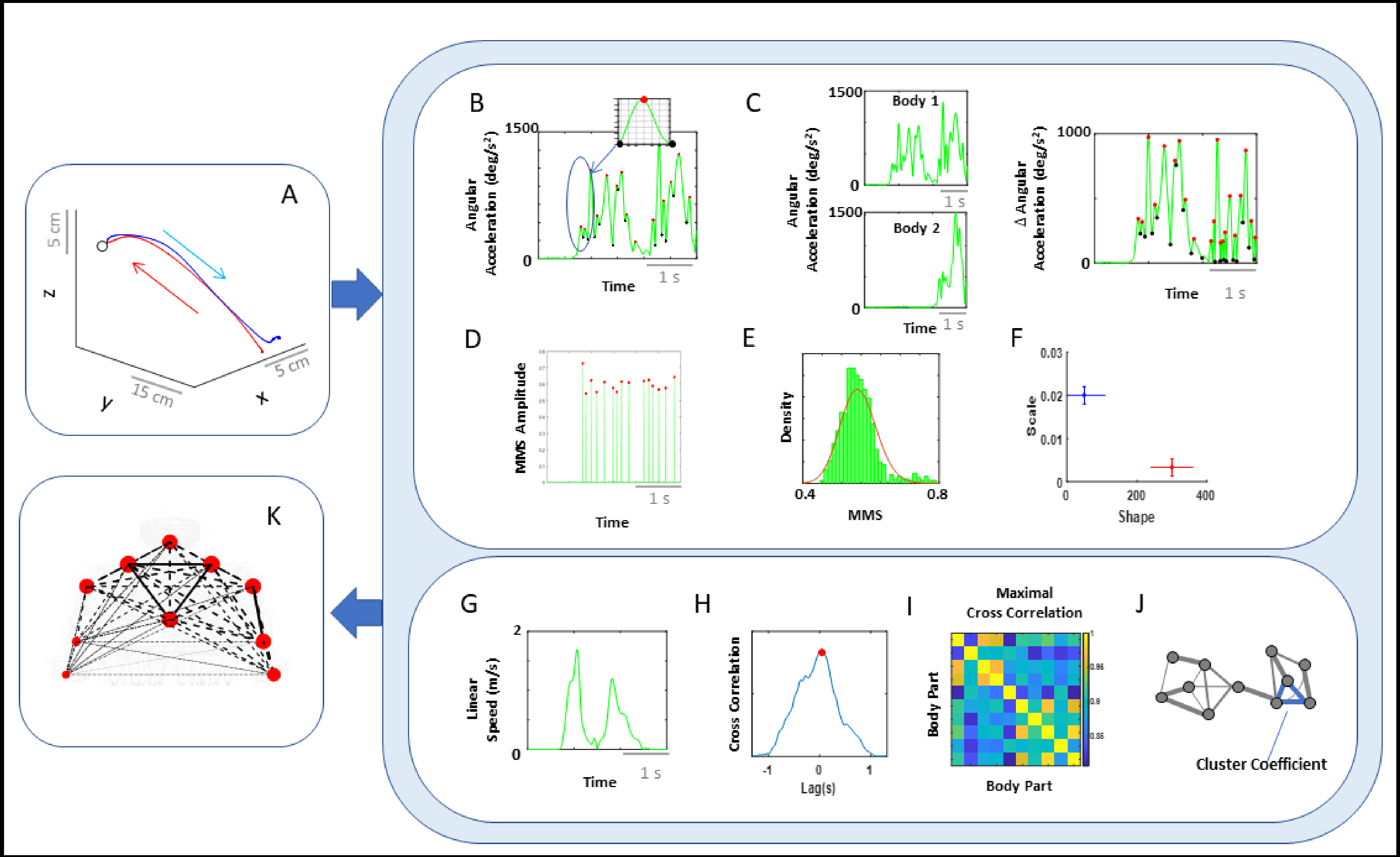
BREAK DOWN OF ANALYSES



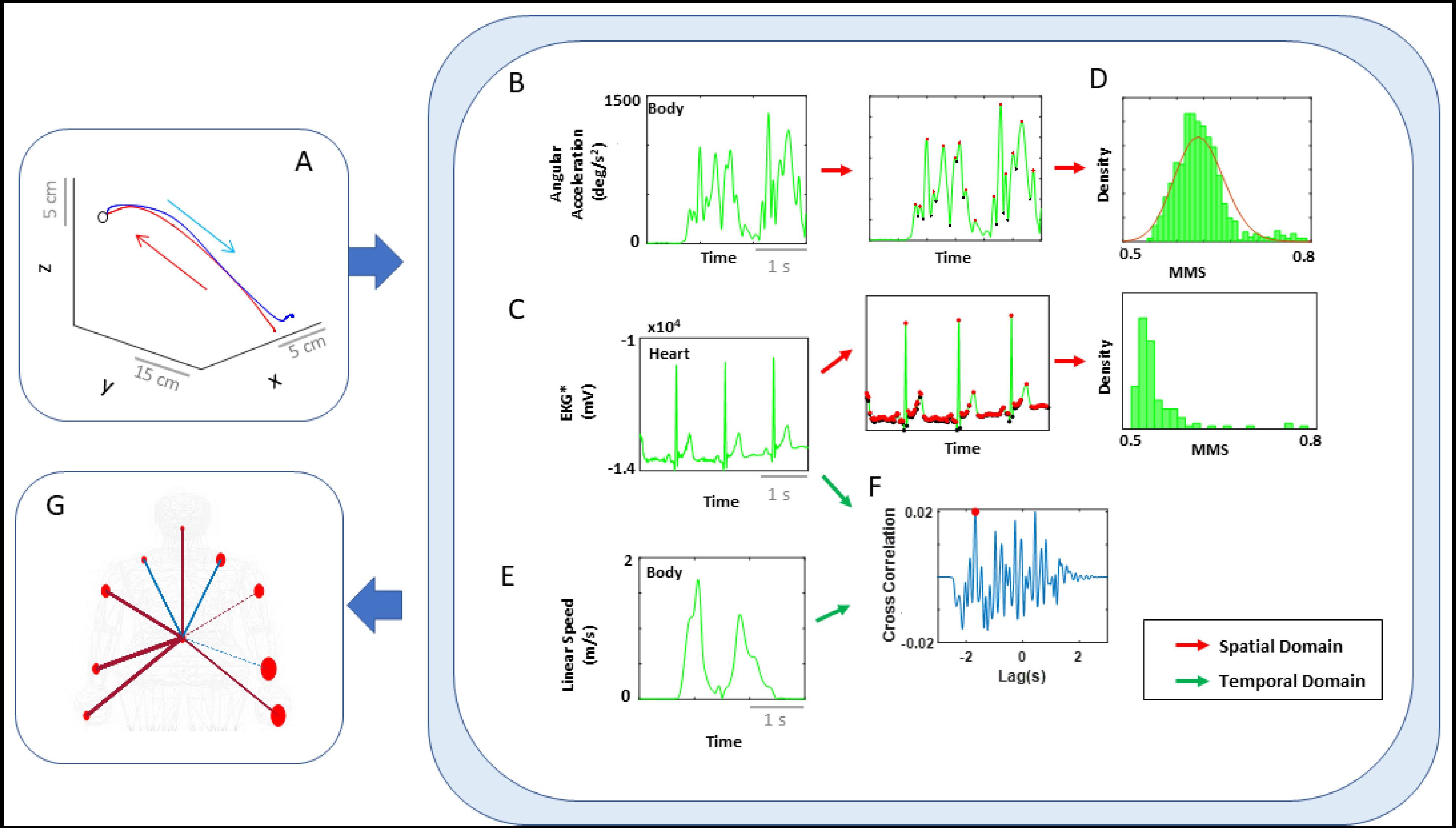
DATA EXPLORATION: PARAMETER ID TO AVOID FATIGUE



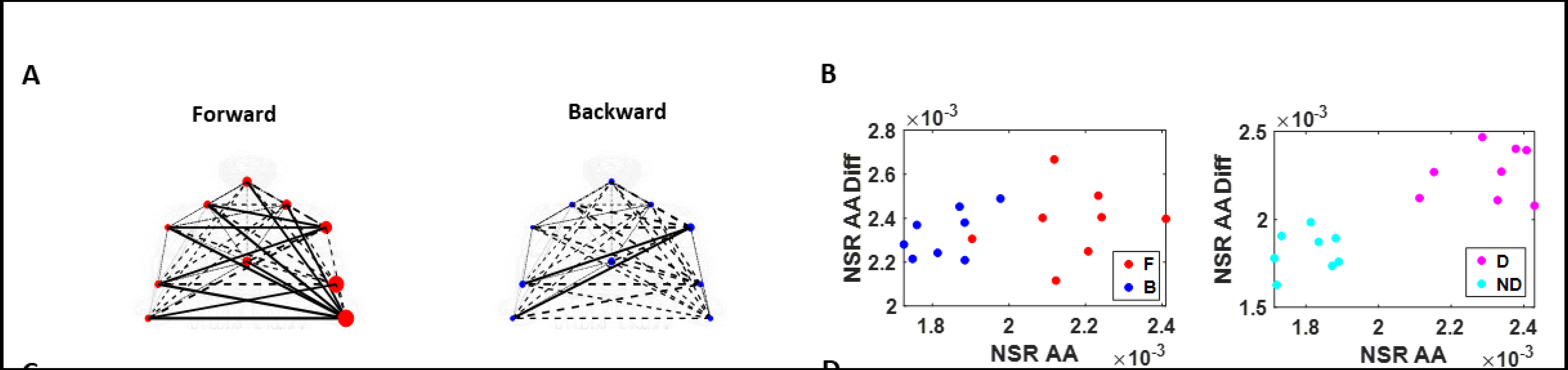
PIPELINE OF ANALYSES PART I (MMS KIN)



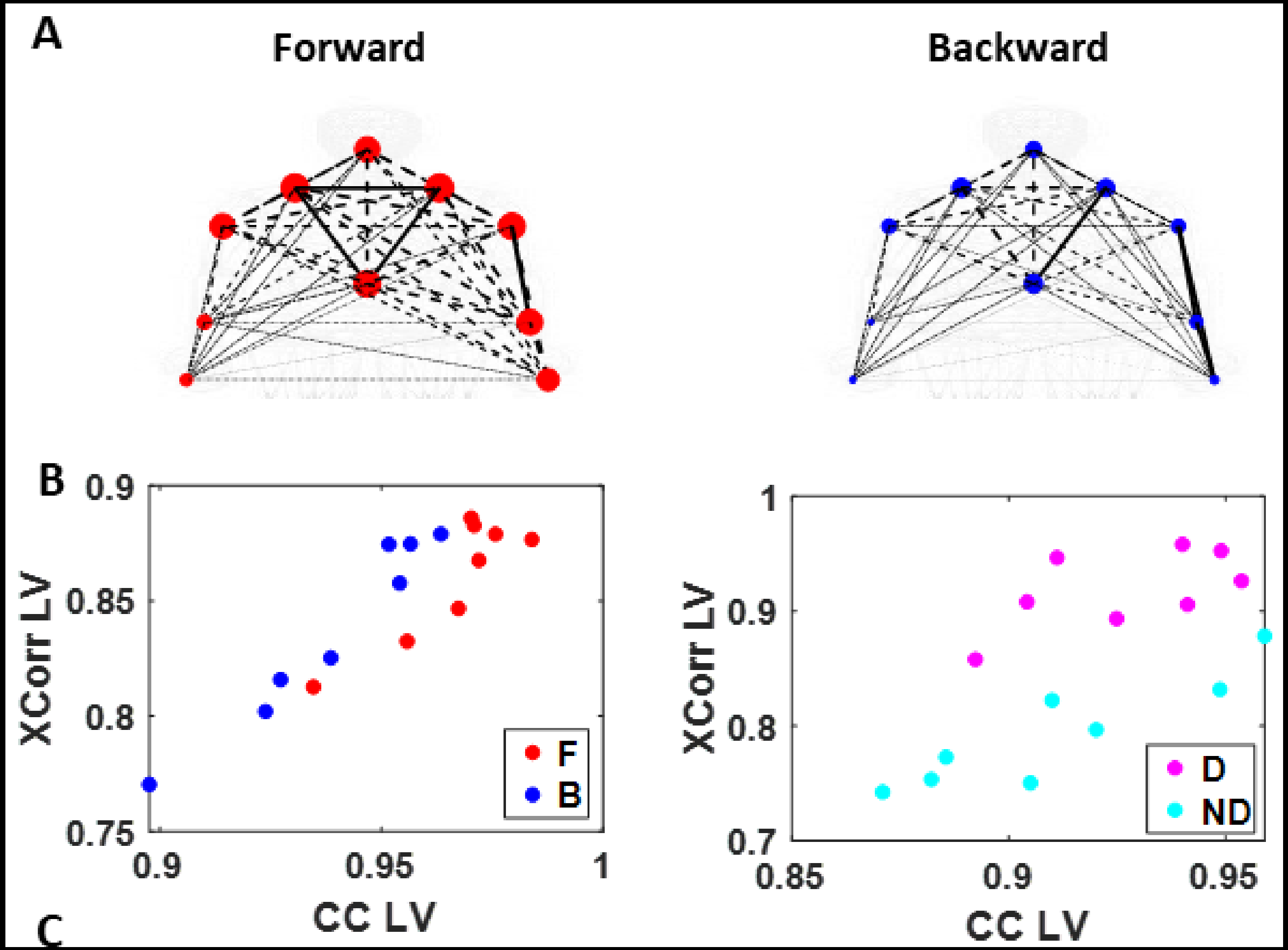
PIPELINE OF ANALYSES PART II (KIN + ECG)



