:) Affectiva



Multi-Modal Emotion Estimation

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Our Emotions, influence how we live and experience life!



But, we're also surrounded by High IQ and no EQ devices



Affectiva mission: humanize technology with Human Perception Al

Pioneers of Human Perception Al.

Al software that understands all **things human** – **nuanced human emotions,** complex **cognitive states**, behaviors, activities, interactions and objects people use.

Only multi-modal in cabin sensing Al.

Using deep learning, computer vision, voice analytics and massive amounts of data, Affectiva analyzes face and voice to understand state of humans in vehicle.



Face:

7 emotions, indicators of attention, drowsiness, distraction, positive / negative, 20+ facial expressions and demographics

Voice:

Arousal, laughter, anger, gender

Emotion AI detects emotion and cognitive states the way people do

Emotion AI

Affectiva's multi-modal

People communicate through multiple modalities



Emotion AI is a multi-modal and multi-dimensional problem

Multi-modal - Human emotions manifest in a variety of ways including your tone of voice and your face

Many expressions - Facial muscles generate hundreds of facial actions, speech has many different dimensions - from pitch and resonance, to melody and voice quality

Highly nuanced – Emotional and cognitive states can be very nuanced and subtle, like an eye twitch or your pause patterns when speaking

Non-deterministic - Changes in facial or vocal expressions, can have different meanings depending on the person's context at that time

Temporal lapse- As an individual's state unfold over time, algorithms need to measure moment by moment changes to accurately capture of mind

Context – Understanding complex state of mind requires contextual knowledge of the surrounding environment and how an individual is interacting with it

Massive data - Emotion AI algorithms need to be trained with massive amounts of real world data that is collected and annotated

Display and perception of emotion is not perfectly aligned

CREMA-D*: large scale study of emotion and perception

- 91 participants
- 6 emotions of varying intensities
- 7442 emotion samples.
- 2443 observers

Human recognition of intended emotion based on

- voice-only: 40.9%
- face-only: 58.2%
- face and voice: 63.6%







Difference in <u>emotion perception</u> from Face vs. Speech modalities



Confusion matrices showing emotions displayed by humans, recognized by other human observers

Difference in <u>emotion perception</u> from Face vs. Speech modalities



Difference in <u>emotion perception</u> from Face vs. Speech modalities



Emotion AI at Affectiva

How it **works**





Data driven approach to Emotion AI





Product Delivery: APIs and SDKs

The classifiers and run-time system are optimized for the cloud or on device or embedded







Massive proprietary data and annotations power our AI



✓ Foundation: Large, diverse & real world data built in the past 7 years

Growing automotive in-cabin data with scalable data acquisition strategy

Deep learning



Affectiva's focus is on deep learning

- It allows modeling of more complex problems with higher accuracy than other machine learning techniques
- Allows for end-to-end learning of one or more complex tasks jointly
- Solves a variety of problems: classification, segmentation, temporal modeling

Vision pipeline

The current vision SDK consists of steps

- Face detection: given an image, detect faces
- Landmark localization: given a image + bounding box, detect and track landmarks
- Facial analysis: detect facial expression/emotion/attributes



per face analysis

Speech pipeline

The current speech pipeline consists of these steps:

- Speech detection: given audio, detect speech
- Speech enhancement: given noisy speech speech segment, mask noise
- Speech analysis: detect speech events/emotion/attributes



per audio segment analysis

Multi-Modal Applications



Media and entertainment



Advertising



Human resources



Automotive



Robotics



Healthcare and quantified self



Video communication



Online education



Devices



Gaming

Multimodal for Automotive



Affectiva Automotive Al





Human Perception AI fuels deep understanding of people in a vehicle

Delivering valuable services to vehicle occupants depends on a deep understanding of their current state



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Affectiva Automotive Al

Modular and extensible deep learning platform for in-cabin human perception AI

- Core technology is shared and reused across different modules
- Modular packaging enables light-weight deployment of capabilities for a specific use case
- Extend existing capabilities by adding more modules

Driver Monitoring	Occupant State	Occupant Activities	Cabin State
Drowsiness levelsDistraction levelsCognitive load	 Facial and vocal emotion Mood (valence) Multimodal emotion: frustration Engagement 	TalkingTextingCellphone in hand	Occupant location and presenceObjects left behindChild left behind

Core Technology				
Facial expression recognition	Object detection	Voice detection	Flexible Platform	
• 20 Facial expressions:	 Object classes: 	 Voice activity detection 	 Support Near IR sensors 	
e.g. smile, eye brow raise	mobile device, bags		 Support ARM ECU 	
 Drowsiness markers: 	 Object location 		 Support multiple camera positions 	
eye closure, yawn, blink				
	 Facial expression recognition 20 Facial expressions: e.g. smile, eye brow raise Drowsiness markers: eye closure, yawn, blink 	Facial expression recognition Object detection • 20 Facial expressions: • Object classes: e.g. smile, eye brow raise • Object classes: • Drowsiness markers: • Object location eye closure, yawn, blink • Object location	Facial expression recognition Object detection Voice detection • 20 Facial expressions: • Object classes: • Voice activity detection • g. smile, eye brow raise • Object location • Voice activity detection • Drowsiness markers: • Object location • Object location eye closure, yawn, blink • Object location • Object location	

Automotive data collection for multimodal analysis



Automotive Data Acquisition

To develop a deep understanding of the state of occupants in a car, one needs large amounts of data. With this data we can develop algorithms that can sense emotions and gather people analytics in real world conditions.

