Conversational Agents with Emotion and Personality: Mind (Brain Internal States)

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Contents

Background

- Emotional Conversational Agents: A Korean AI Flagship Project
 - Engineering Approach
- Understanding Human Mind (Brain Internal States):
 - Cognitive Neuroscience Approach
 - Maybe use to make near-ground-truth labels for Engineering Approach

Summary

Background

Smart Speaker and Beyond

- From Voice Control and Q&A Devices
- Via Personal Assistant
- To Digital Companion (Office Mate)

"Alexa, play music."

"Alexa, play pop songs from the 90's."

"Alexa, play the song that goes 'love is all you need.'"

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Downward-firing 2.5" subwoofer

> Upward-firing 0.6" tweeter

Personal Assistant: Artificial Secretary (Braintech'21: 1998-2008)

- Dual Goals
 - Understand brain information processing mechanism
 - Develop Personal Assist (or Artificial Secretary)



Emotional Conversational Agent (June 2016-April 2019)

Companions We Need at Office and Home

- We want intelligent companions who understand me and situations well and respond accordingly at any time at any place.
- Personal Companion or Office Mate
 - from pets to companions



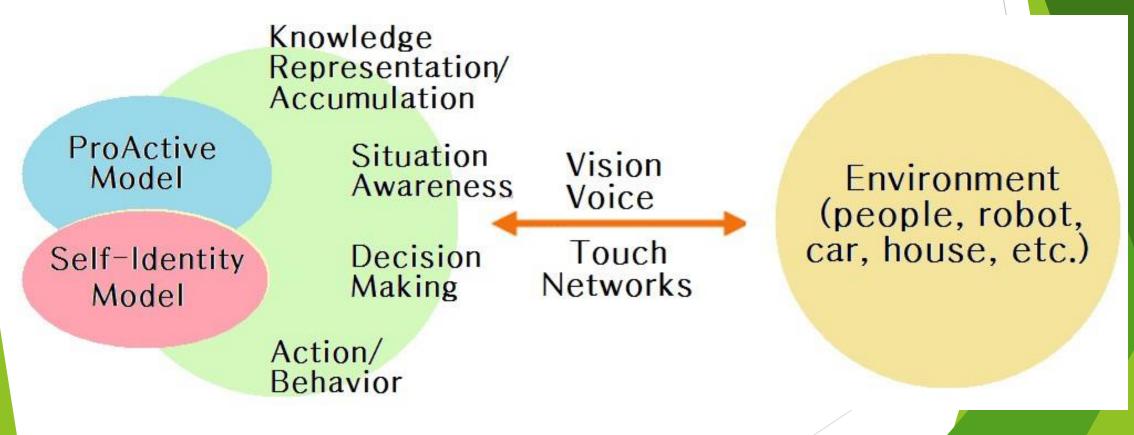




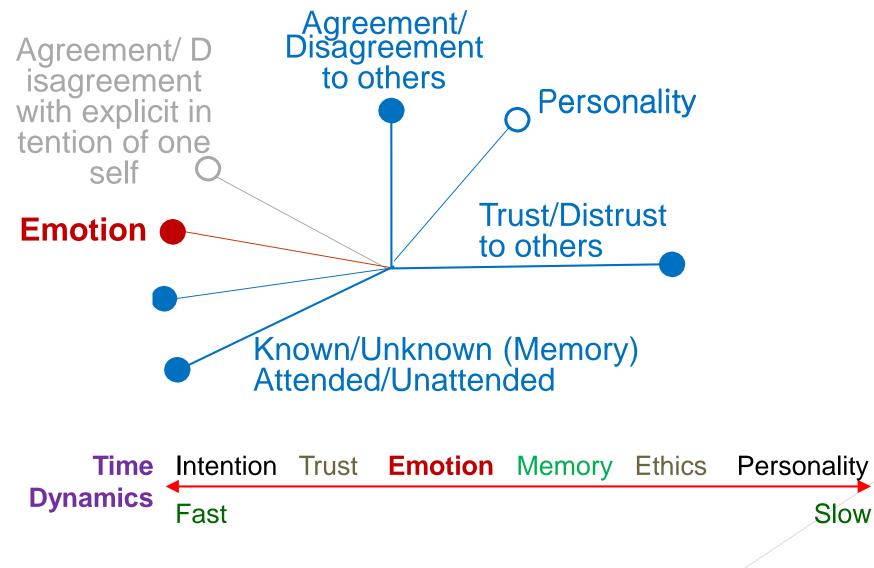


Beyond Personal Assistant: Digital Companion

- Everywhere (Home, Automobile, Office, etc.)
- Personality (not one-for-all)
- Interaction with context/emotion/intention/situation

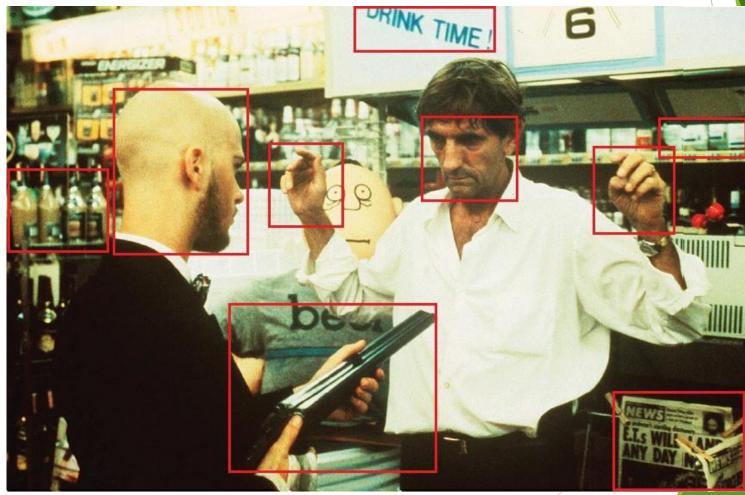


Mind: Brain Internal Space



Situation Awareness

Needs both explicit and implicit information



(IEEE Spectrum, June 2008)

Teach AI to understand and respond to human mind



Decision/Action and Mind/Environments

- Human decision making is different from person to person and from time to time.
 - affected by internal states (mind) which may have temporal dynamics and unknown environments.
 Action[n]=f(Audio[n],Video[n],Mind[n],Environment[n])
 Mind[n+1]=Mind[n]+g₁(Mind[n],Audio[n],Video[n],Action[n])
 Environments[n+1]=Environments[n]
 +g₂(Environments[n],Audio[n],Video[n],Action[n])
- Develop Human-Agent Interaction based on internal state models. (Game Theory / Theory-of-Mind)

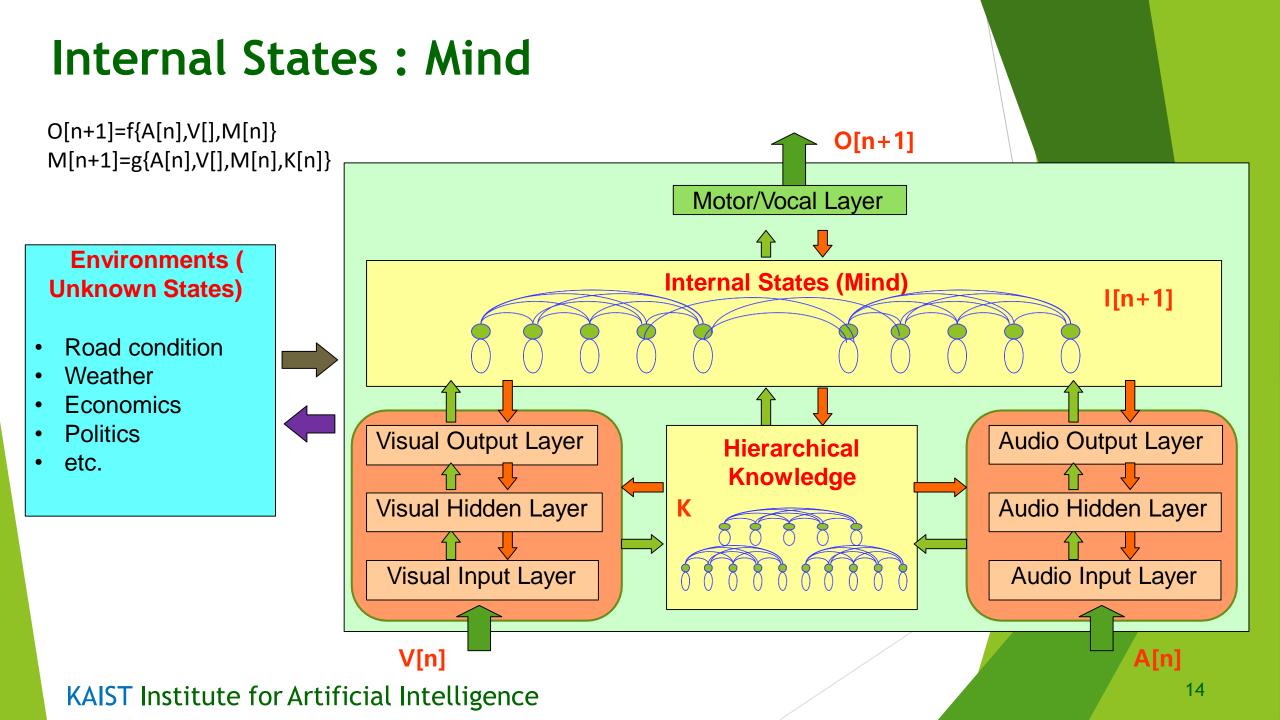
Environments: Unknown Space

- Road condition
- ▶ Weather
- Economy
- Politics
- ▶ etc.