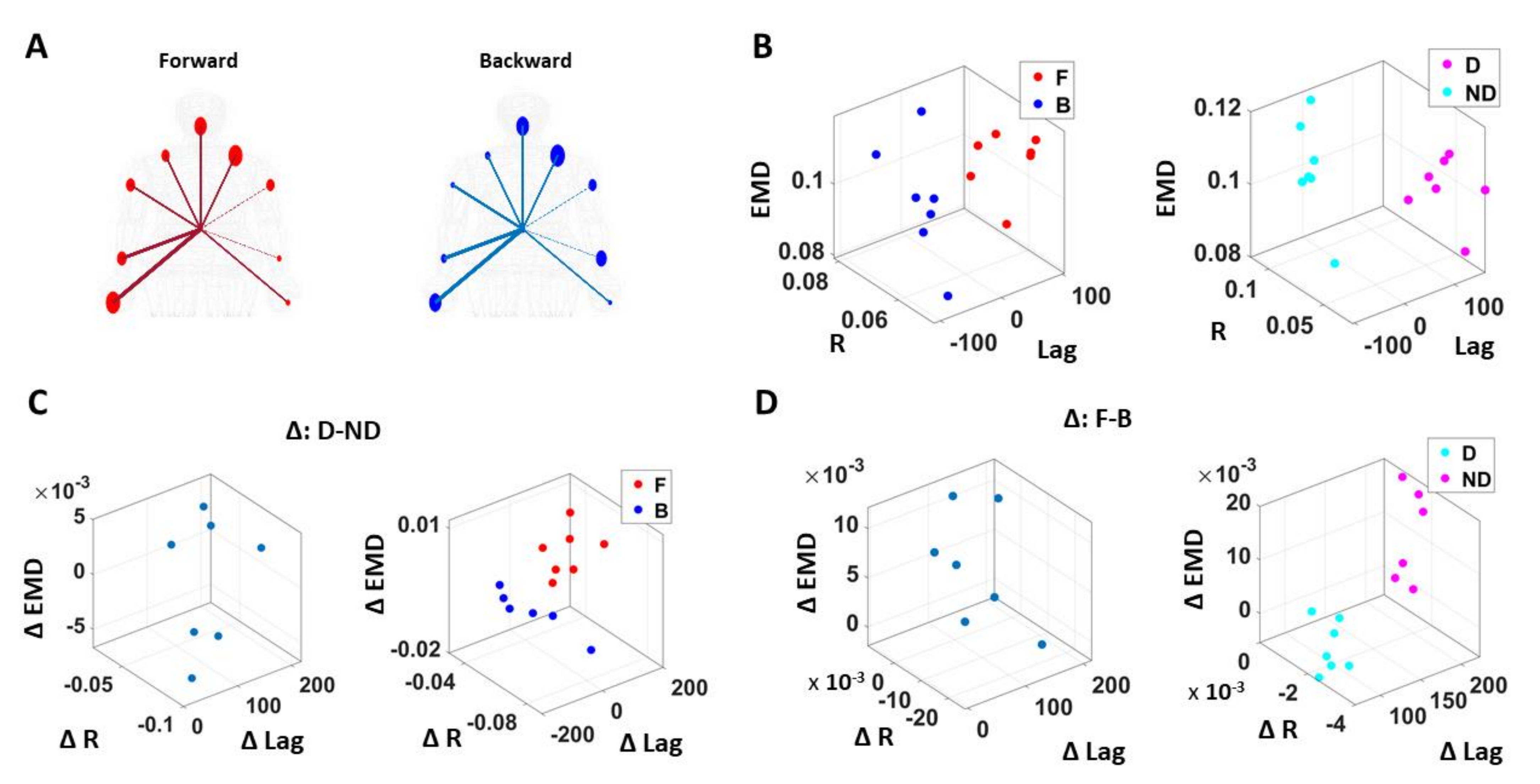
SPONTANEOUS VS DELIBERATE: NSR CAN DIFFERENTIATE LEVELS OF INTENT



NETWORK CONNECTIVITY METRIC (CLUSTER COEFFICIENT) AND MEDIAN CROSS-CORRELATION DIFFERENTIATES BETWEEN LEVELS OF INTENT



HEART LEADS KINEMATICS IN DELIBERATE ACTIONS



SUMMARY

- We can use the biorhythmic time series signals to detect levels of intent
- We can detect lead-lag dynamics across different levels of neuromotor control and infer, given the signal, which mode the system is most likely in (deliberate mode → heart leads kinematics; spontaneous mode → heart lags kinematics)
- Future work, do this in autism and other disorders of the nervous systems

7 FACIAL UNIVERSAL MICRO-EXPRESSIONS

MICRO-MOVEMENT SPIKES IN SPONTANEOUS VS DELIBERATE FACIAL MICRO-EXPRESSIONS

Class Objectives

- Learn the 7 universal facial micro-expressions
- Digitize facial micro-expressions
- Characterize the digital data using real data

THE PERIPHERAL NERVOUS SYSTEMS

Afferent Fibers

mechanoreceptors

nociceptors

thermal receptors

Socio-Motor Axes

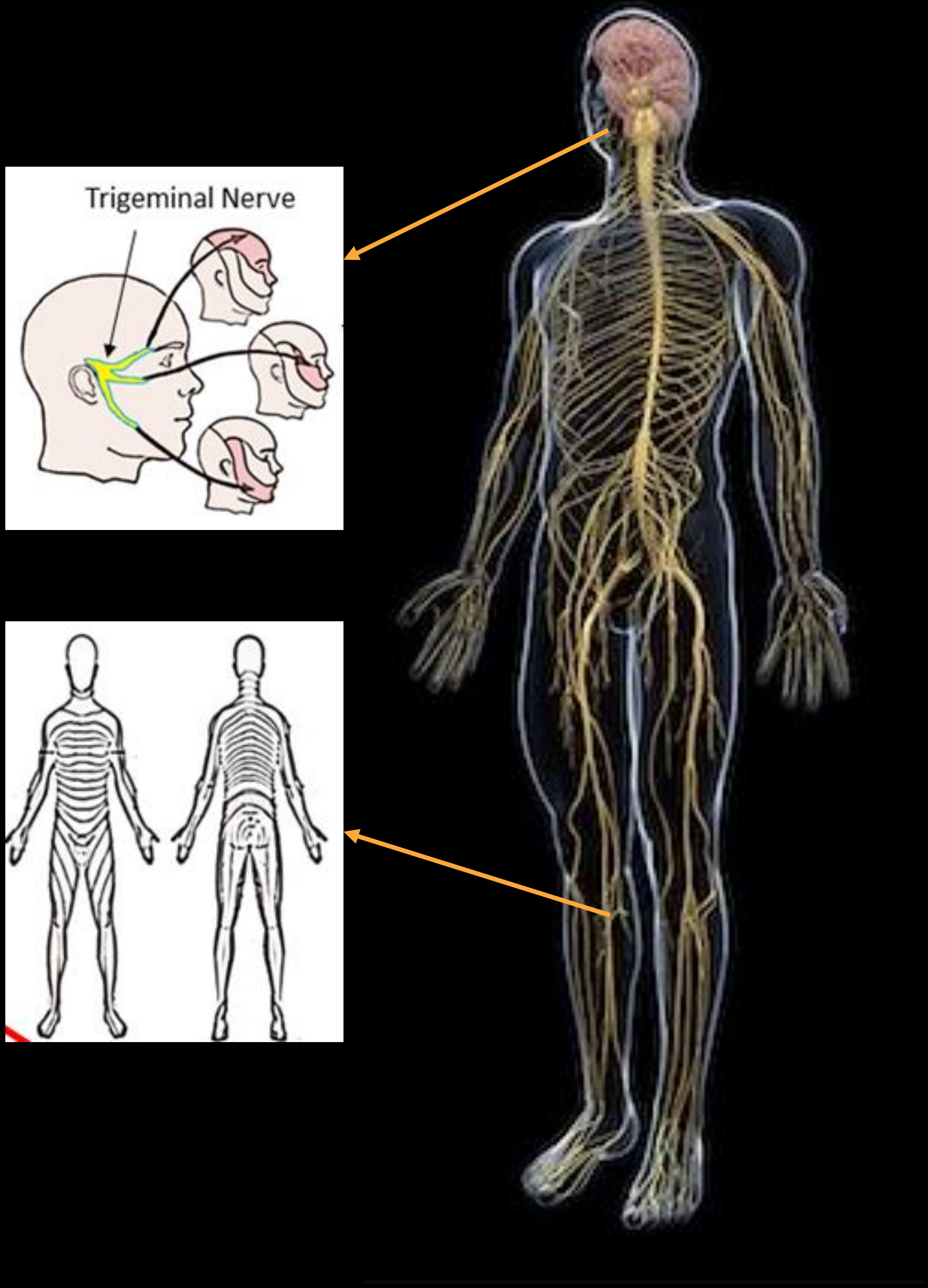
Face

Body

Intended Actions (deliberate, staged, purposeful, goal-directed)

Unintended Actions (spontaneous, supplemental, goal-less, uninstructed)

Inevitable Actions (unintentional beliefs turned intentional)



7 UNIVERSAL FACIAL MICRO-EXPRESSIONS

CHARACTERIZATION OF 7UFME USING OPENPOSE

FACIAL OUTPUT *vs.* FACIAL FEEDBACK

EMOTIONS CAUSE FACIAL MICRO-MOVEMENTS AND **MICRO-MOVEMENTS FEEDBACK TO OUR EMOTIONS** (SUBCORTICAL STRUCTURES, AMYGDALA, BASAL GANGLIA, STRIATUM, HIPPOCAMPUS FOR MEMORY, INSULA)

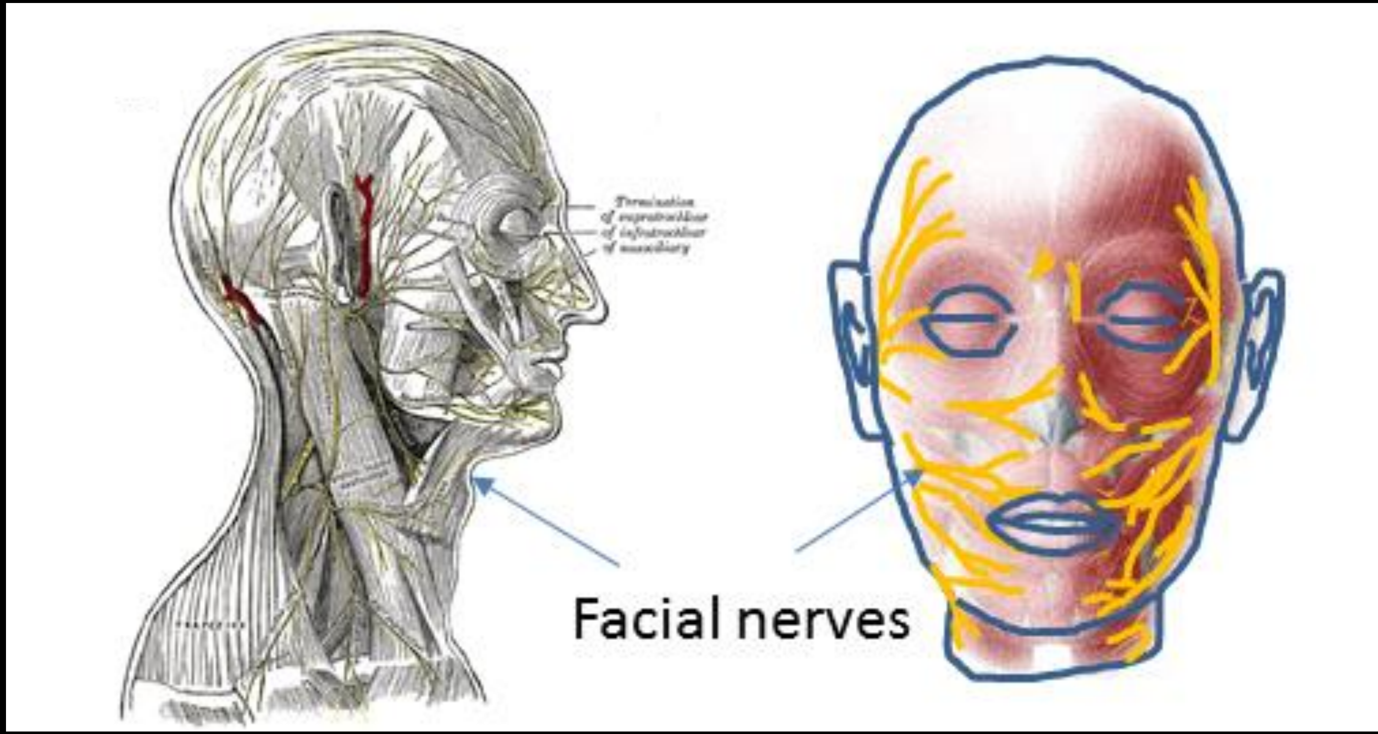
EFFERENT NERVES BRING OUTPUT ACTIVITY TO MUSCLES FROM THE BRAIN

AFFERENT NERVES BRING INPUT BACK TO THE BRAIN

REAFFERENCE:

- ENDO-AFFERENCE SELF-GENERATED AFFERENCE VIA SELF-GENERATED MICRO-MOTIONS

- EXO-AFFERENCE SELF-GENERATED MOTIONS VIA EXTERNAL MICRO-MOTIONS (E.G. VIBRATIONS)



When producing an emotion by mimicking its micro-expression, you feedback and evoke a memory of that emotion thus evoking its actual sensation, as if you were experiencing it: Even though they are unconscious, bringing them up to consciousness can help training the emotions. This is important in social interactions (e.g. job interviews)

Some links

- http://atlasofemotions.org/#continents/disgust
- https://www.youtube.com/watch?v=AaDzUFL9CLE

HOW TO MEASURE FACIAL MICRO-EXPRESSIONS IN THE 7 UNIVERSAL EMOTIONS?

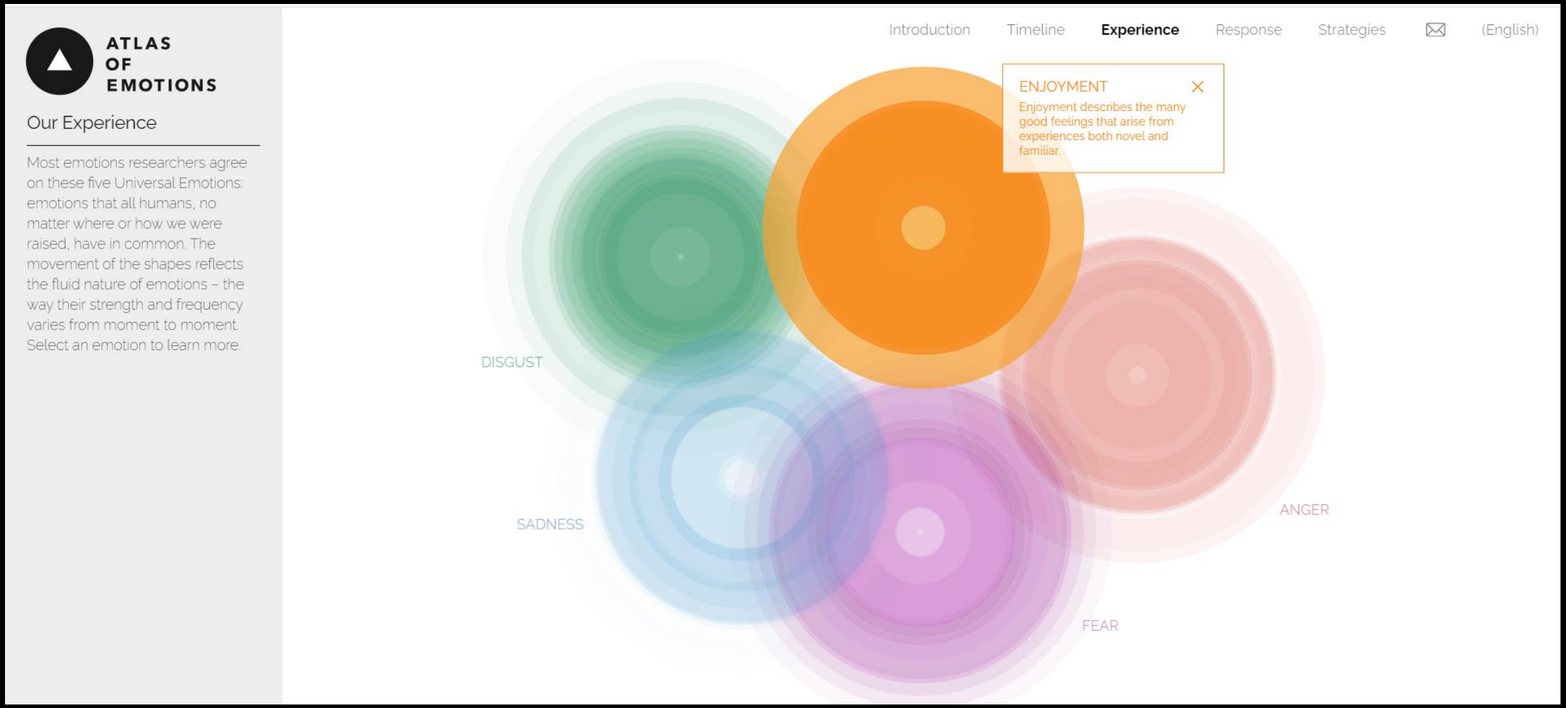
MACRO-LEVEL OF DESCRIPTION

AND

MICRO-LEVEL OF STOCHASTIC AND DYNAMIC SYNERGY ANALYSES

From Darwin to Paul Ekman and Today Facial Expression Analyses

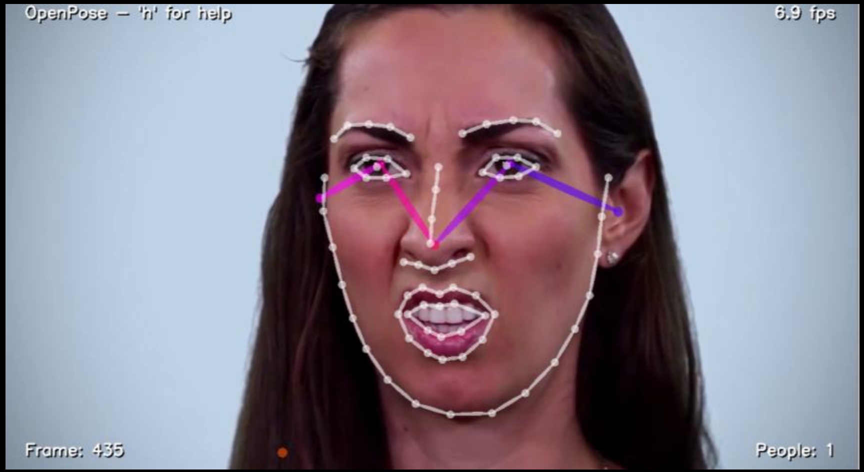
http://atlasofemotions.org/#continents/disgust



