mmFER: Millimetre-wave Radar based Facial Expression Recognition for Multimedia IoT Applications

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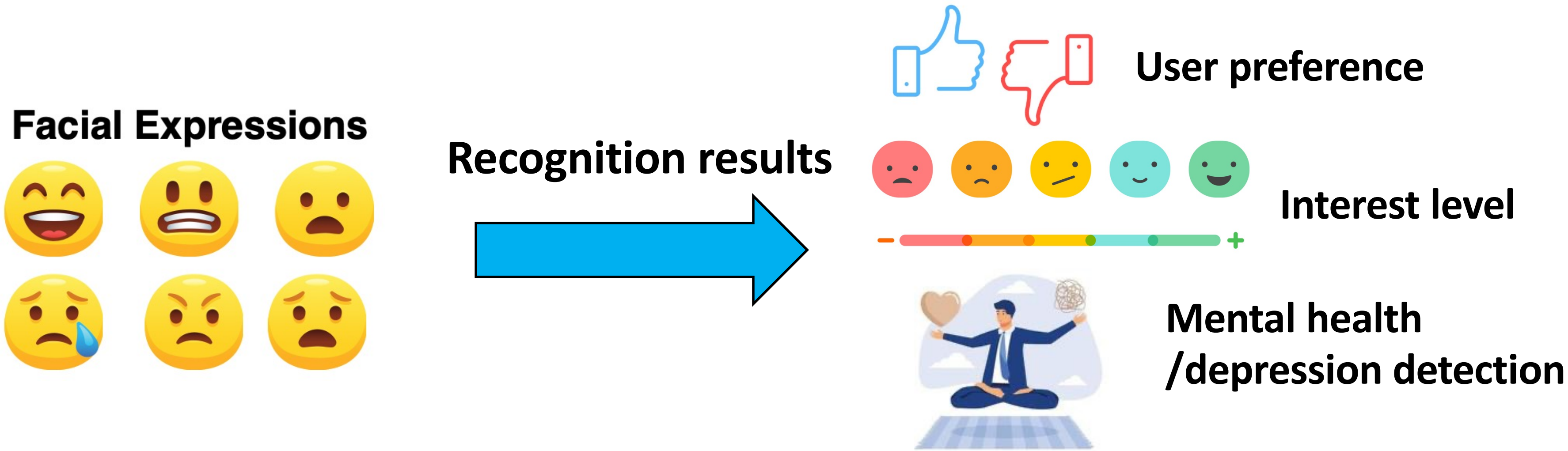
Facial Expression Recognition (FER)

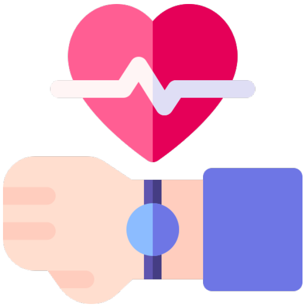
- **Emotional awareness by FER** for interaction (CHI), communication (feedback), and well-being (healthcare)
- Deliver a valuable assessment of **audience's preference**, **interest level**, **engagement** and **reactions**, etc.
- Enabling a fundamental capability that IoT system can **"better understand" users**, actively create more **personalized** and **responsive user experiences**



State-of-the-Arts

Vision-based approach:

- Privacy concerns
- Ambient light conditions (e.g., in the dark)
- Blocking (e.g., wearing masks)



Wearable based approach (PPG, EEG, earphones):