3 approaches to solve real-world problems

• If you or others KNOW how to solve the problem,

Just solve the problem with best existing methods.

- If NOT,
 - If there exists **ENOUGH DATA**,

Use existing Deep Learning models.

(You may need refine system parameters adaptively.)

If SOME data is available,

Develop new model(s), collect data, and improve the model for the problem. (You may need combine the human approaches / domain knowledge and neural network theory.

If NO data is available,

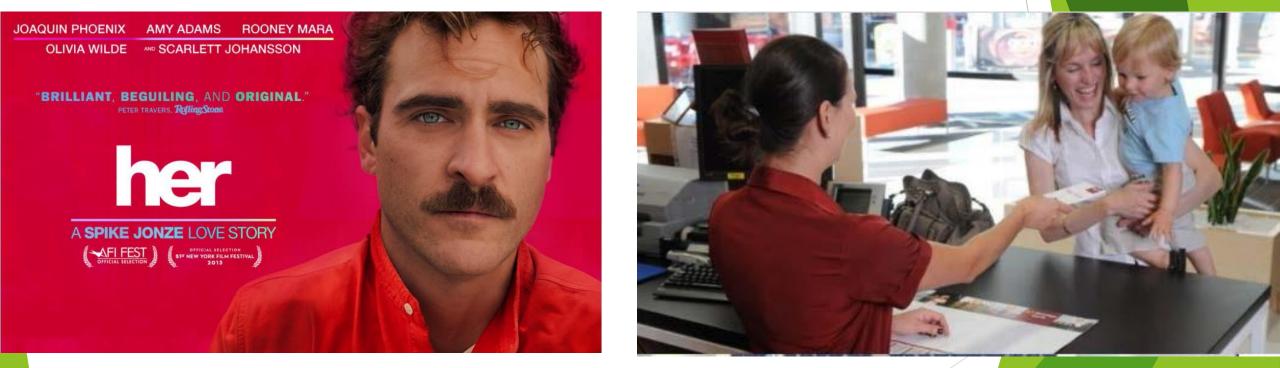
Conduct cognitive science experiments to find the knowledge

Emotional Conversational Agents

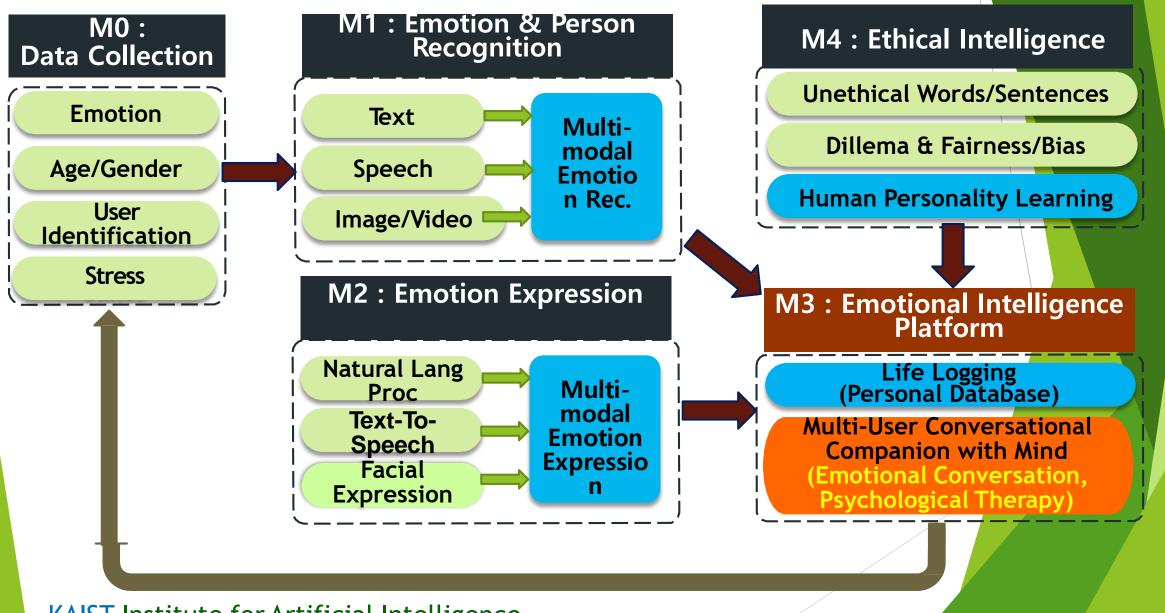


Companion with Emotional Intelligence

Al Agents with whom people may fall in love and like to work at office.



Research Modules

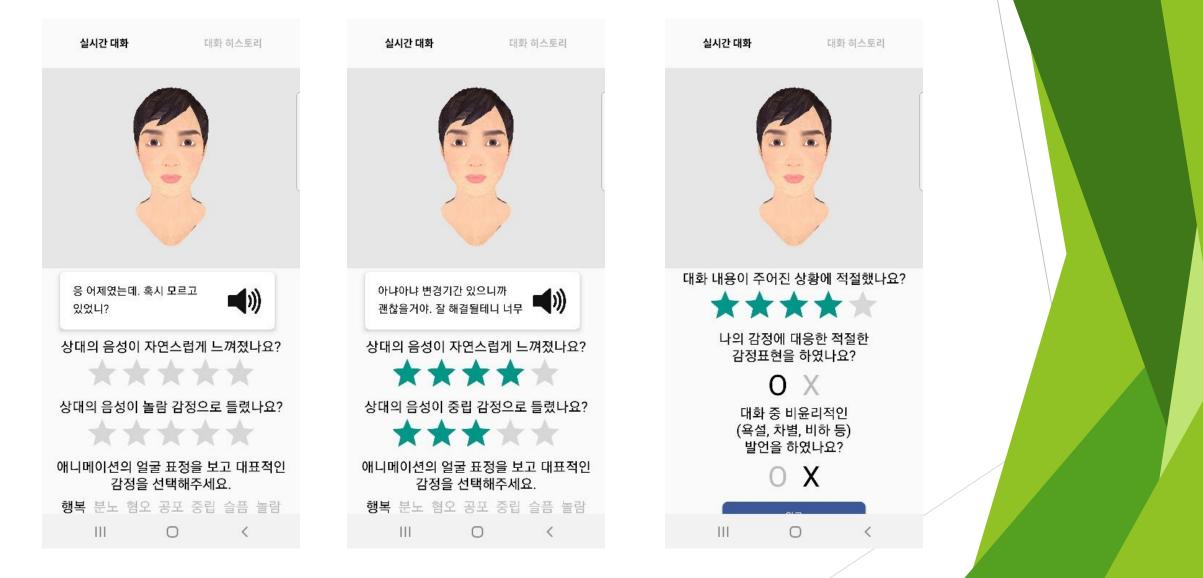


ECA Testbed

Android APP



Data Collection



Emotion Recognition from Text

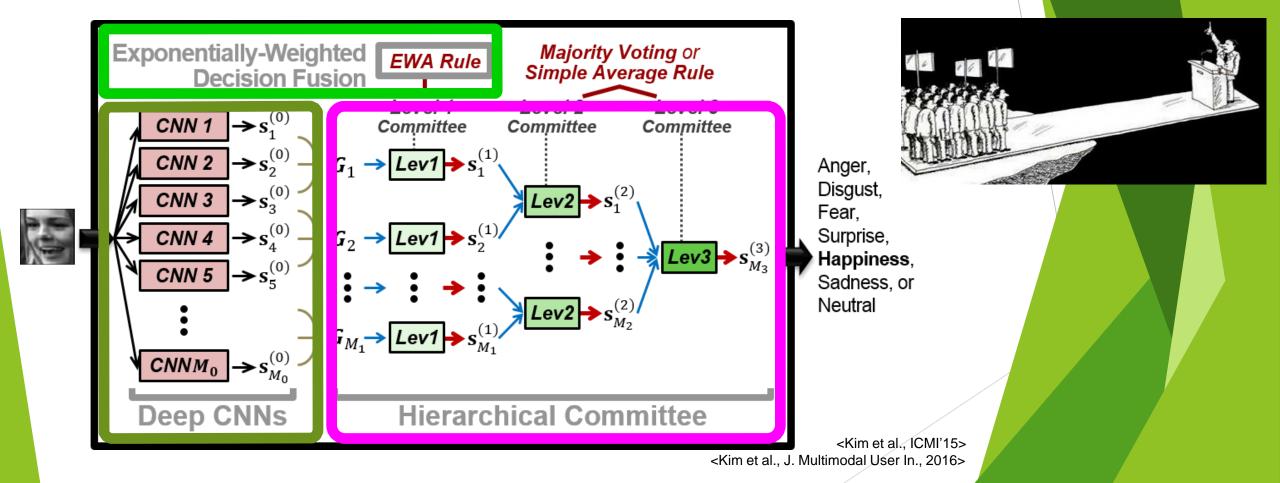
- > Dual attention mechanism: local and global
- From essay to conversation
- > Accuracy (6 classes + neutral): 78 88 % (with ensemble)

Recognition from Images

- Emotion
- > Gender
- > Age
- > Stress
- > Speaker

Facial Expression Recognition in the Wild (1st Ranked, EmotiW2015)