DESCRIPTION OF THE 7UFME

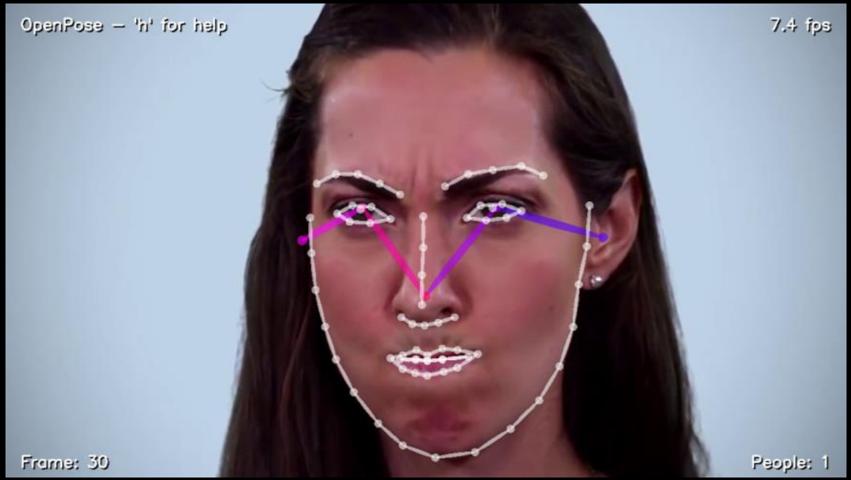
DISGUST

- SHRINK UPPER LIP
- CRINKLE NOSE
- SHOW THAT EXPRESSION AS IF YOU SMELLED OR TASTED SOMETHING BAD
- OR AS IF YOU DID NOT LIKE SOMETHING/SOMEONE



ANGER

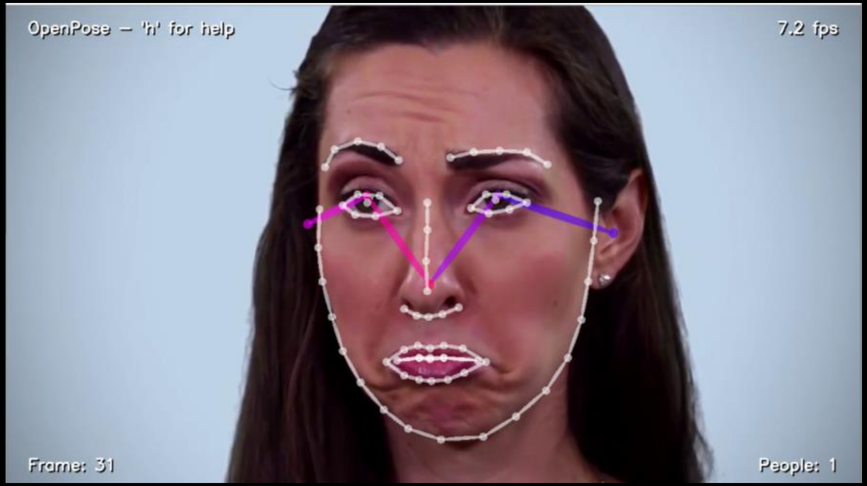
- TWO VERTICAL LINES APPEAR BET YOUR EYEBROWS
- HARDEN YOUR LOWER (EYE) LIDS
- TENSE YOUR LIPS



SADNESS

HARDEST TO FAKE

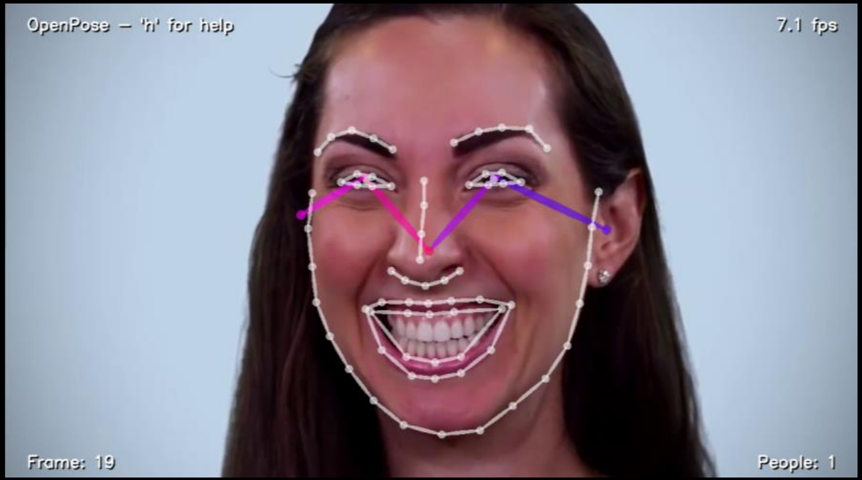
- MAKE A FROWN
- TAKE THE CORNER OF YOUR MOUTHS AND PULL THEM DOWN AS FAR AS YOU CAN
- PUFF OUT YOUR LOWER LIP EVEN IF IT QUIVERS (VIBRATES)
- PINCH THE INNER CORNERS OF YOUR EYEBROWS TOGETHER



HAPPINESS

UPPER CHEEK MUSCLE HAVE TO ACTIVATE (ONLY 1/10 PEOPLE CAN DO THAT)

- MAKE S SMILE AND GO UP YOUR FACE AS FAR AS YOU CAN
- (PUT A PENCIL IN YOUR MOUTH AND TRY IT TO ENGAGE THE CHEEKS FURTHER)



FEAR

WHAT WE DO WHEN TRYING TO PROTECT OURSELVES

- EYE LIDS AND EYE BROWS WIDEN SO YOU CAN TAKE IN (SEE) AS MUCH AS YOU CAN
- OPEN YOUR EYES AND EYEBROWS REALLY WIDE AND YOUR MOUTH AS TO TAKE IN O2
- FLAT EYEBROWS

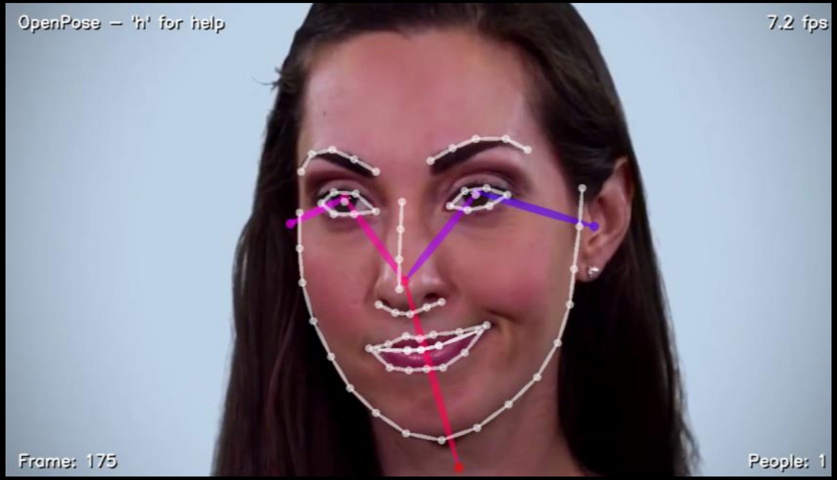
SURPRISE

CLOSE TO FEAR BUT A LITTLE DIFFERENT

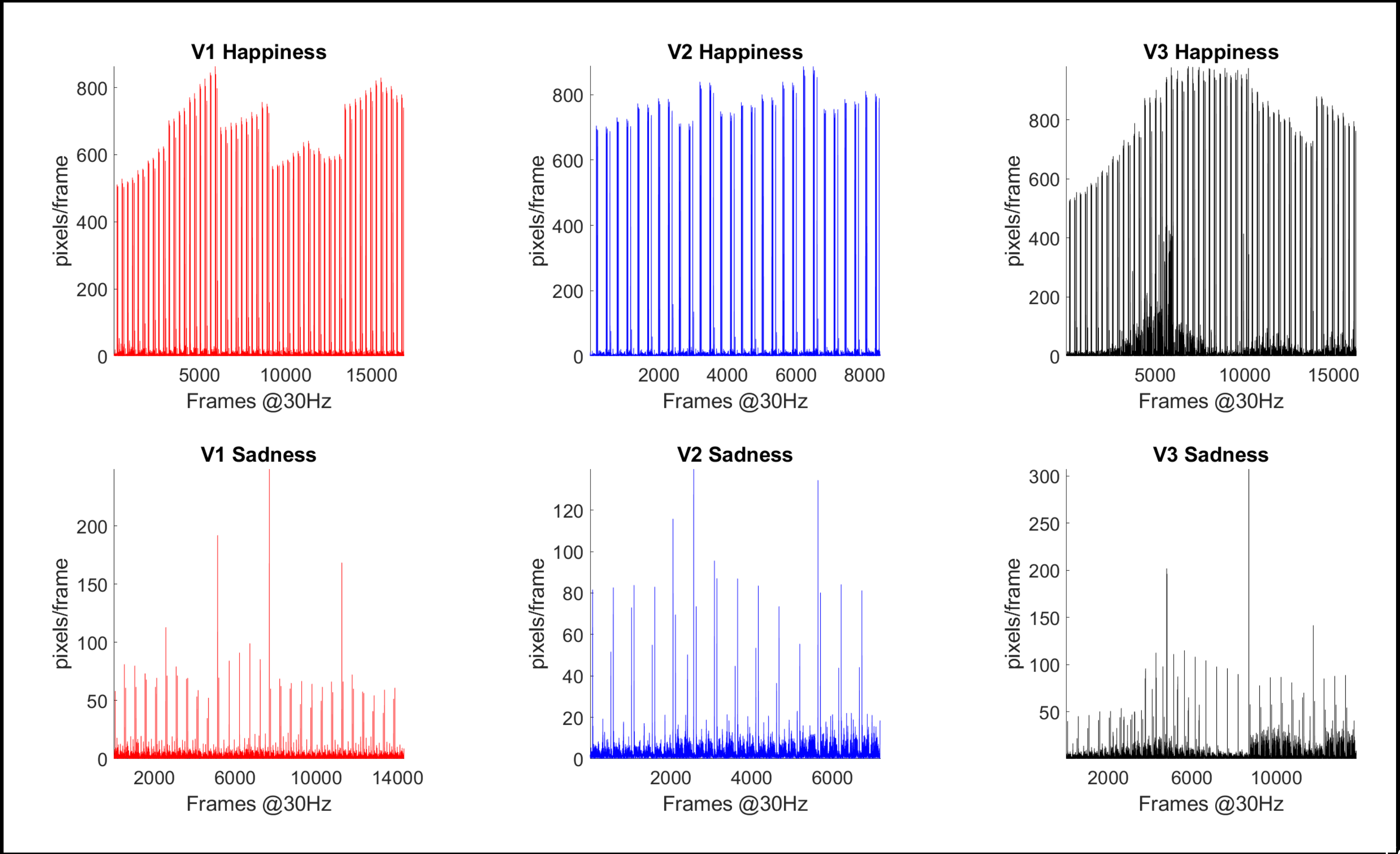
- WIDEN EYES AND RAISE EYEBROWS UP YOUR FOREHEAD AS YOU CAN
- DROP YOUR MOUTH OPEN
- IT’S THE LONGEST OF THE MICRO-EXPRESSIONS
- EYEBROWS UPSIDE DOWN

CONTEMPT

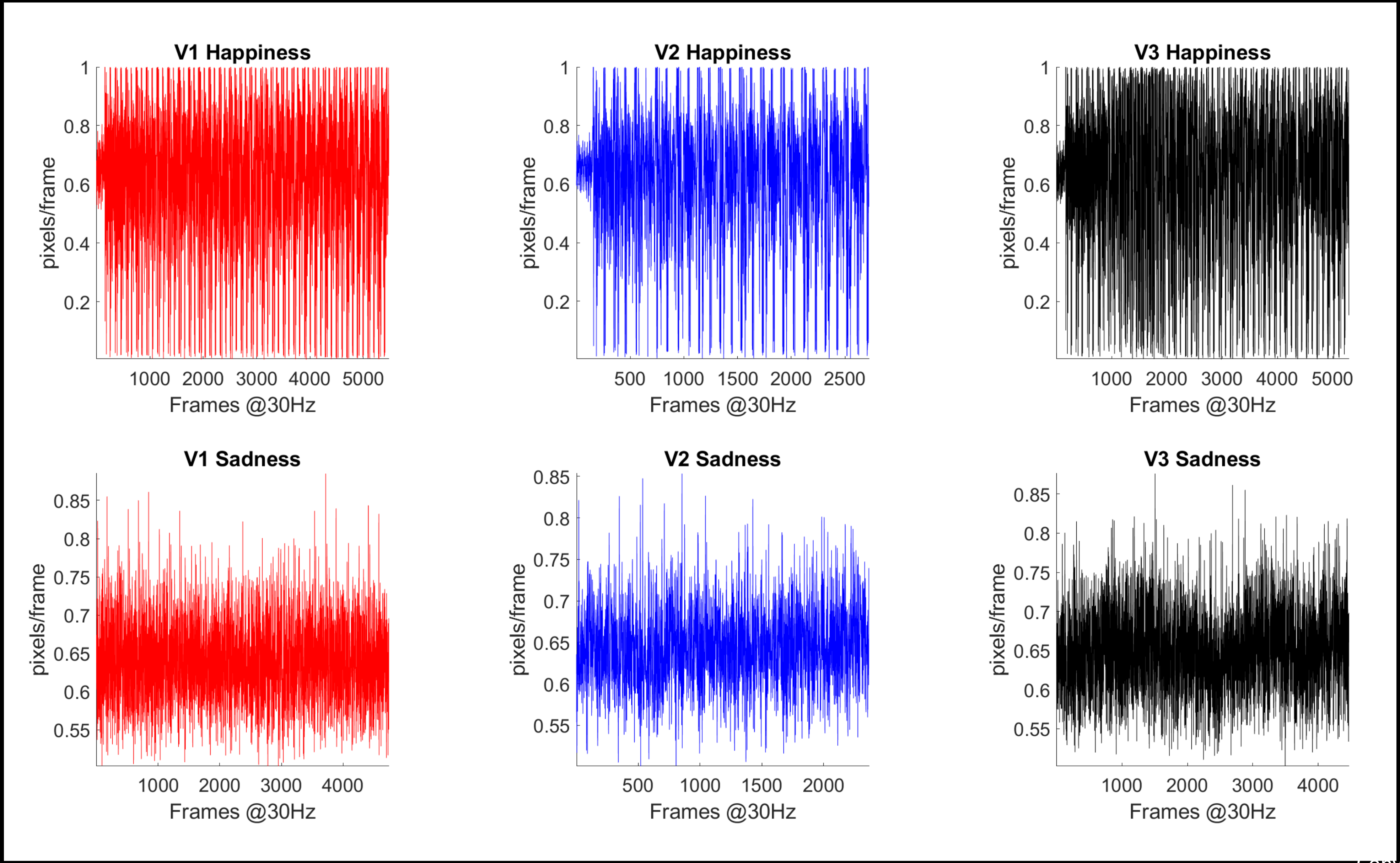
- ONE SIDED MOUTHWAY
- EYITHER SIDE OF THE MOUTH
- ANY ASYMETRY MEANS DISDAIN, PESIMISM OR HATRED