Spontaneous occupant data

Using Affectiva Driver Kits and Affectiva Moving Labs to collect naturalistic driver and occupant data to develop metrics that are robust to real-world conditions





Data partnerships

Acquire 3rd party natural in-cab data through academic and commercial partners (MITAVT, fleet operators, ride-share companies)

Simulated data



Collect challenging data in safe lab simulation environment to augment the spontaneous driver dataset and bootstrap algorithms (e.g. drowsiness, intoxication) multi-spectral & transfer learning.

Automotive AI data

Automotive AI 1.0 tracks metrics for driver monitoring as well as emotion estimation



Driver Drowsiness Detecting eye closure and yawning events

Emotion detection Detect driver emotions including surprise and joy

Multimodal frustration: A case study





Why detect frustration?

Frustration is "the occurrence of an obstacle that prevents the satisfaction of a need" [Lawson, 1965].

A frustrated driver can be a dangerous driver.

- Frustration has been shown to be accompanied by various driving behaviors, such as, horn honking, purposeful tailgating and flashing high beams [Hennessey and Wiesenthal, 1999].
- Overtaking was found to be correlated with a state of frustration [Kinnear et al., 2015]
- Malta et al. found that the intensity of pedal actuation signals --- hard braking --- correlated with frustration [Malta et al., 2011].

Automatic in-cabin sensing of affective states such as frustration can utilize that information to provide effective interventions that attempt to minimize unsafe behavior. For example, If driver is irritated because of a traffic jam, agent suggests an alternative route.



In-lab data collection to elicit Frustration

• Participants were asked to do 6 timed tasks requiring interactions with a voice agent (Alexa) to mimic interactions with car HMI in 2 sessions.

Multi-tasking: interacting with the voice agent while driving Uni-tasking: only interacting with the voice agent; no driving

- Tasks designed to mimic real interactive conversations that people might have with an in-car assistant.
 - Make a shopping list
- difficulty Request system t Request a particu
 - Request system to say something funny
 - Request a particular song by name
 - Request a particular radio station call number and frequency
 - Dictate an email to a particular person
- Wizard-of-Oz setting: dialogue from Alexa pre-recorded and played by study administrator.
- 105 participants: 55 female, 47 male and 3 did not specify gender





Instrumentation

- Multi-cameras and audio setup (4 pairs of NIR and RGB cameras, 2 additional cameras, 3 microphones): The multi-camera audio-video setup was used to capture multiple views of the participant as well as their audio stream.
- ECG: Subjects were asked to put 4 ECG sensors on their body to measure heart rate.
- **GSR:** Subjects also wore a skin conductance sensor.
- Integration platform: An software platform that allowed study admin to see and hear the participant, their vitals, and their performance on the driving sim, so that pre-recorded voice responses could be played appropriately to simulate HMI.
- Total: 24 pieces of hardware and matching software.





Challenges of data collection

Setup and syncing multiple sensors.

- 24 pieces of hardware and matching software
- Individually not difficult to set up
- But setup and sync non-trivial

Eliciting "real" frustration in participants.

- Engagement constraint: Frustration had to be managed. Some tasks purposely frustrating but not all --- otherwise people would give up; some tasks had to be easy to accomplish so people could win at it and stay engaged.
- Believability constraint: Requests and responses in scenarios had to be believable/acceptable yet frustrating.



Example: Frustrated due to difficulty getting radio to play



Analysis of frustration from face and voice





Self report: Is multitasking more frustrating?

Multitasking defined as driving + HMI interaction







Self-reported Frustration, Difficulty and Stress Values for each task

Automatic analysis: Is multitasking more frustrating?

Multitasking defined as driving + HMI interaction





Average percentage of anger activation for different tasks

Automatic analysis: Is multitasking more frustrating?

Multitasking defined as driving + HMI interaction









Average percentage of activation of metrics for different tasks

How much more frustrating is multitasking compared to free driving?









Chin raise



Average ratio of facial activations for different tasks with respect to its average value for free driving

Unexpected observation: Laughing while frustrated

Laughter

Confidence



Next steps: multimodal frustration detection





Analyzing other markers of frustration

Driving behavior

• Examine behaviors such as honking, tailgating and flashing of high beams [Hennessey and Wiesenthal, 1999], overtaking [[Kinnear et al., 2015] and pedal actuation signals [Malta et al., 2011].

Gestures and body posture

• Hand movements provide a means for displaying frustration [Dittmann and Llewelyn, 1969]

Physiological responses

- Fernandez and Picard, 1998 showed that electrodermal response (GSR) is indicative of human frustration in interacting with systems.
- Belle et al. 2010 analyzed ECG data of students and found that the ECG profile of person who is calm can be distinguished from a person who is frustrated.



Multimodal Training Strategies for Frustration detection

Decision Level Fusion



Feature Level Fusion



Human Perception AI fuels deep understanding of people in a vehicle

Delivering valuable services to vehicle occupants depends on a deep understanding of their current state



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