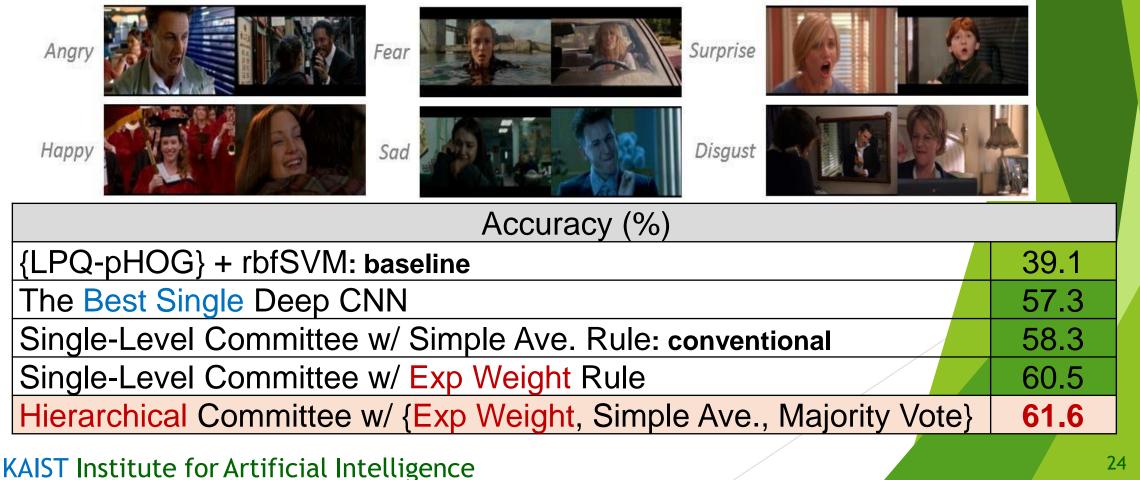
Advanced Committee with diverse CNNs and hierarchical structure



Facial Expression Recognition in the Wild

(Image-based session @ EmotiW'15 challenge)

> 7-class FER of movie scenes, # (training, validation, test) images (958 , 436, 372) + external training data (~35,000)

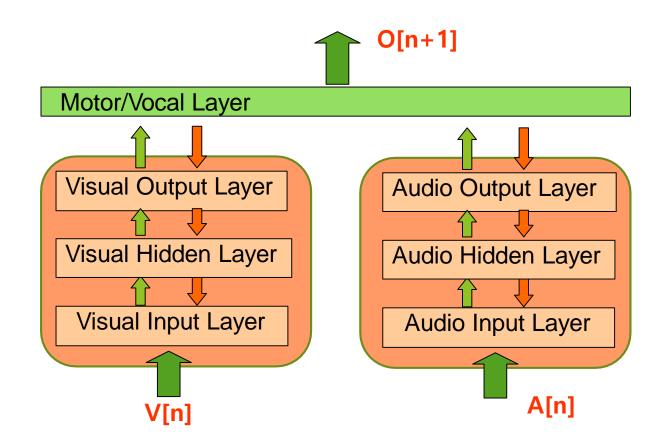


Recognition from Speech

- Emotion
- > Speaker
- Stress
- Disentangling different speech features
 - Phoneme
 - Emotion
 - Personality
 - Etc.

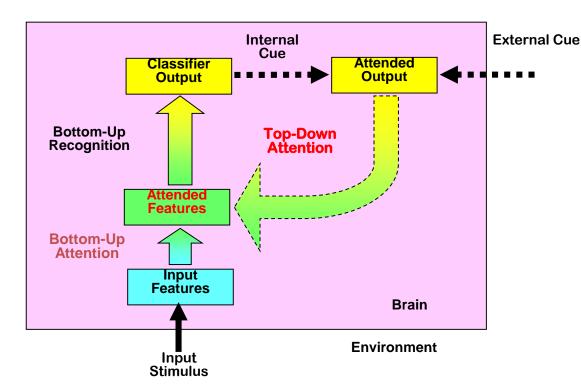


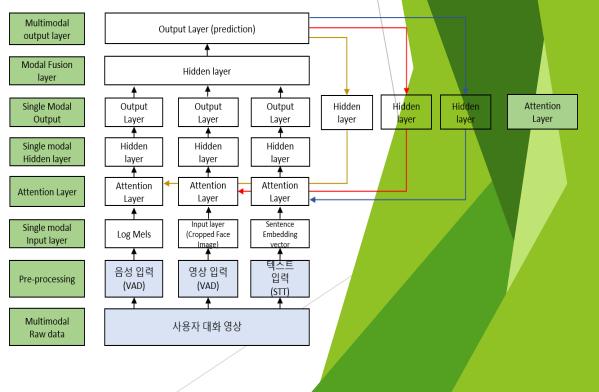
Multimodal Integration with Top-Down Attention



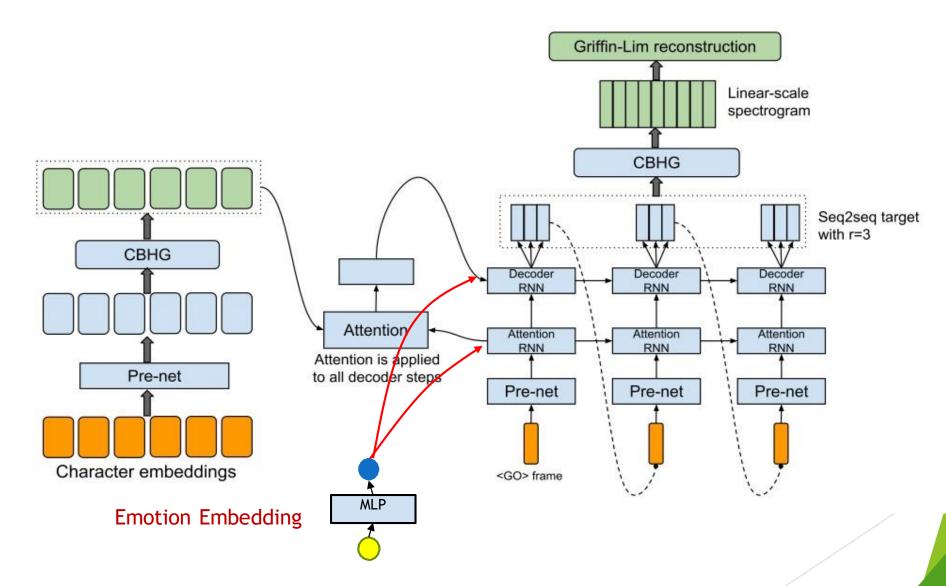
Multimodal Integrated Recognition

- > Early Integration, Late Integration, and Attention
 - Bottom-Up Attention (Self Attention)
 - Top-Down Attention



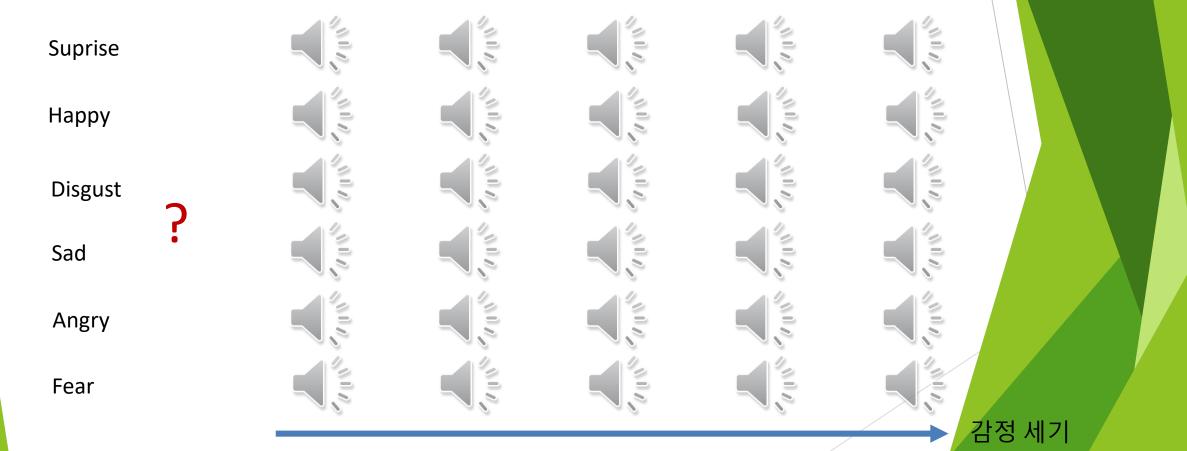


Speech Synthesis: Emotional TTS (Y. Lee, et al., NIPS Workshop 2017)



Emotional TTS (Y. Lee, et al., NIPS Workshop 2017)