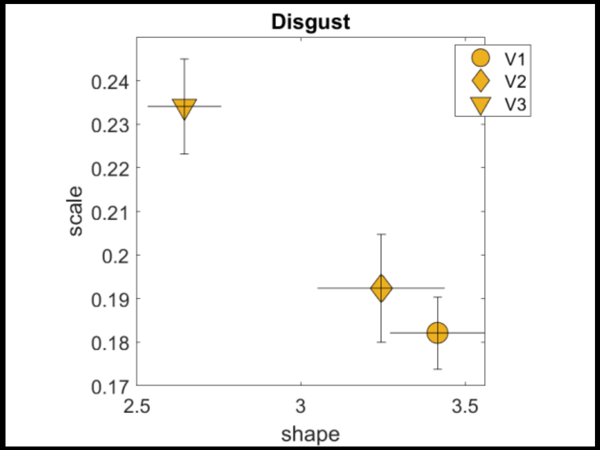
Raw Data from Facial Micro-Expressions

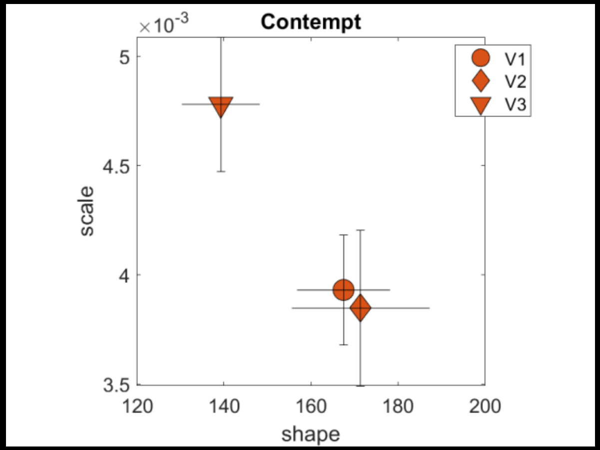


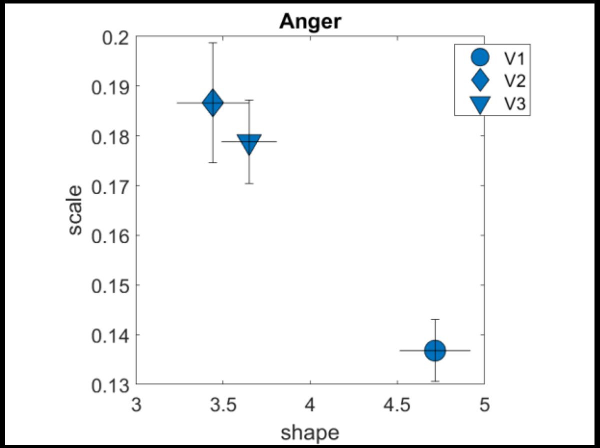
MMS from Facial Micro-Expressions

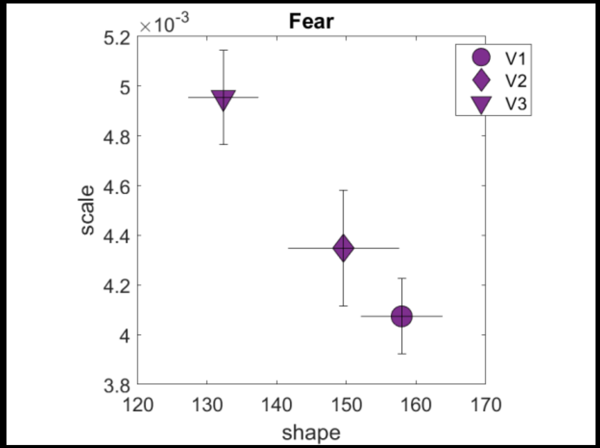


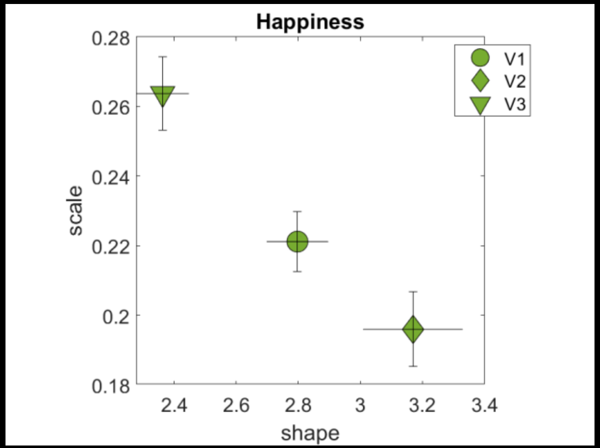
Gamma Signatures

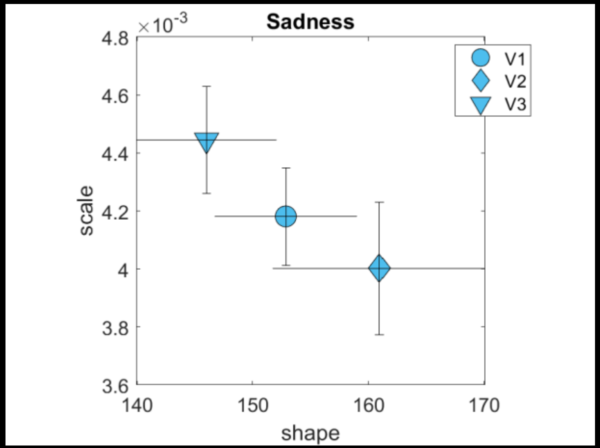


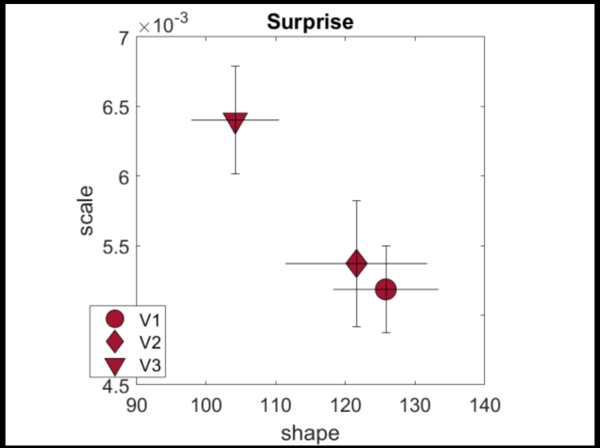




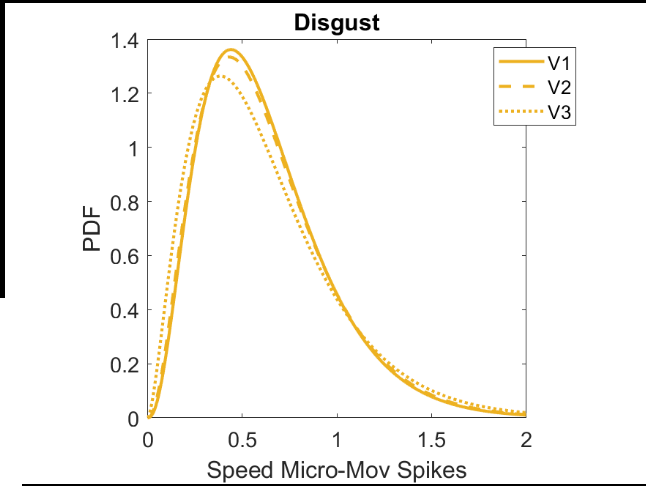


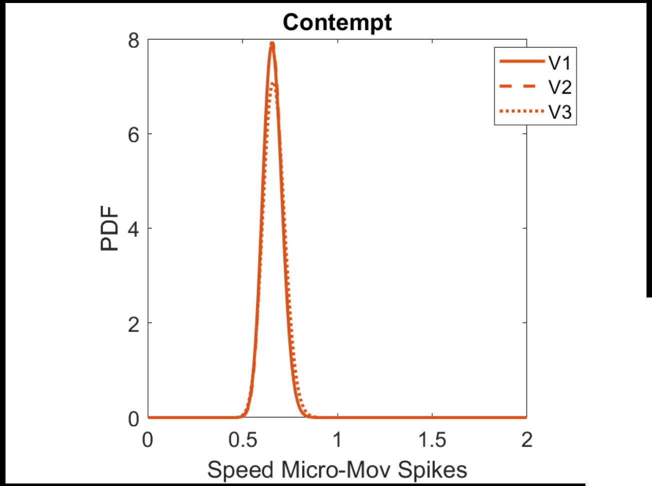


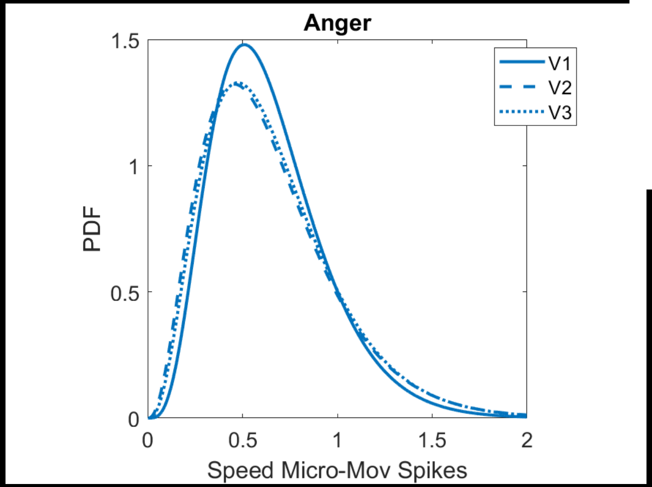


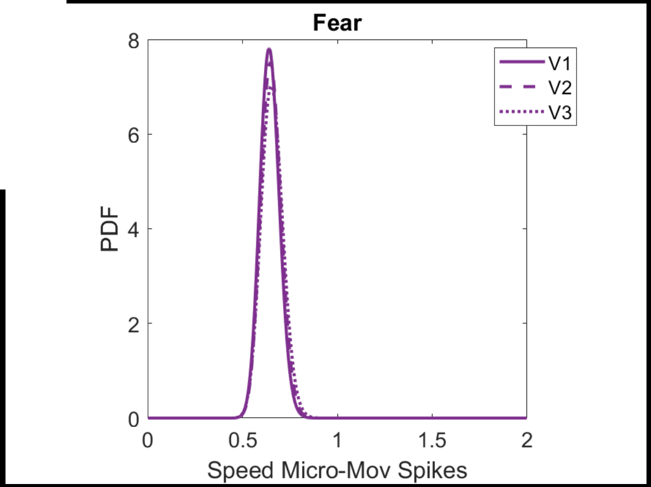


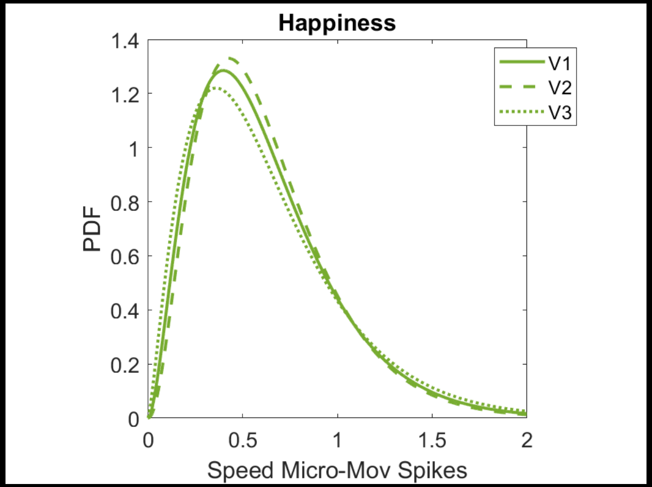
PDFs

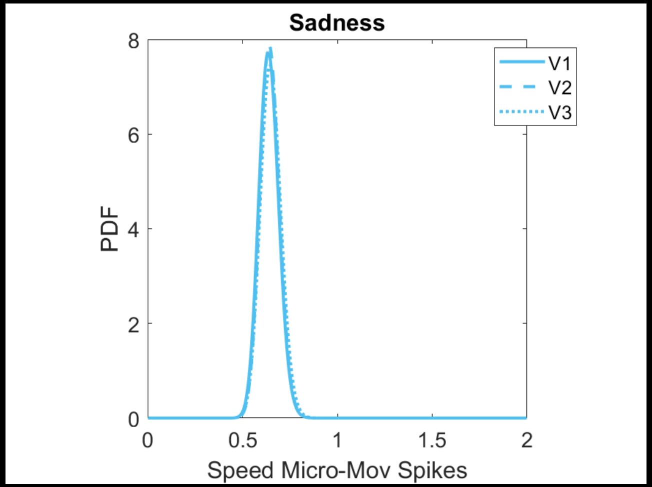

Disgust
PDF
Speed Micro-Mov Spikes
V1
V2
V3

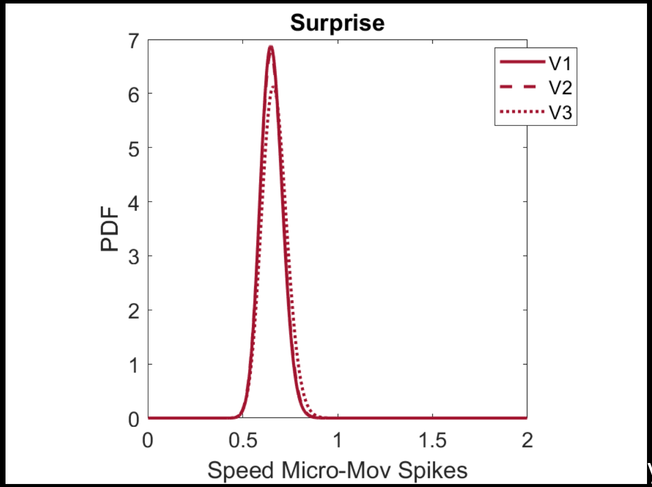

Contempt
PDF
Speed Micro-Mov Spikes
V1
V2
V3


Anger
PDF
Speed Micro-Mov Spikes
V1
V2
V3

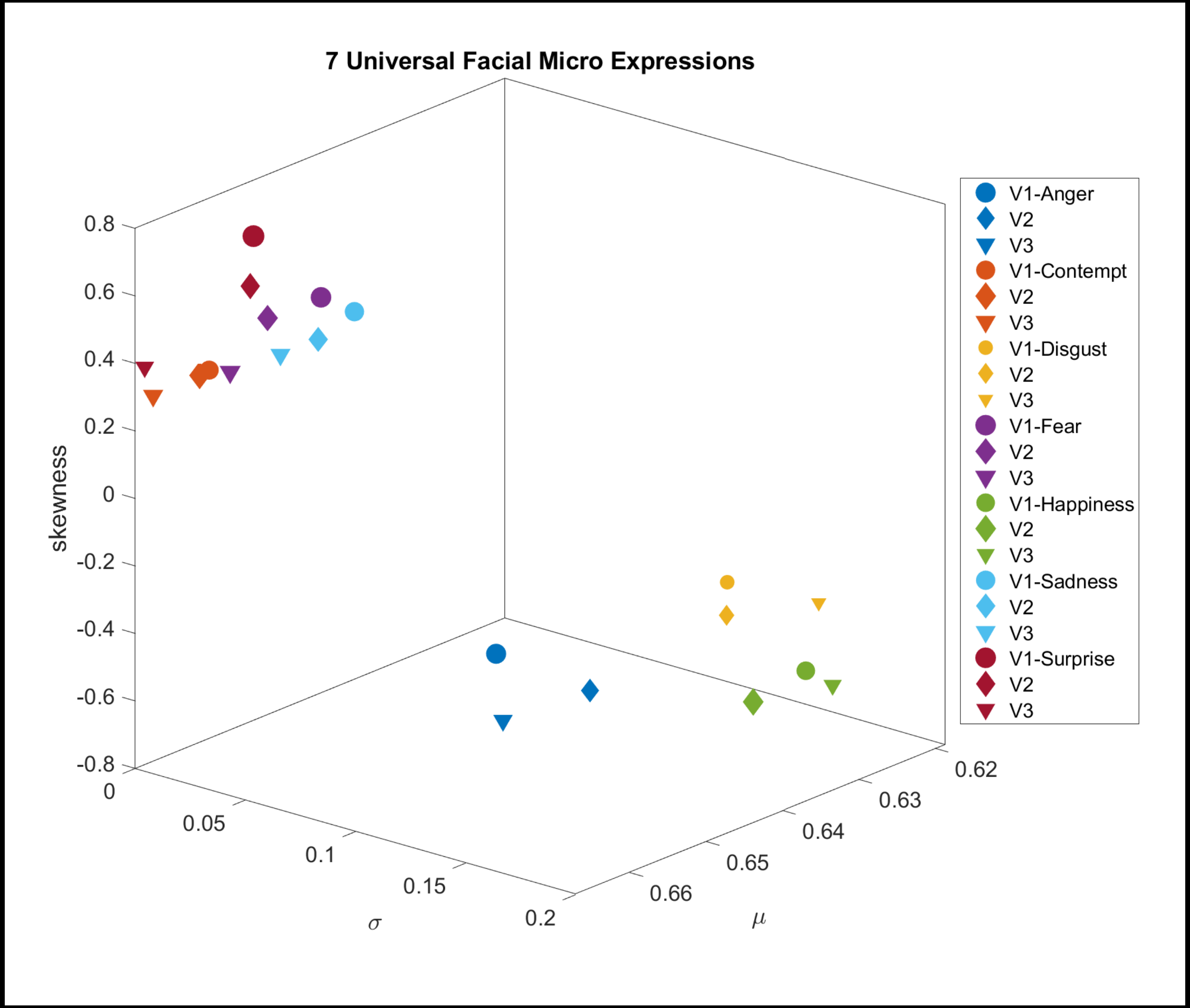

Fear
PDF
Speed Micro-Mov Spikes
V1
V2
V3

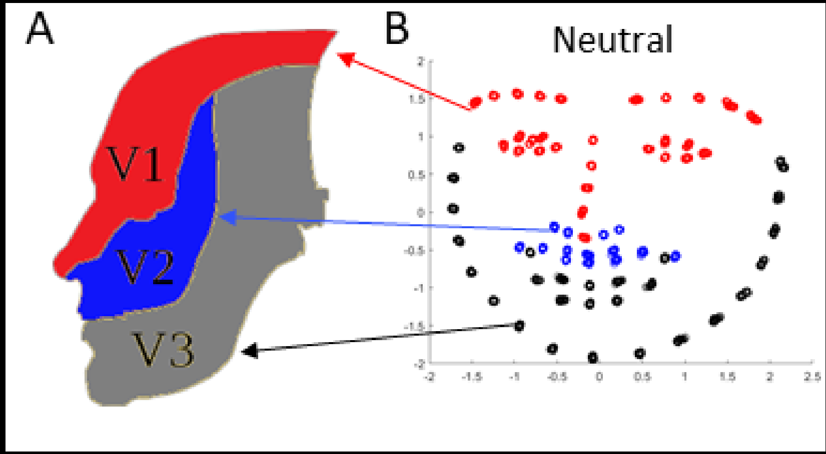

Happiness
PDF
Speed Micro-Mov Spikes
V1
V2
V3


Sadness
PDF
Speed Micro-Mov Spikes
V1
V2
V3

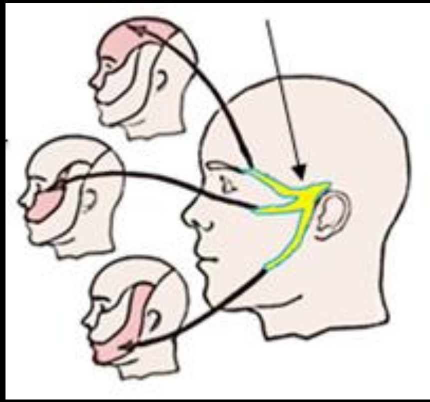

Surprise
PDF
Speed Micro-Mov Spikes
V1
V2
V3

Parsing out stochastic signatures of emotions





Trigeminal Nerve



POSE ESTIMATION – OPENPOSE

FREE SOFTWARE FROM CS CARNEGIE MELLON

EXERCISE – FAKE MICRO-EXPRESSIONS

- IN CLASS (Social context)
  - MAKE THESE FACES TO GENERATE A DATA SET
  - PROCESS THE MOVIE TO ISOLATE THE FRAMES FOR EACH ONE
  - RUN OPEN POSE TO OBTAIN THE SKELETON
  - MMS, STOCHASTIC ANALYSIS
  - CLASSIFY INDIVIDUAL/CLASSIFY AS GROUP – PENCIL AND PAPER
  - CLASSIFY USING PATTERN RECOGNITION AND ML DECODERS
- AT HOME (ON YOUR OWN)
  - CREATE SAME DATA SET OF EMOTION'S MICRO-EXPRESSIONS
  - RUN STEPS ABOVE
  - COMPARE RESULTS