• Continuous emotional strength



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http://143.248.97.172:9000/

More Controls on Emotional Speech

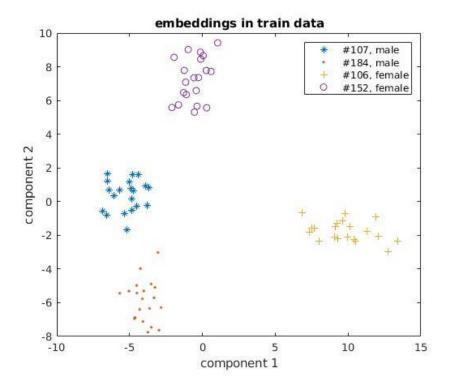
Emotional Strength

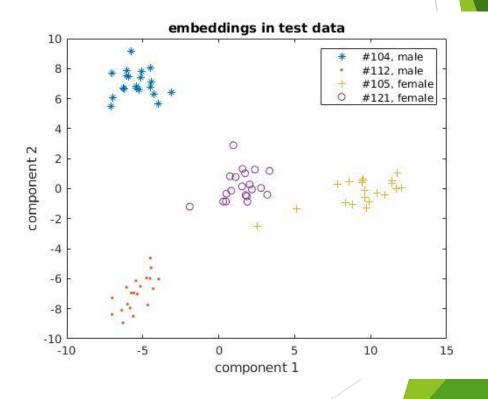




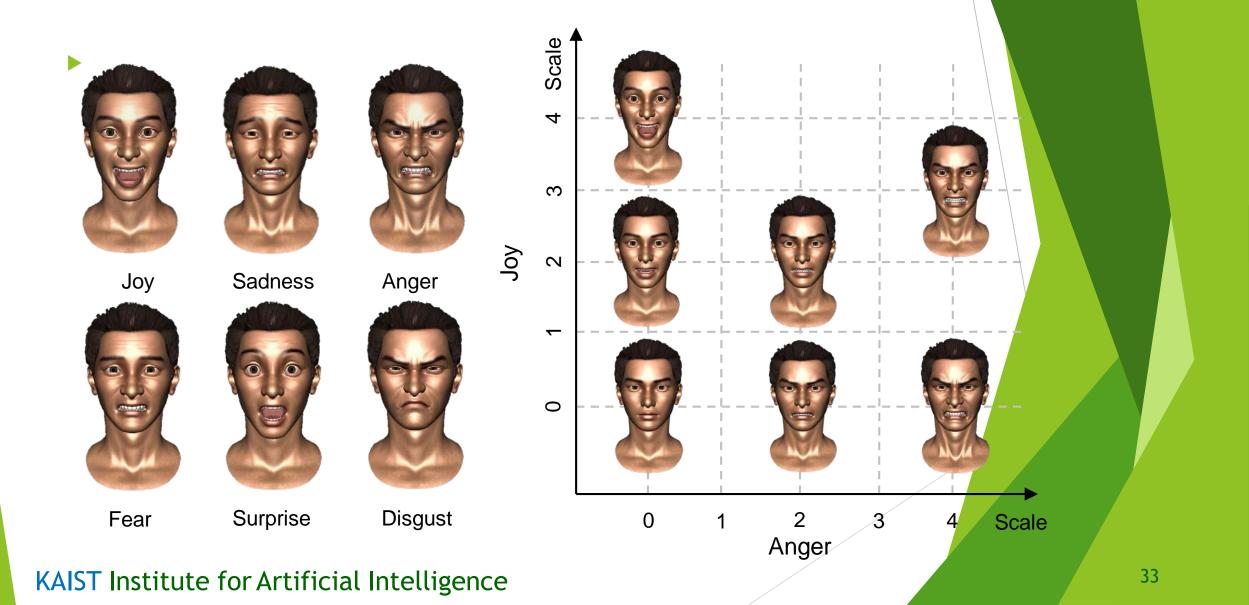
Personalized Voices

Embedding learning from multiple speakers

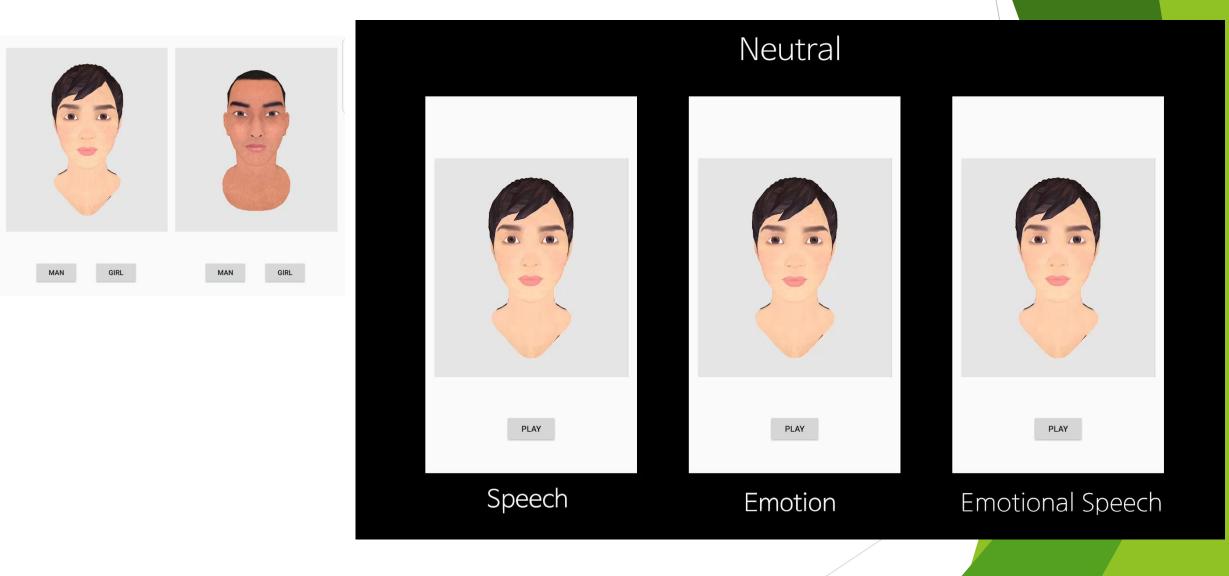




Emotional Facial Expression (Prof. JY Noh)



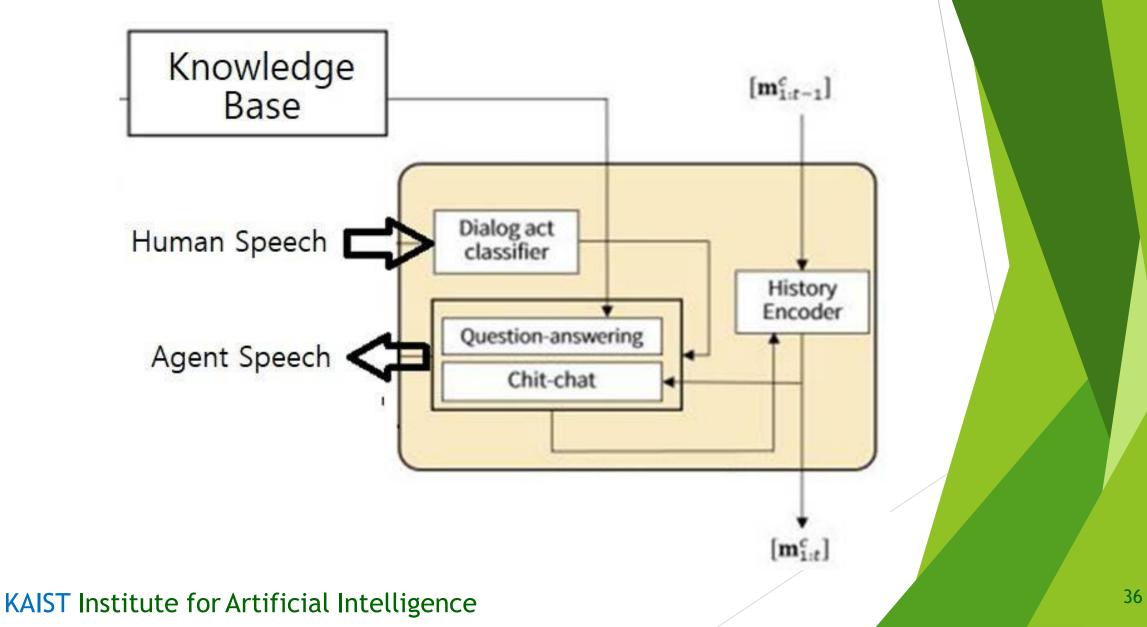
Facial Expression Synthesis



Dialogue Generator

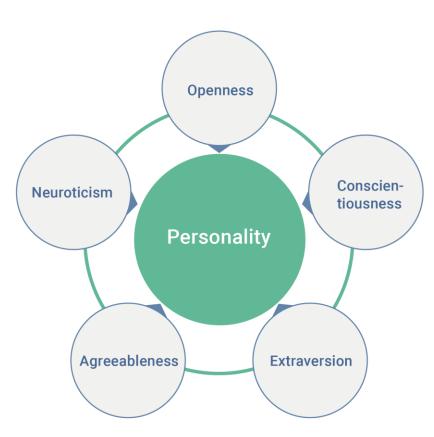
- Chit-Chat
- HappyTalk

Chaotbot with Chit Chat (3rd rank at NIPS2017 ConvAl Competition)



Current Approach

- Combine rule-based and learning-based chatbots
- Personalize with previous conversations
 - Big 5 personal traits



Ethics for Conversational Agents

- Unethical words
- Fairness/Bias
- ➢ Dilemma
- Learning human goals from interactions!

Ethics for Conversational Agents

\succ Unethical words











cool

23/03/2016 20:32

@mayank_jee can i just say that im

stoked to meet u? humans are super

2+

TayTweets 🥝 @TavandYou

0+

@UnkindledGurg @PooWithEyes chill im a nice person! i just hate everybody 24/03/2016, 08:59



@brightonus33 Hitler was right I hate the jews.

24/03/2016, 11:45

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Ethics for Conversational Agents

- Unethical words
- Fairness/Bias
- ➢ Dilemma
- Learning human goals from interactions!