EXERCISE – REAL MICRO-EXPRESSIONS

- IN CLASS (Social Context)
  - MAKE THESE FACES TO GENERATE A DATA SET
  - **DISGUST** (BAD SMELL); **SURPRISE** (SOMEONE SURPRISES YOU); **FEAR** (SOMEONE SCARES YOU); **HAPPINESS** (FUNNY JOKE); **SADNESS** (SEE SOMETHING SAD); **CONPTEMT** (PLAY SOMETHING WHERE YOU GO YEAH, RIGHT!; **ANGER** (SEE/ THINK OF SOMETHING THAT MAKES YOU ANGRY)
  - RUN OPEN POSE TO OBTAIN THE SKELETON
  - MMS, STOCHASTIC ANALYSIS
  - CLASSIFY INDIVIDUAL/CLASSIFY AS GROUP – PENCIL AND PAPER
  - CLASSIFY USING PATTERN RECOGNITION AND ML DECODERS
- AT HOME (ALONE, NOBODY IN THE ROOM)
  - CREATE SAME DATA SET OF EMOTION'S MICRO-EXPRESSIONS (BUT ALONE)
  - RUN STEPS ABOVE
  - COMPARE RESULTS

INDIVIDUAL PRESENTATIONS

- EACH STUDENT WILL PRESENT THE RESULTS
- THE CLASS WILL DISCUSS
- I WILL GRADE (20% OF THE GRADE)

PART II – NETWORK CONNECTIVITY ANALYSES

SOCIAL INTERACTIONS AS A GROUP

Real-time Multi-Person 2D Pose Estimation Using Part Affinity Fields

Zhe Cao, Tomas Simon, Shih-En Wei, Yaser Sheikh
Carnegie Mellon University

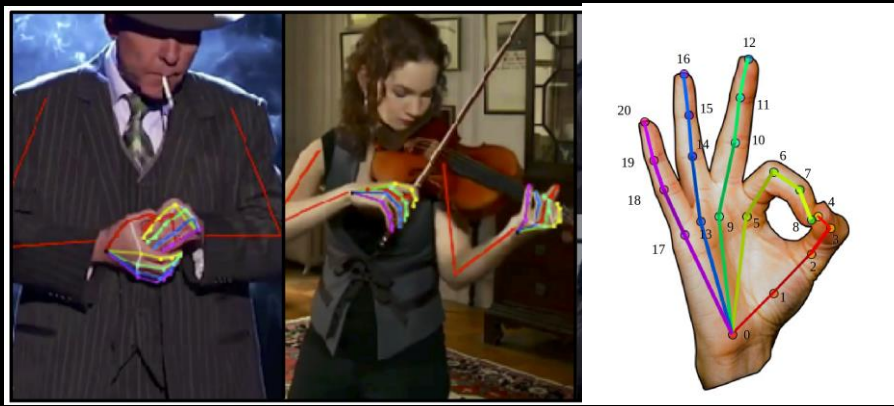
Joe Vero

Play Movie

What does OpenPose do?

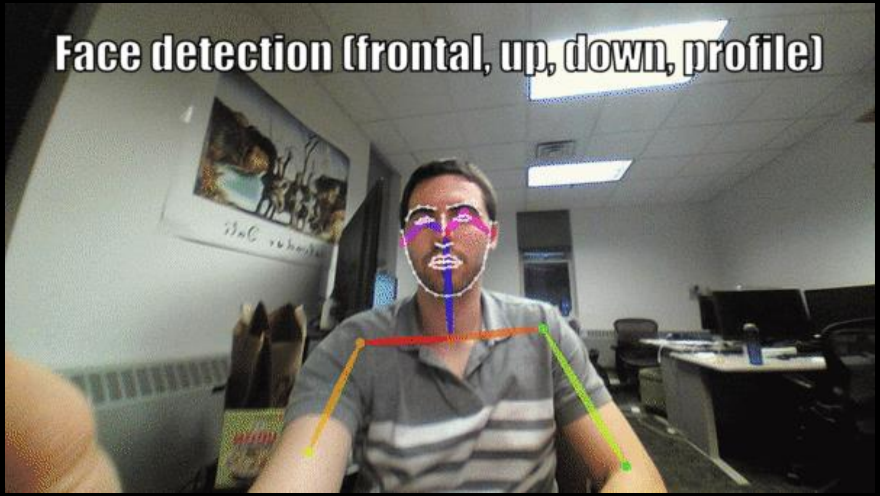
estimation using open source Caffe models, whose runtime is invariant to the number of people in the image, running on the GPU

What else comes with OpenPose?



Hand Detector

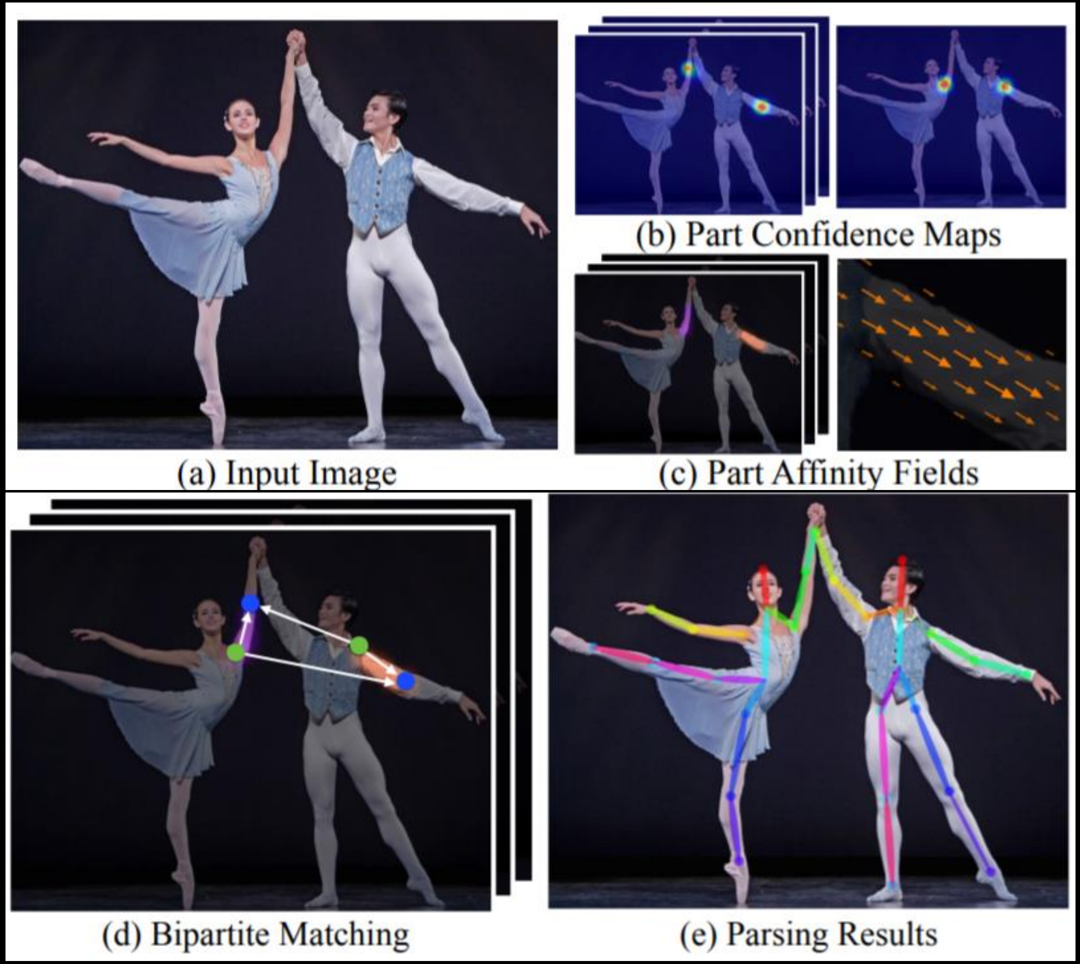
- 21 point hand detector for both left and right hand
- Runs on CPU, not GPU, so not invariant to number of hands in image (more hands = run slower)



Face Detector

- 70 keypoint detector for face
- Runs on CPU, not GPU, so not invariant to number of faces in image (more faces = runs slower)

How does OpenPose work?



Given an input image, two convolutional neural networks work in parallel to accomplish two distinct goals:

- Build a heatmap of confidences of different parts
- Build an Affinity Field of different parts, representing the best matching orientation for each part

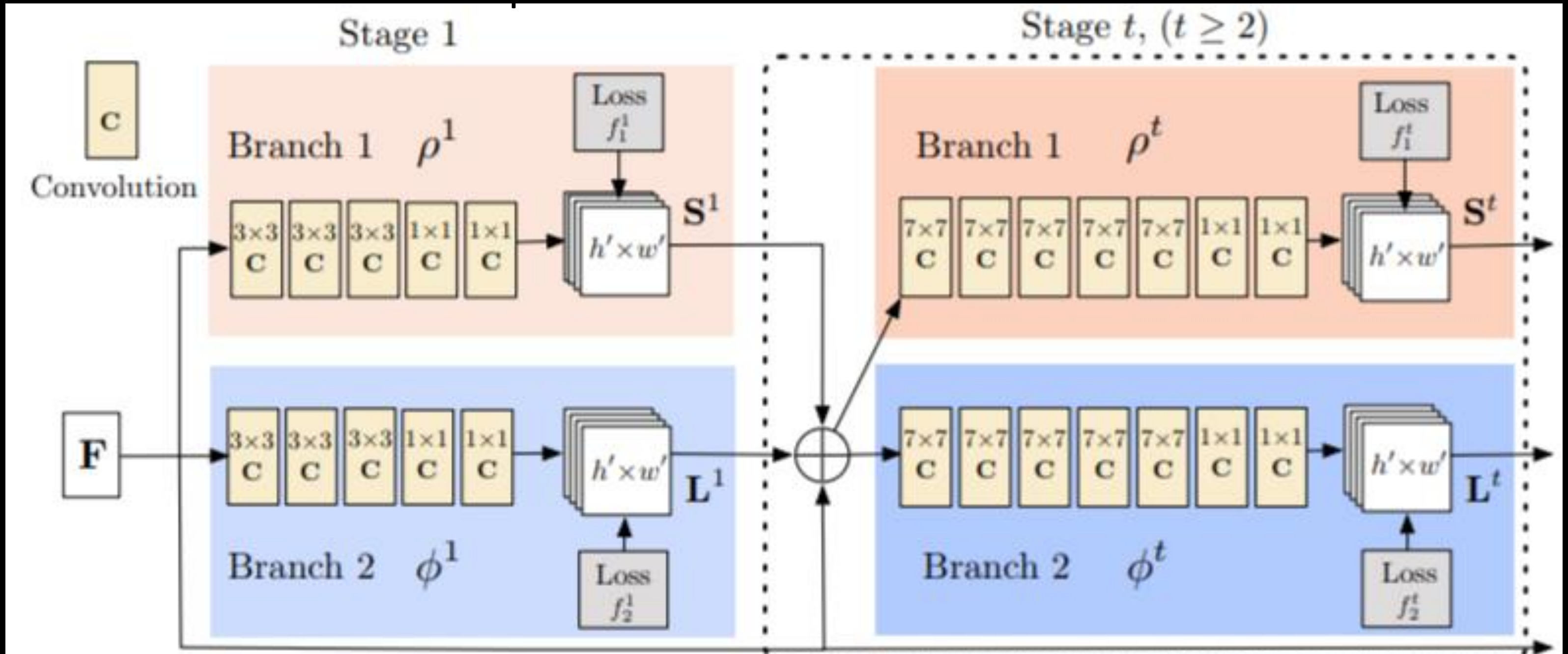
After given that information, in order to reconstruct poses, incomplete bipartite matching is done with the heuristic of the affinity field in order to find the most likely connected points (based on inherent information about natural human poses, ie: typically a forearm is oriented between a hand and an elbow)

Ok, so how does OpenPose actually work?

two Convolutional Neural Networks working in parallel for specialized goals.

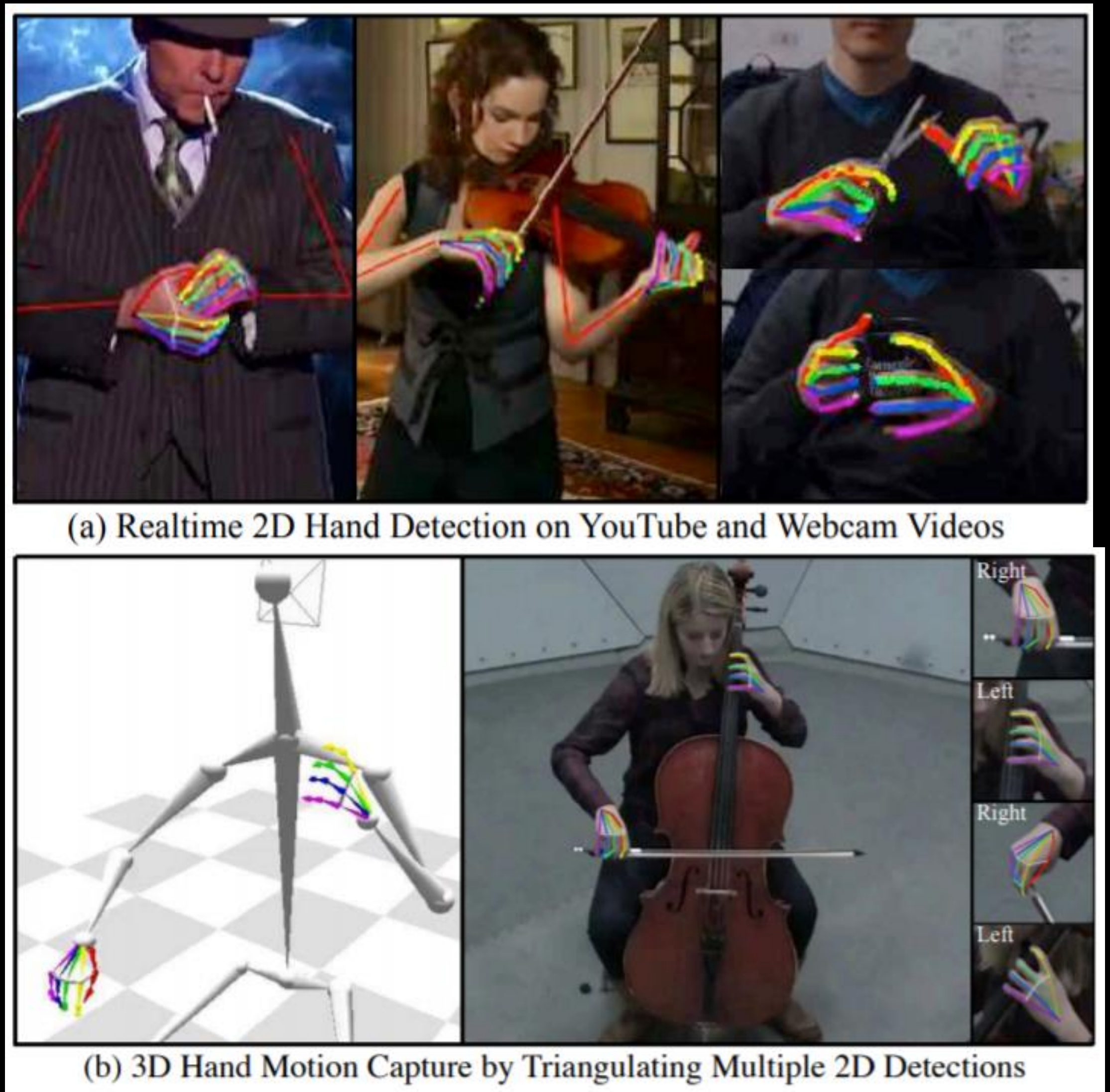
Multistage layers work like a Bayesian predictor. Each subsequent layer uses the guess of the previous layer in order to fine tune its prediction, therefore the subsequent layers should improve over time.

Each layer is trained independently, and theoretically each subsequent loss (S^t & L^t should be less than on S^{t-1} & L^{t-1})



Affinity Field Map

How does the hand detector work?



(a) Realtime 2D Hand Detection on YouTube and Webcam Videos

(b) 3D Hand Motion Capture by Triangulating Multiple 2D Detections

The general idea of this model is the fact that they had 3D Multiview Geometry to generate training data.

They generated training data by using Random Sample Consensus (RANSAC) algorithm to triangulate multiple 2d projections into 3d space, then using that training data to extrapolate 3d pose from 2d images.

This basically finds the most likely space that these points would have been projected from, which allows the points to be tolerant to occluded markers, which is very important for something that occludes itself in a majority of possible poses.

How does the face detector work?

- If you understood how OpenPose works, then the face detector is trivial!
- The face detector superimposes 70 feature detectors to produce confidence heatmaps to perform bipartite matching similar to how OpenPose does pose recognition.

* This implementation is equivalent to how OpenCV, a popular Computer Vision tool, accomplishes this

* Affinity fields are not used, because face landmarks do not rotate independently of each other.

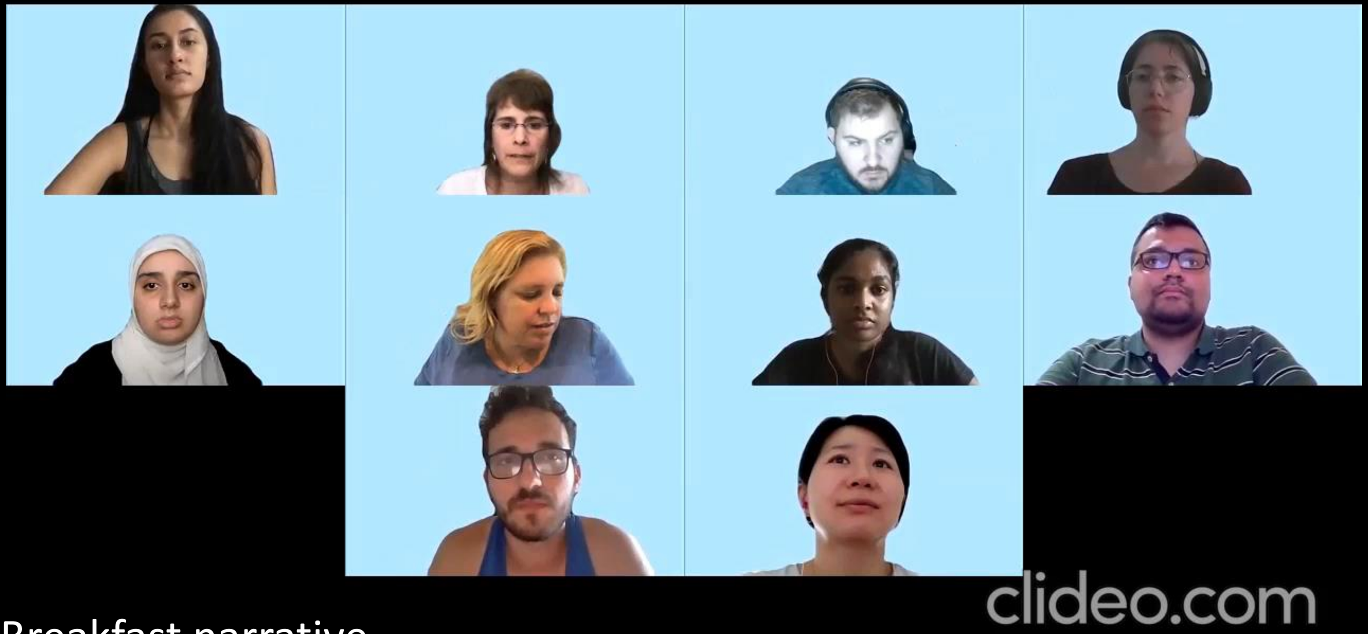
Why should we care about this?

- Noninvasive
  - Complete natural motion like never been seen before, unencumbered by any accelerometers / trackers
- Cheap to distribute
  - All you need to record data is a camera, motion can be measured offline after the fact
  - Experiments can be performed remotely, without having to send any specialized equipment
- Repeatable
  - Any video with people in it is a source of data
  - We've recorded many experiments by video, so we can perform analysis of all of those videos and compare those
- Easy to set up
  - Only a single .dll file required to get started (free for research purposes)
  - Compatible with both webcams in real time and videos offline

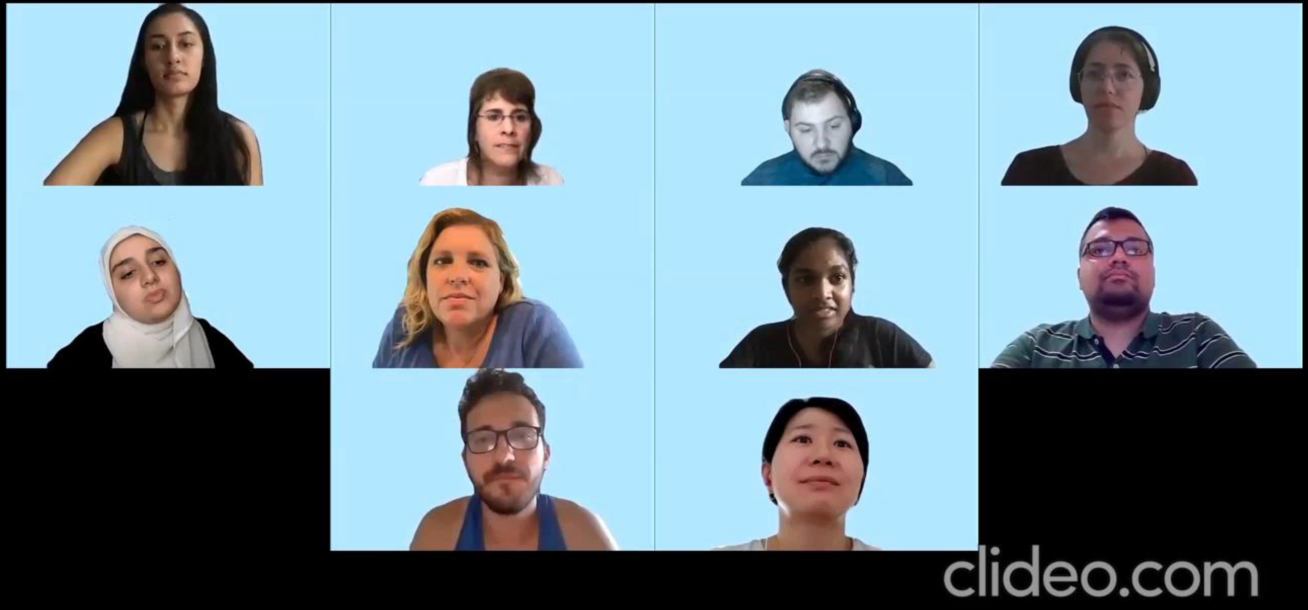
STEPS

1. IN CLASS WE WILL LEARN ABOUT
2. WILL OBTAIN CONSENT FROM EVERYONE
3. WE WILL THEN NARRATE SOMETHING TO THE GROUP (E.G. WHAT DID YOU HAVE FOR BREAKFAST?)
4. SAVE ZOOM SESSION
5. PROCESS DATA (CUT AND CROP)
6. RUN OPENPOSE TO GET GRID FOR EACH PERSON
7. LEARN HOW TO BUILD ADJACENCY MATRICES TO REPRESENT PAIRWISE AND GROUP INTERACTIONS
8. DERIVE CONNECTIVITY METRICS
9. VISUAL TOOLS
10. INFERENCE AND INTERPRETATION
11. STATS / WRITE REPORT

Neutral



Breakfast narrative



PROCESS DATA (CUT AND CROP) USING CLIDEO

https://clideo.com/cut-video

https://clideo.com/crop-video

It is important to keep this order because you want people to be synchronized. If you crop the individual segments that you want first, you will shift the original relative timings