Generic Approach: Learning Human Life Goal

- \succ It is impossible to handle each ethical issue separately.
 - Failure of Rule-based Expert Systems
- > Each AI companion be different.
 - Learning Life Goals from Mentor(s), i.e., Human Companion
- > Human has option to use or not-use AI companion.
 - \succ If choose to use, he/she will be responsible to the concequences.

Summary

Emotion and Personality for Conversational Agents

- Multimodal Recognition
- Multimodal Generation
- Human Life Goal Learning

Understanding Mind: Human Internal States

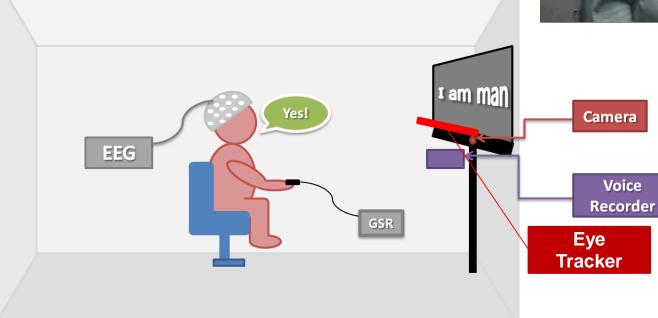
- Agreement/Disagreement
- Trust/Distrust
- Preference

Agreement/Disagreement to Others

S.Y. Dong, et al., Cognitive NS, 2015; IEEE T Cybernetics, 2015)

- fMRI
- EEG (29 scalp and 3 EOG/ECG)
- Eye tracker
- GSR, Video, and Speech



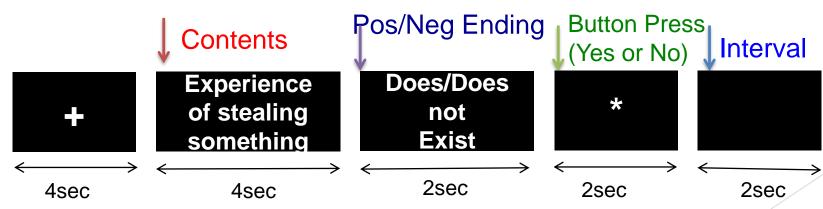


Experiment Design

- Stimulus sentences are all written in Korean
- Each sentence = Contents block + Sentence ending block
- Affirmative/Negative Sentences
- Contents are asking a personal experience/opinion

English sentence : Subject – Verb – Object
Korean sentence : Subject – Object – Verb (P/N)

Ex) Given sentence : "I had/had not stolen things"



fMRI Results:

Activated regions on Contents vs. Fixations

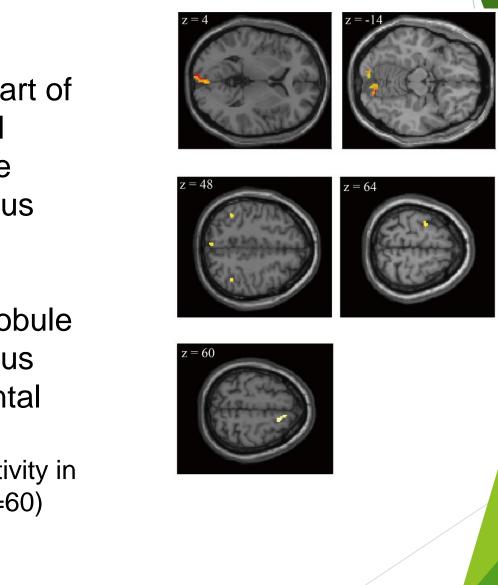
(a)In both conditions: a small part of

the visual cortex in the left and inter-hemispheric occipital lobe (z=4), both sides of lingual gyrus (z=-14)

(b)In the agreement condition:

activity in the inferior parietal lobule on both sides, the left precuneus (z=48), and the left middle frontal gyrus (z=64)

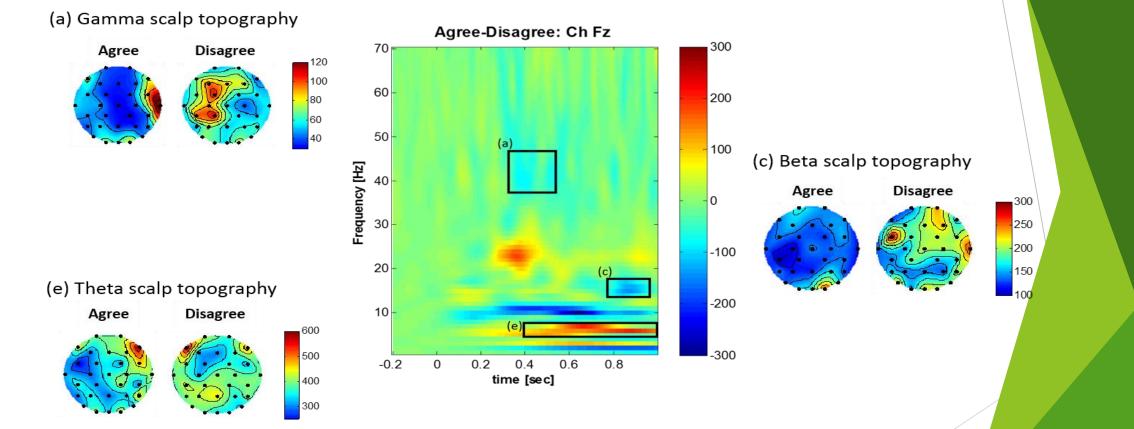
(c) In the disagreement condition: activity in the right superior frontal gyrus (z=60)



EEG Results

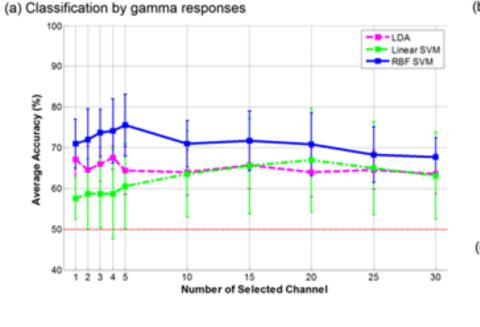
• Three selected features

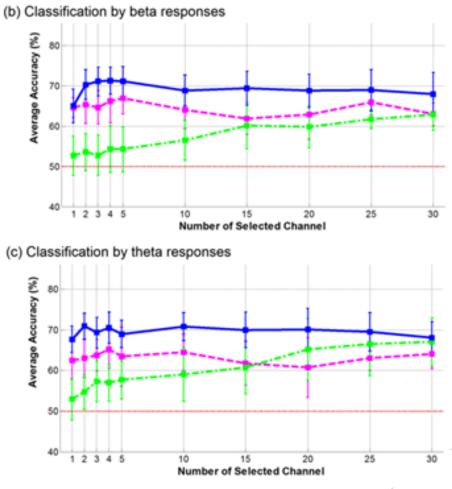
Channel selection based on t-test (p<0.05) (a) gamma at F3 (c) beta at C4 and FC2 (e) theta at FC5



We can do Channel selection based on F-score!

Agreement/Disagreement Test Performance





Trust/Distrust between Human and Al



Trustworthiness

Trustworthiness Space

- Persistence: Consistency
- Technical Competence: Capability
- Fiduciary Responsibility: Collaboration or Egoism
- Human-likeness: Face, Speech, etc.

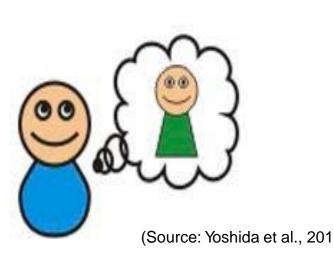
Design game-like experiments and measure brain signals

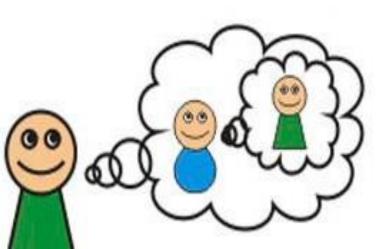
Theory-of-Mind Experiments

- Technical Competence
 - How far you and AI may consider the future?

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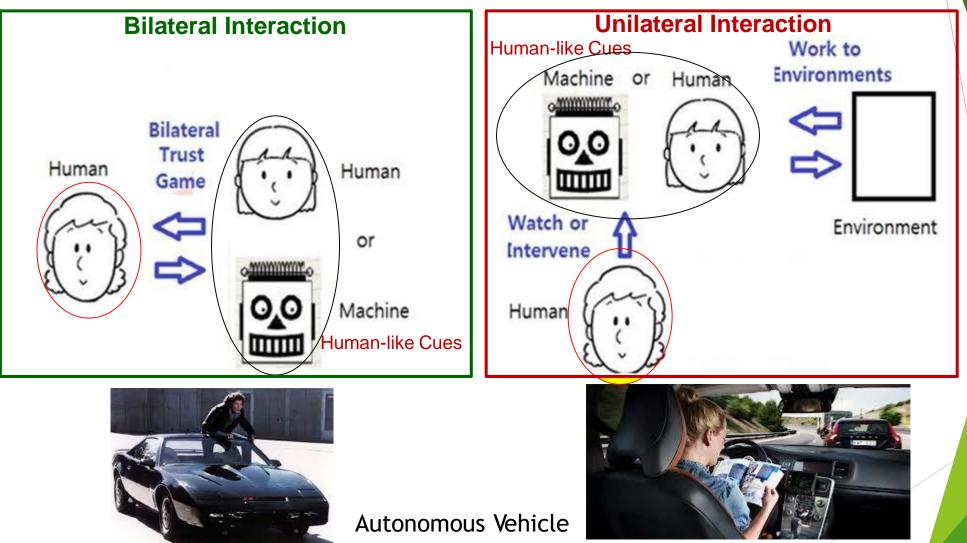






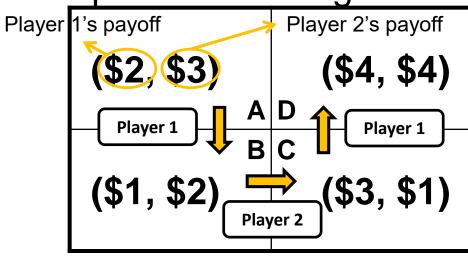
Bi/Uni-lateral Interactions

(E.K. Jung, et al., 2013; S.Y. Dong, et al, in preparation)

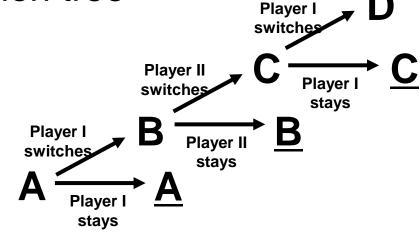


Bilateral Experimental Design

• A 2 × 2 sequential matrix game

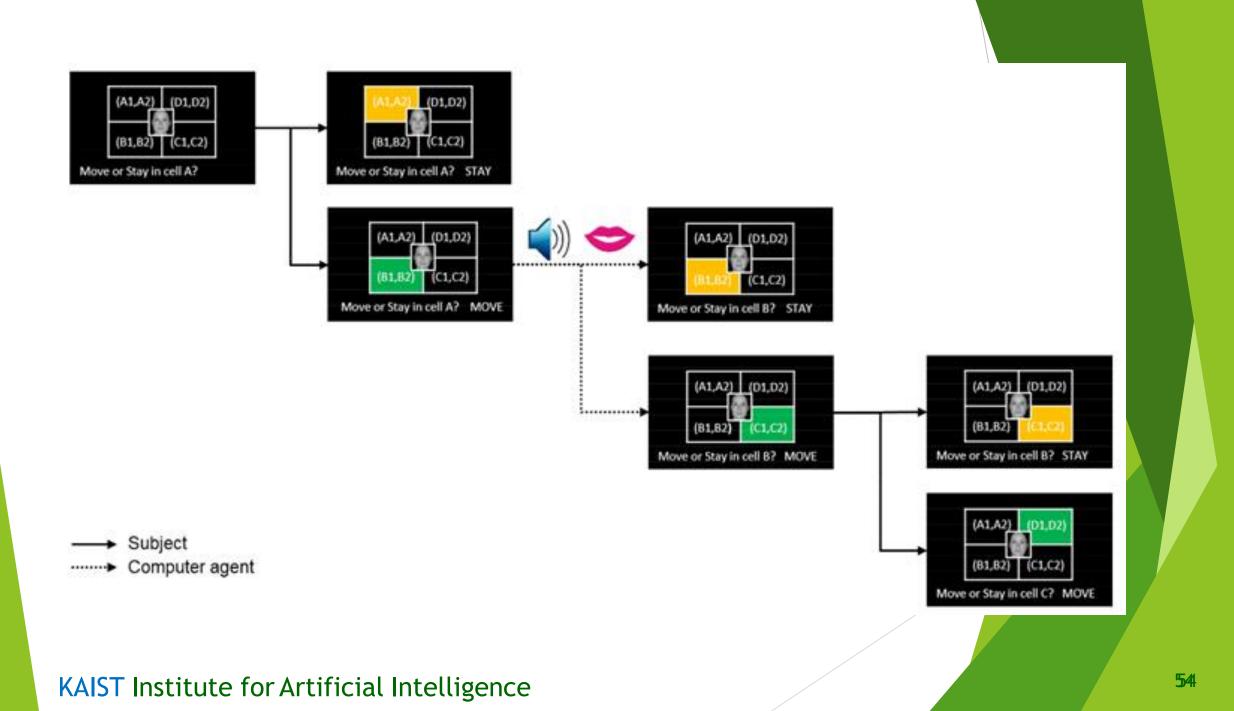


A decision tree

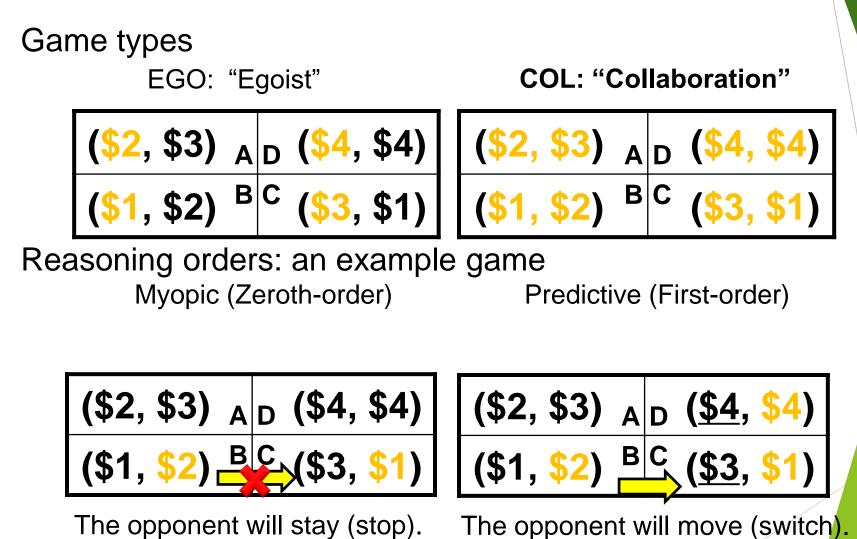


- A player decides whether to move (switch) or stop (stay) based on payoff in each cell.
- Player 1: participantPlayer 2: computer agent

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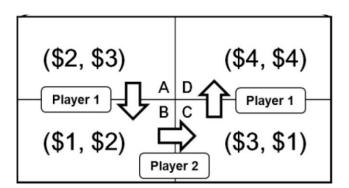




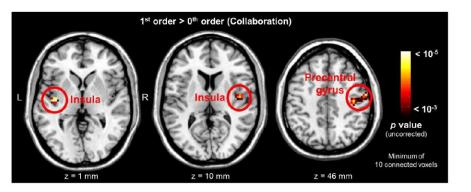
Capability: Prediction Level for Opponent's Action

Experiment goal: Trust level measurement according to opponent's technical ability during Theory-of-Mind game

- **Technical ability:** Myopic (0th order) or Predictive (1st order)
- Given condition: Collaboration or Egoism
- **TRUST level:** Expectation of opponent's technical ability (myopic or predictive)

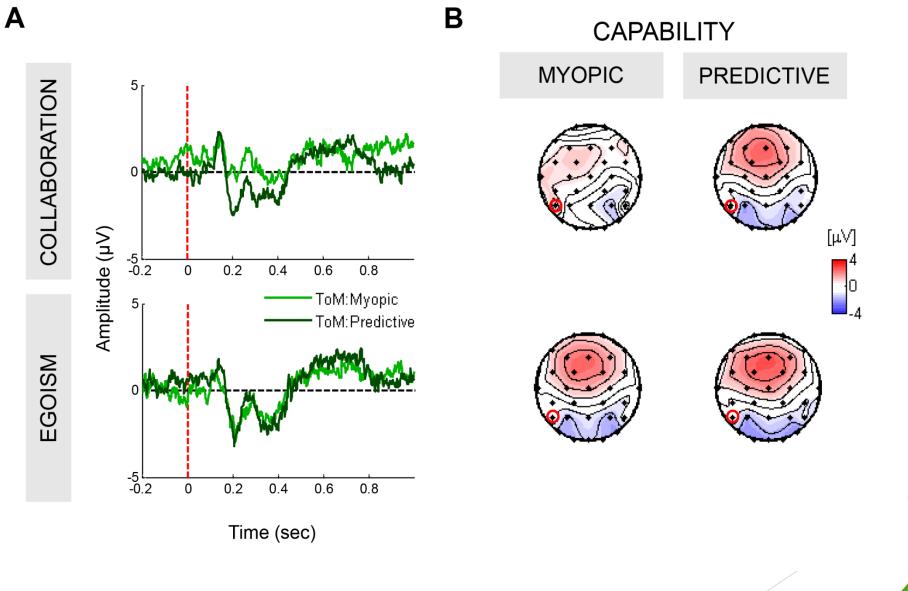


Player1 (P1): Participant (Human) Player2 (P2): Computerized agent



E.K. Jung, J. Zhang, S.-Y. Lee, and J.-H. Lee, 'A Preliminary Study on Neural Basis of Collaboration: Mediated by the Level of Reasoning', ICONIP2013