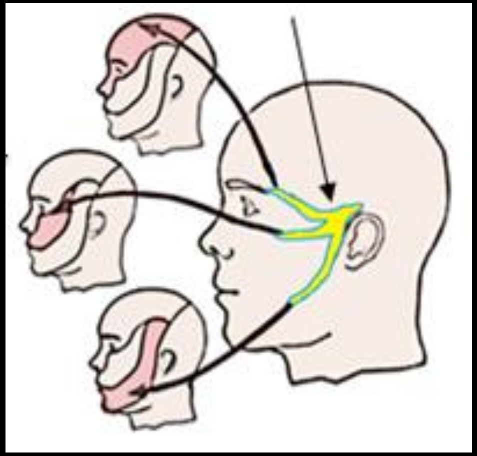
Cut the segment with all the people in it, then crop the individual people out

Neutral

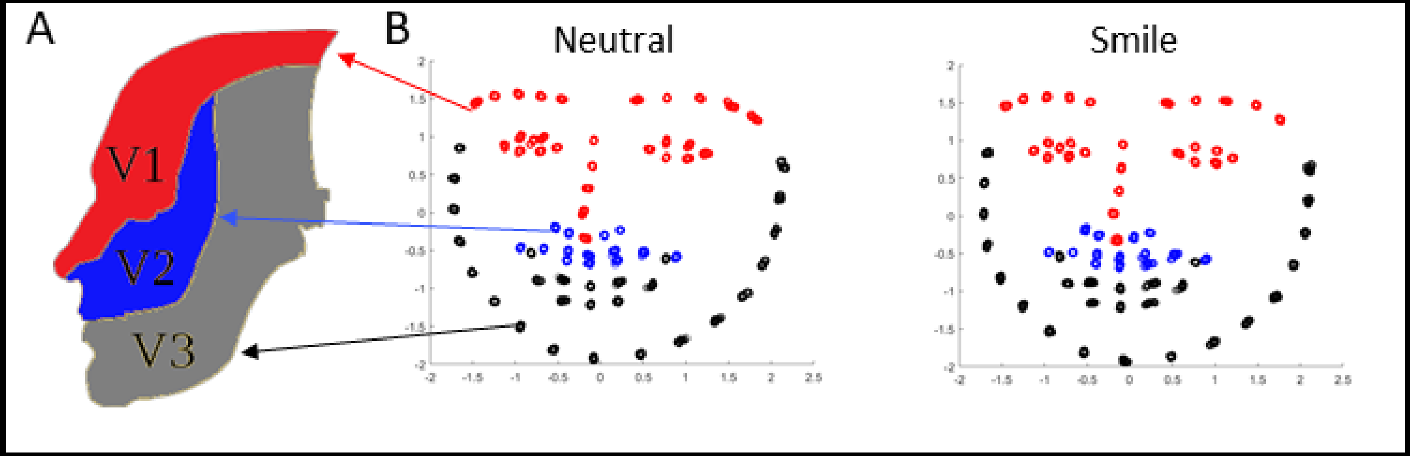
Fake Smile

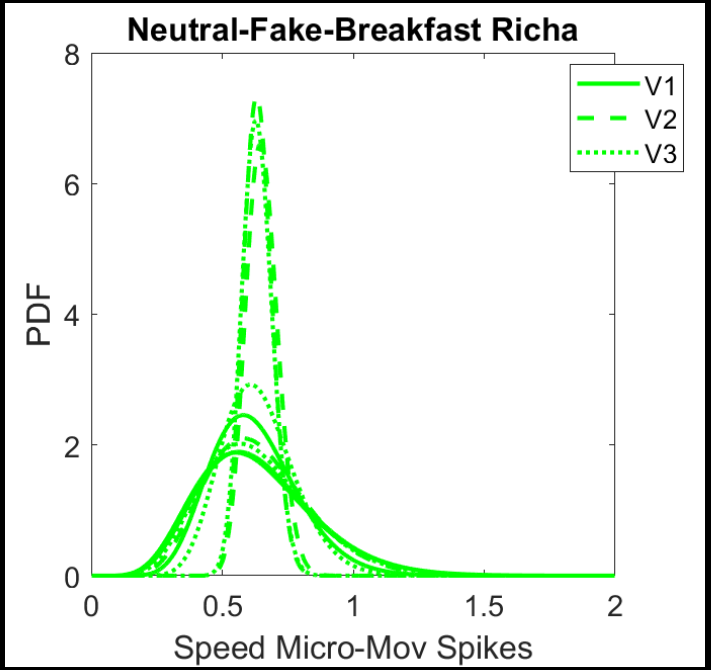
Breakfast Narrative

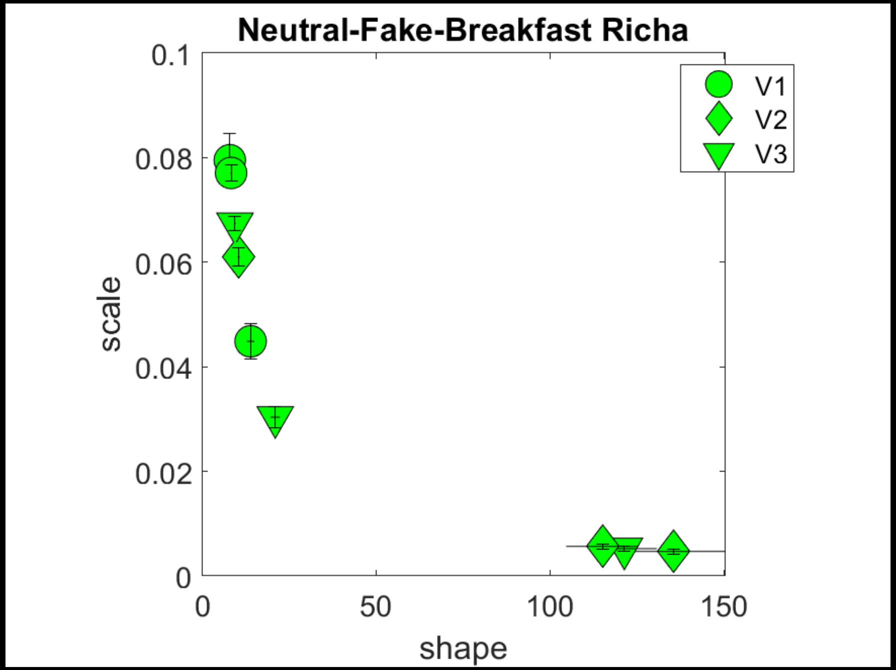
Trigeminal Nerve

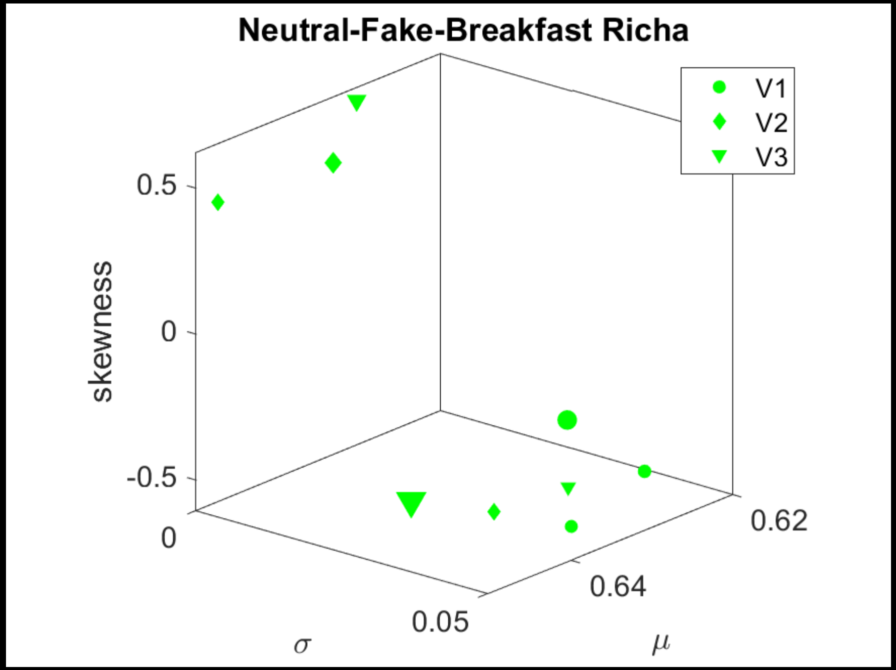


Digitize Trigeminal Nerve Representation

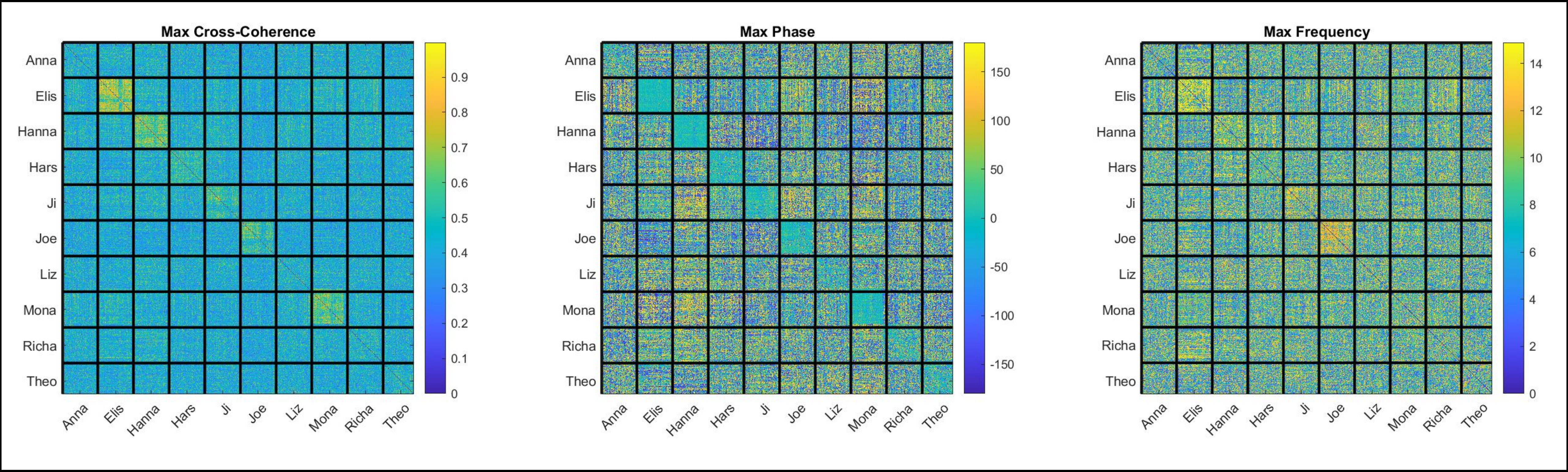




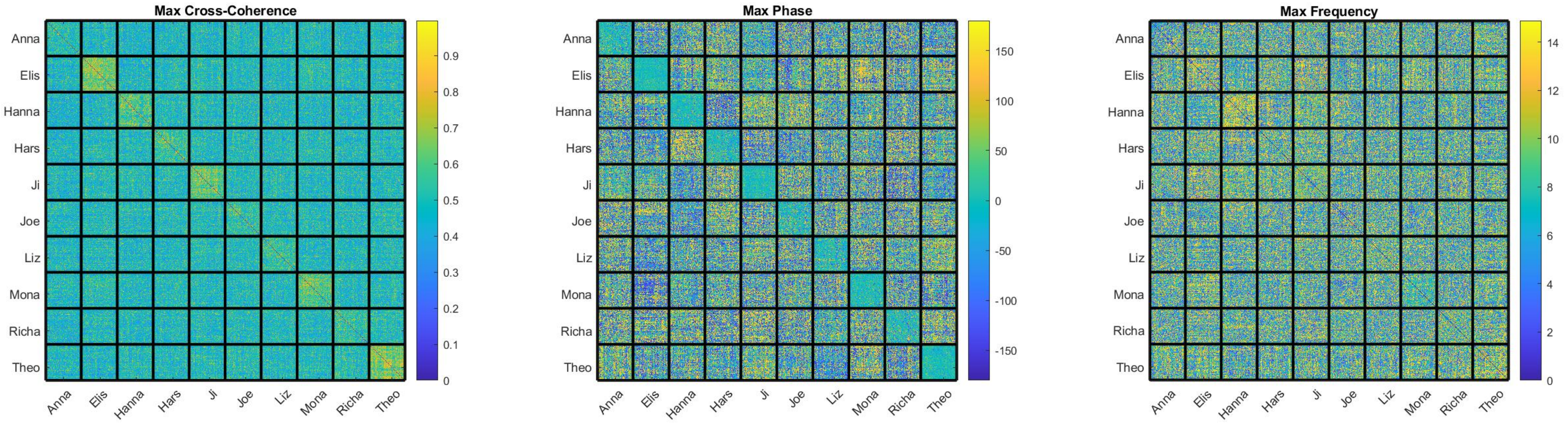




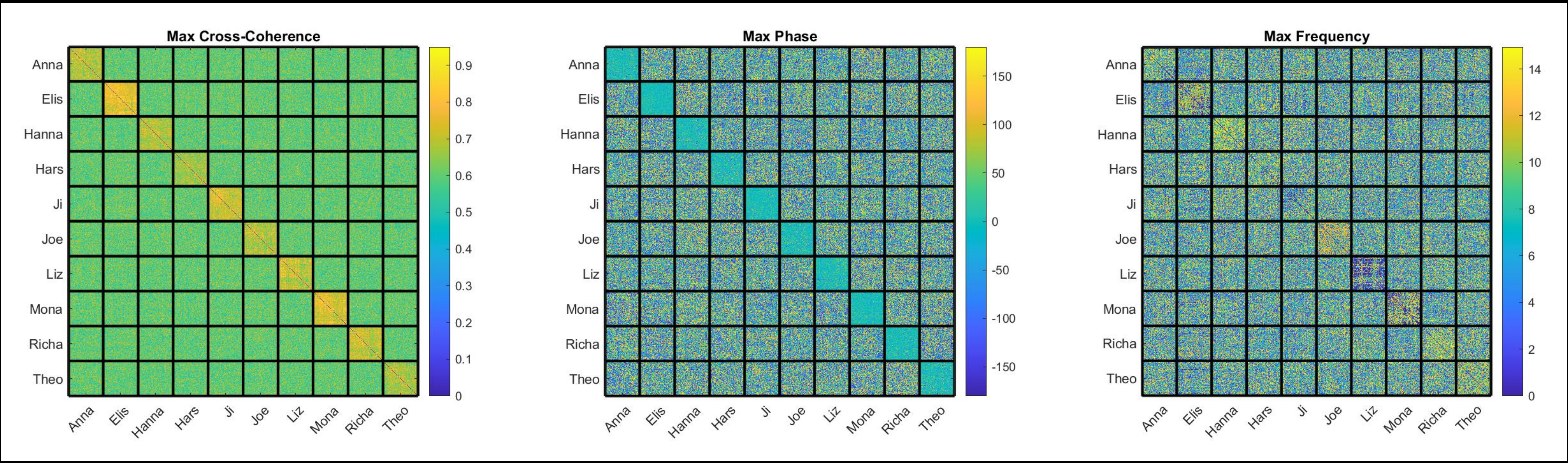
Cross-coherence, Phase, Frequency Analyses