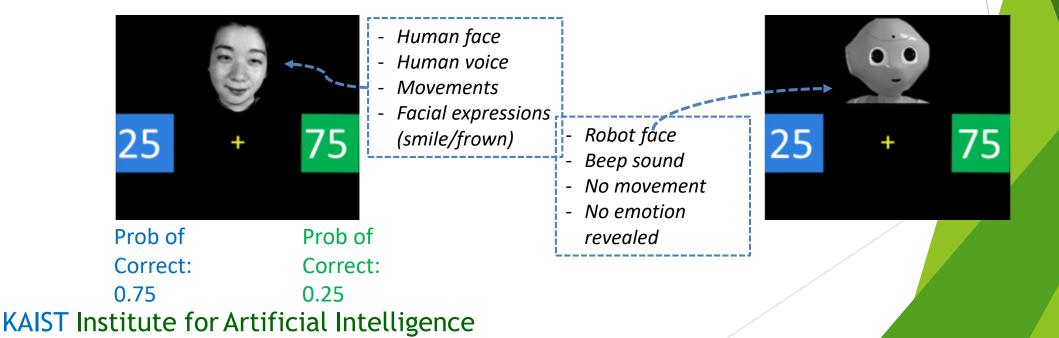
Averaged ERP from ToM Trials



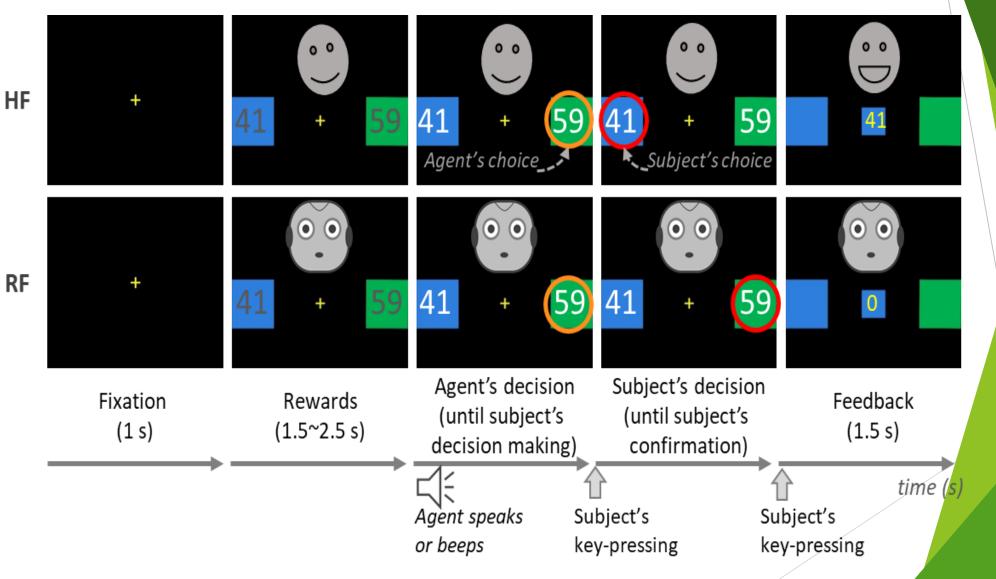
Unilateral Interaction (Player-Supervisor Mode)

(E.S. Jung, et al., 2019; Scientific Reports)

- Iterative game play by machine agent *Player* with human *Supervisor*
 - Human trust on Agent iff Trustworthiness > Risk
- Effect of agent's human-likeness on Trustworthiness
 - {human-faced, robot-faced} agents
- Risk taking personality
 - {Low, Medium, High} risk taking

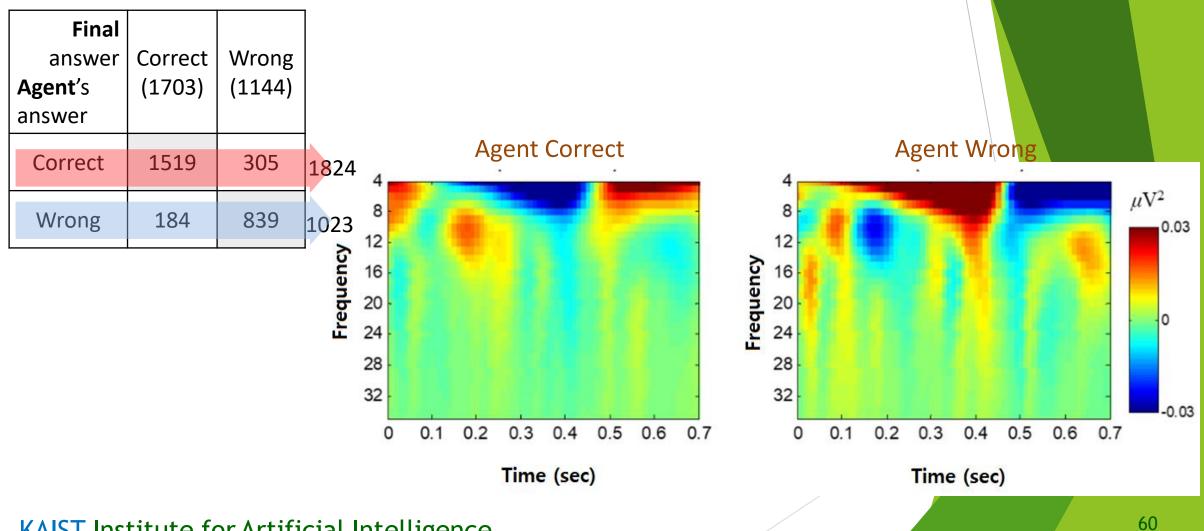


Experimental Design



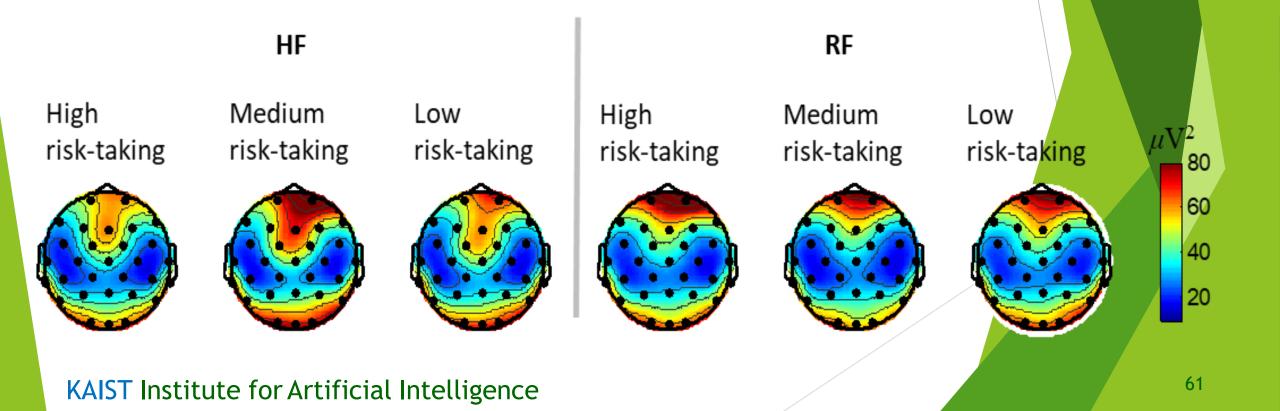
EEG Analysis

 EEG differences due to trust increase/decrease with t-test # of trials



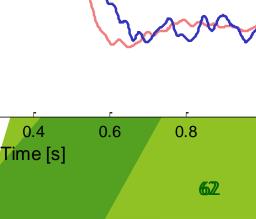
EEG Analysis: Personality Dependence

 $g_{\text{blue}} = F(p_{\text{blue}}, \gamma) \cdot r_{\text{blue}}$ $F(p_{\text{blue}}, \gamma) = \max[\min[\gamma(p_{\text{blue}} - 0.5) + 0.5, 1], 0]$ $\gamma = 0.7 (High Risk Taking), 1, 1.5 (Low Risk Taking)$



EEG Analysis

- The number of intervenes on agents represented subjects' implicit trusts
 - More intervenes \rightarrow low trust level
 - Each subject's intervenes reflected his/her own risktaking personality
- Trust changes during feedback period
 - Different EEG responses



Agent was correct

Agent was wrong

Fz

0.2

0

3

0

-3

×۲

Human Trust on Al

Human trusts AI more with

- Similar personality (such as driving style)
- Human-likeness (such as facial expression and speech)
- Maybe adopted to Human-Al Interfaces
 - For Digital Companion (Office Mate, Silver Mate, etc.), autonomous vehicles, etc.

User Authentication based on Preference

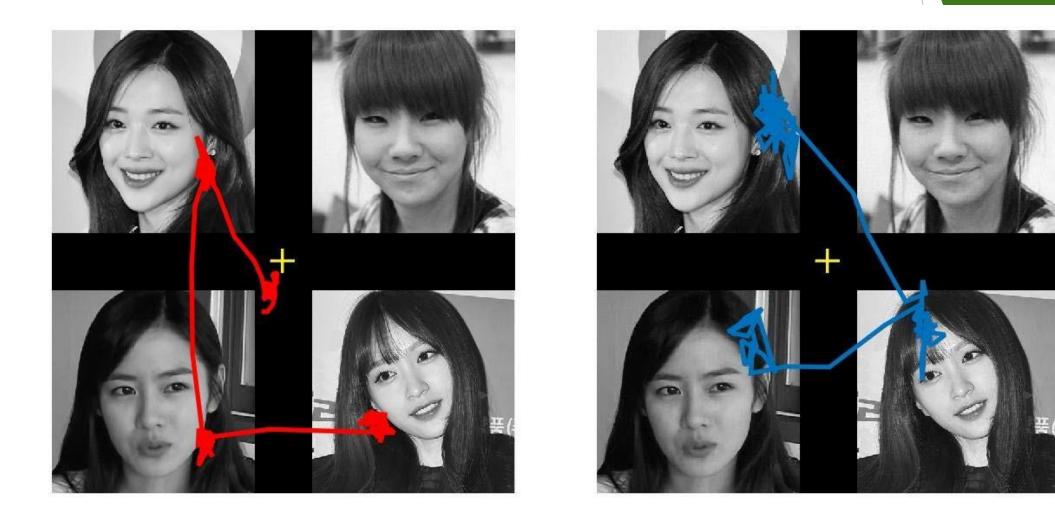
(E.S. Jung. et al., Scientific reports 2017)

Knowledge Authentication	Authentication Tokens	Biometric Authentication	Inferential Authentication
Textual Words, phrases, numbers and so on	OOB Authentication Using another channel	Biological Trait A physiological trait of the user	Q&A Known answers to specific questions
Graphical Images, patterns or gestures	OTP Token Using a secret key to generate an OTP	Behavioral Trait The way the user performs an action	Contextual Authentication Analysis of contextual data
	X.509 Token Using PKI credentials		

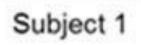
New Safest Authentication Technology

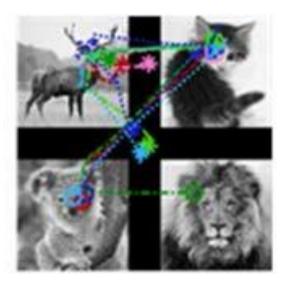
- Inferential Authentication
 - Question by Images
 - Answer by EEG or Eye Tracking
 - Safety: Involuntary responses can not be copied not stolen
 - Accuracy: Multiple Q&A for one authentication

Preference-based Eye Trajectory

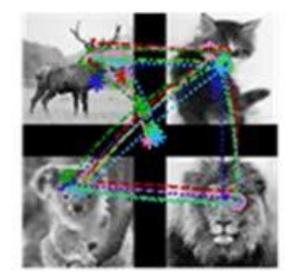


Multi-Image Eye Trajectories





Subject 23

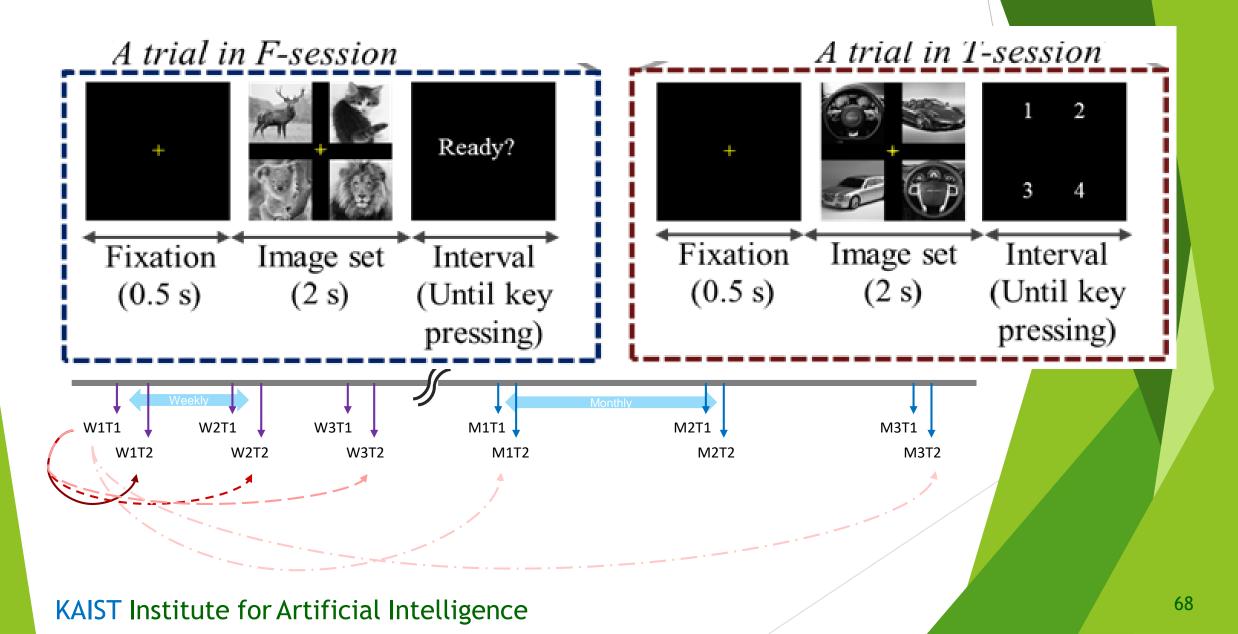




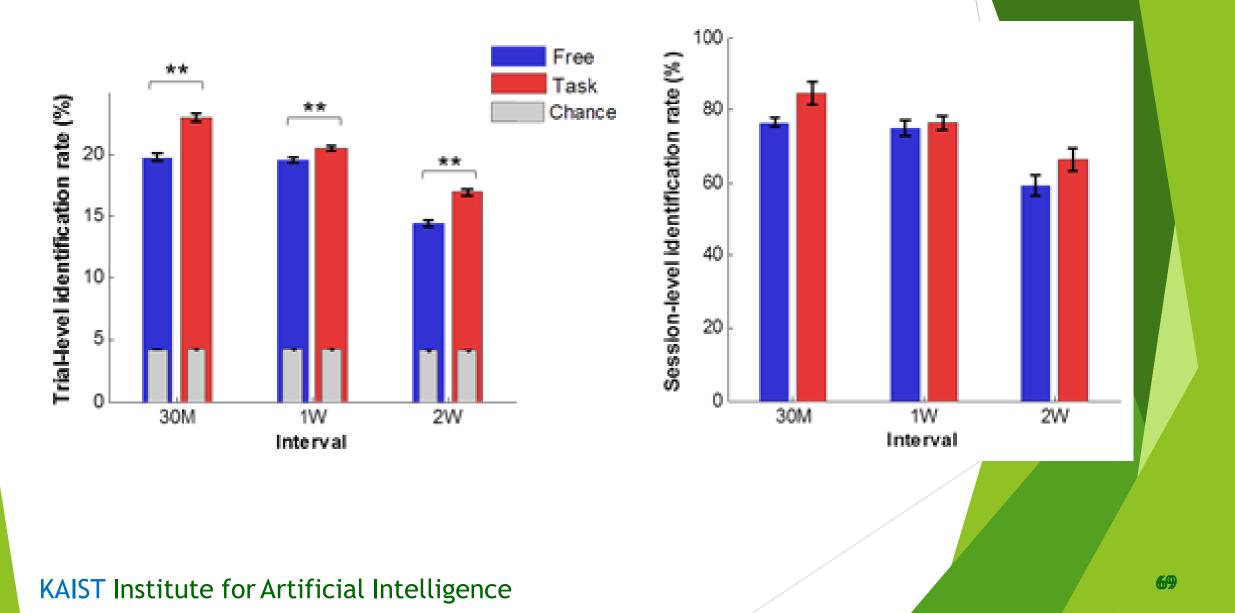


W1F1
 W1F2
 W2F1
 W2F2
 W3F1
 W3F2
 Start
 O End

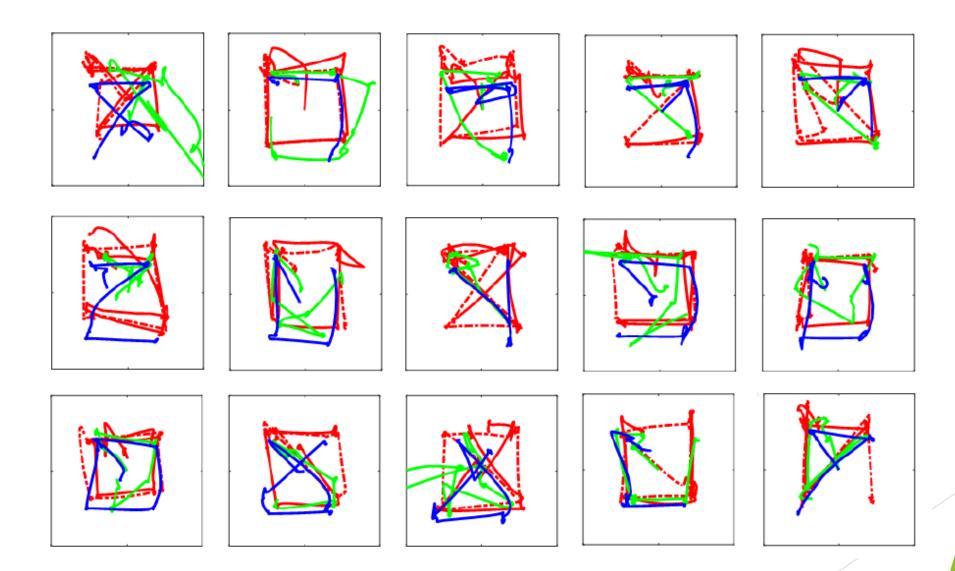
User-Authentication by Eye Tracking (Scientific Report 2017)



Identification Accuracy: Scanpath



Intrusion Experiments



Summary

Next-Generation Office Mates and Data Analytics

- Develop Digital Companions (Office Mate) with Mind (Internal States) and Environmental States
 - Internal states: personality and experience of human and agents, emotion of agents, trust and binding between human and agents, etc.
 - Environmental and unknown states: road condition, economy, politics conditions, social events, etc.
 - Learning internal and environmental states from data
 - Top-down attention for accurate and fair analytics with multimodal integration
 - Personal and Interactive at Anytime Anywhere