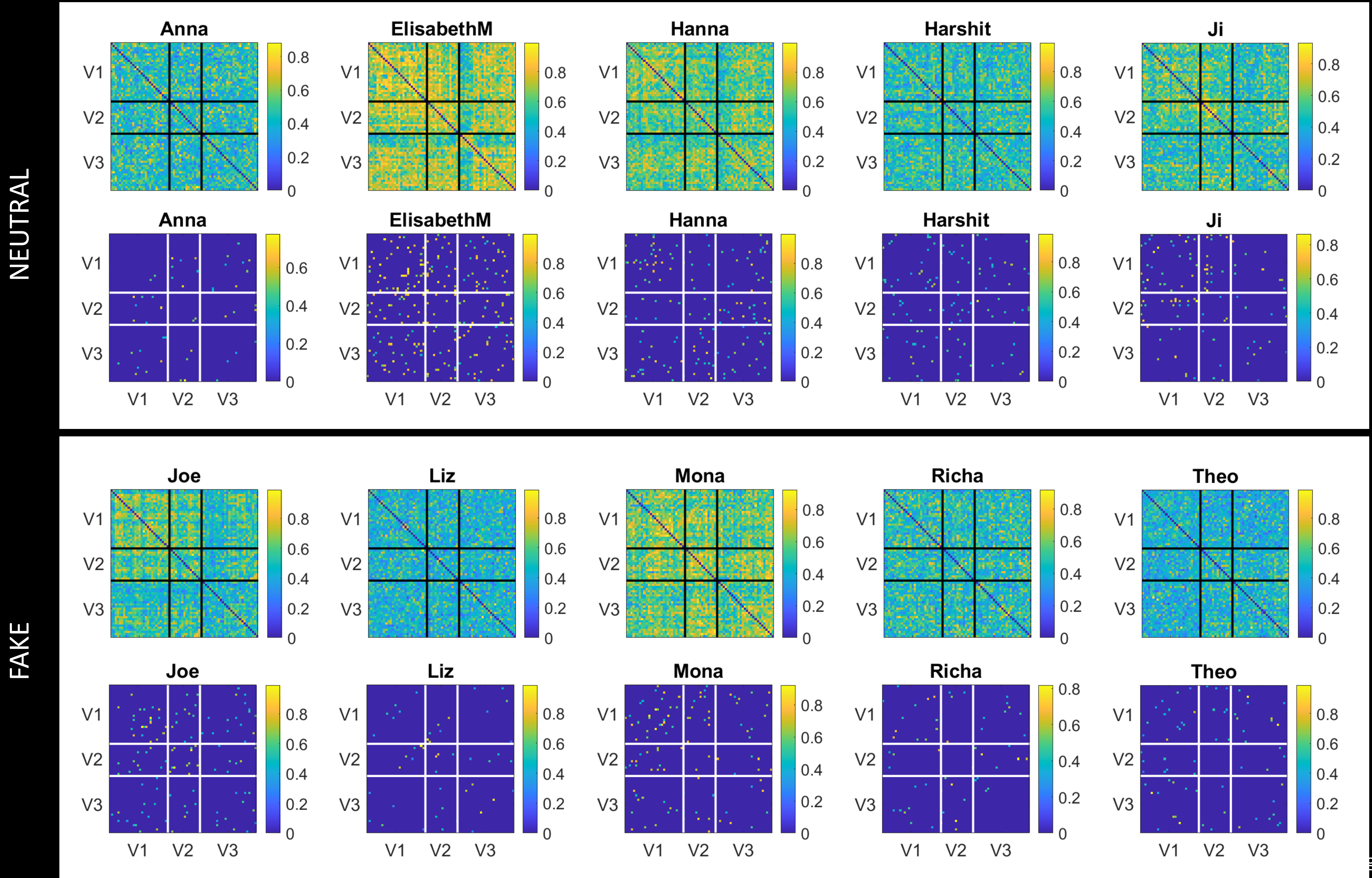


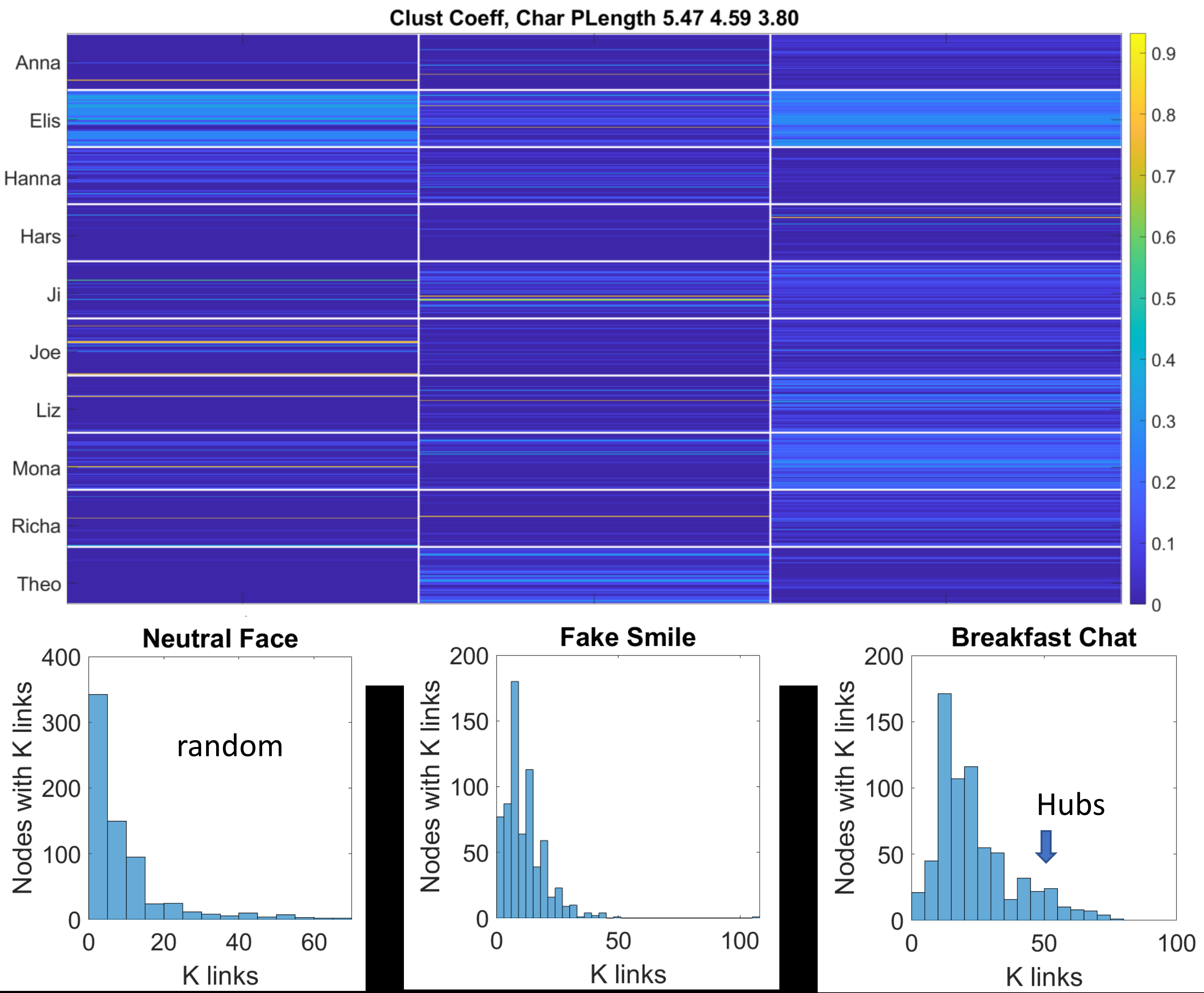
Cross-coherence, Phase, Frequency Analyses



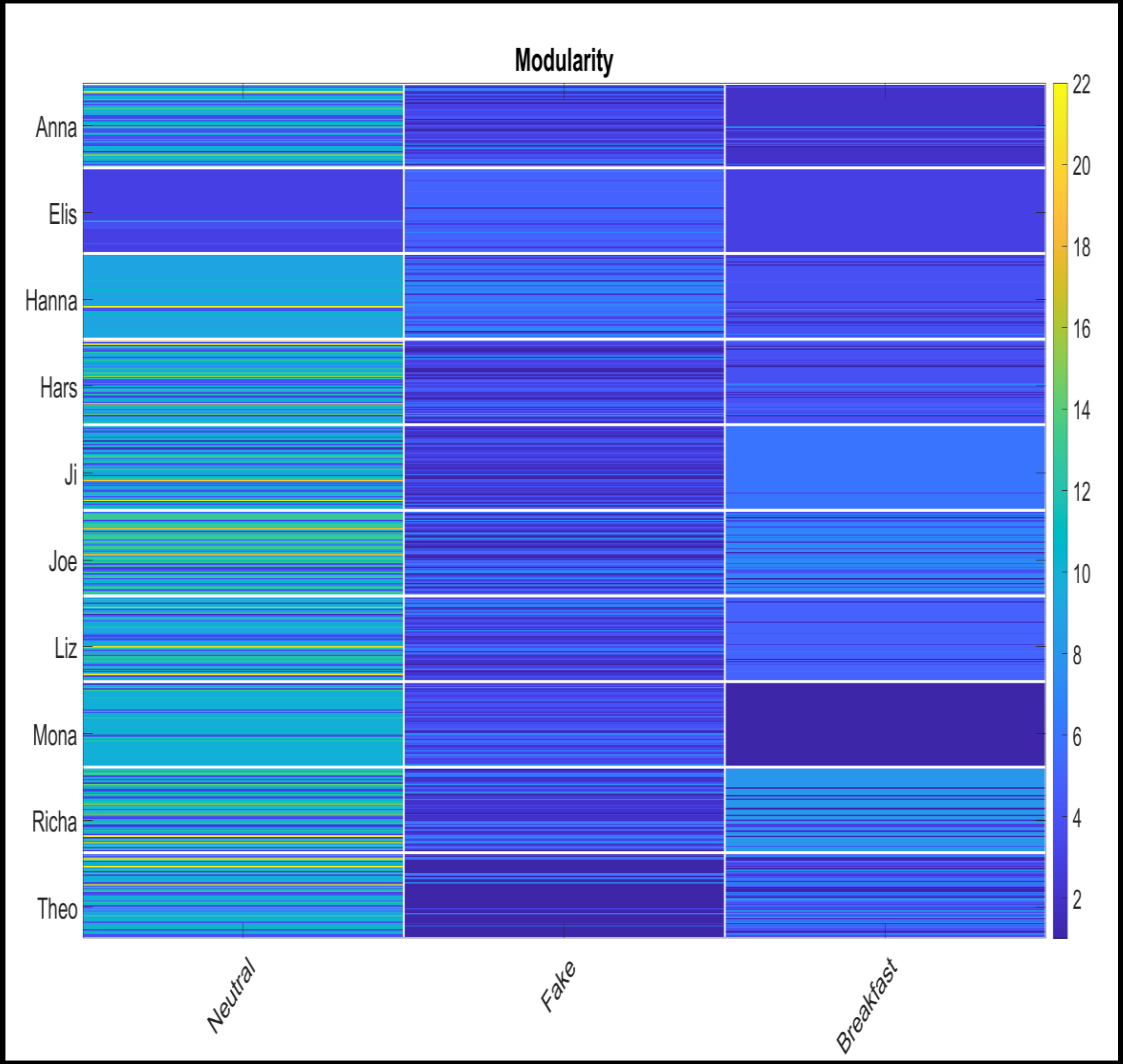
Cross-coherence, Phase, Frequency Analyses

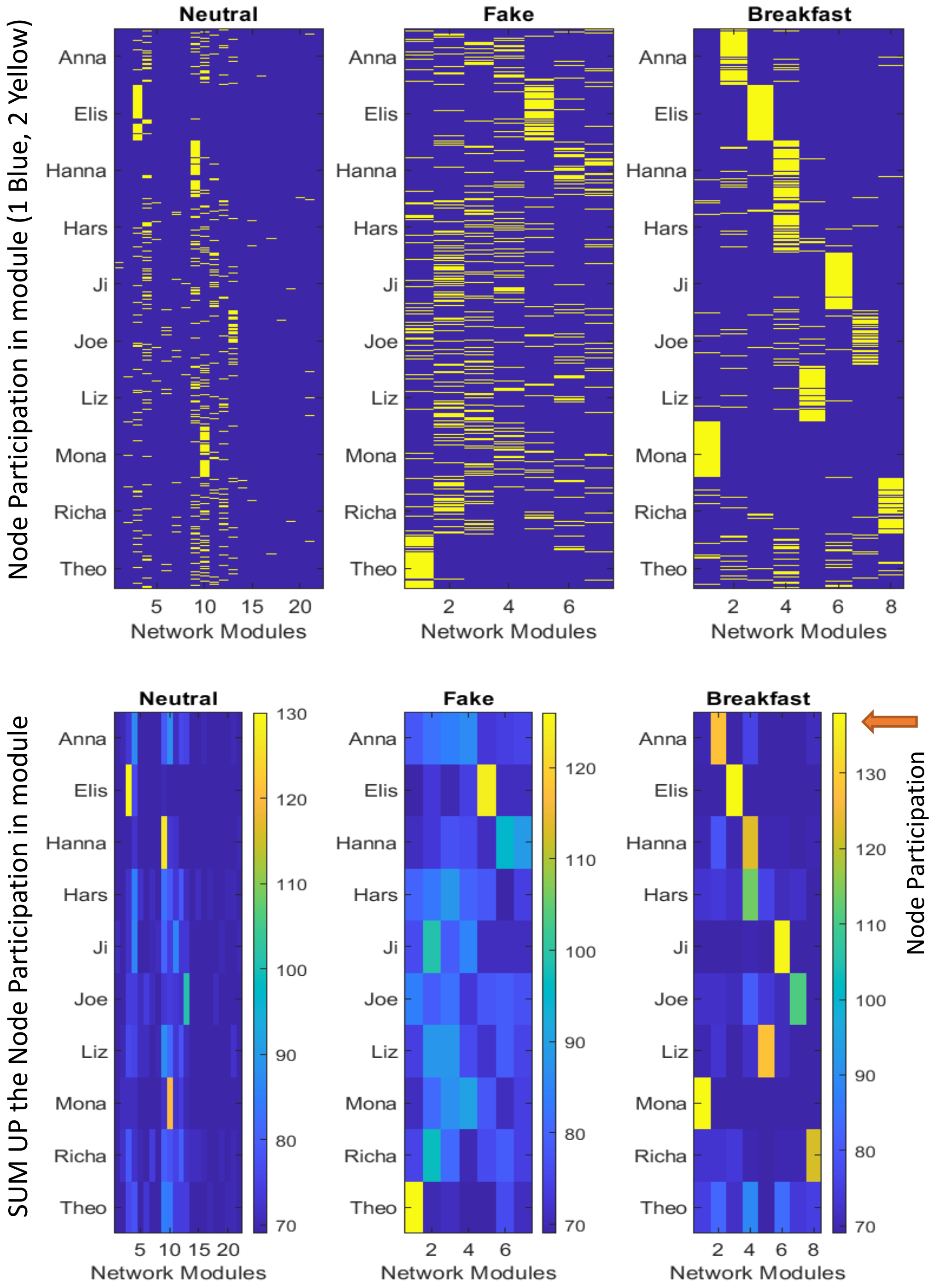



NEUTRAL
Anna
ElisabethM
Hanna
Harshit
Ji
FAKE
Joe
Liz
Mona
Richa
Theo
V1
V2
V3


Clust Coeff, Char PLength 5.47 4.59 3.80
Anna
Elis
Hanna
Hars
Ji
Joe
Liz
Mona
Richa
Theo
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
Neutral Face
random
Nodes with K links
K links
Fake Smile
Nodes with K links
K links
Breakfast Chat
Hubs
Nodes with K links
K links

Community Structure: Random heavily interconnected to modular whereby each module is a person (during the social exchange in breakfast)





B Torres 2020

Other applications

- https://news.mit.edu/2020/sensor-als-communicate-1022

Track transition from staged to spontaneous – real laughter