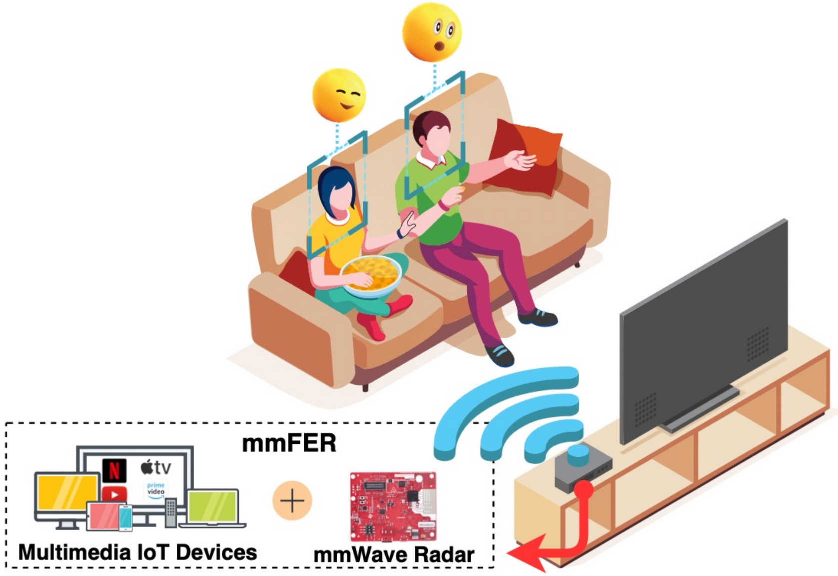
- Discomfort to users for long-time wearing
- One device for each user

Wireless sensing approach (Ultrasound, Wi-Fi):

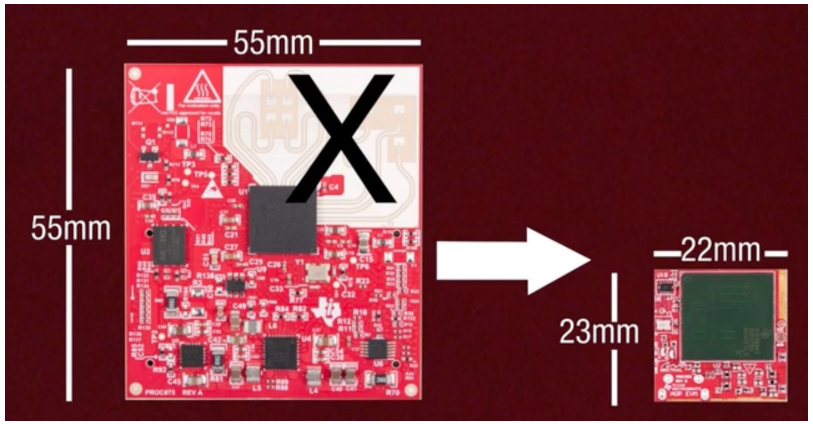
- Fail by impact of body motions
- Short detection range (e.g., <= 60cm)
- Poor support for multiple users

Our Solution: mmWave Radar Sensing

- **High robustness:** robust to work in different environment conditions, e.g., dark
- **Large bandwidth:** high resolution for detecting objects and tiny motions
- **Long-range detection**
- **Fine spatial resolution:** fine spatial resolution enabled based on the MIMO
- **Wide Field of View (FOV):** cover a large area with a single sensor
- **Penetration**: can easily penetrate materials such as glasses, masks
- **Privacy-preserving manner**

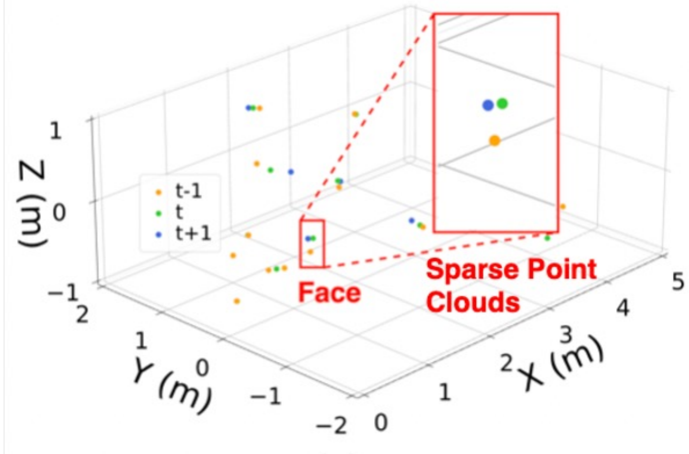


Easy for IoT device integration



Challenges

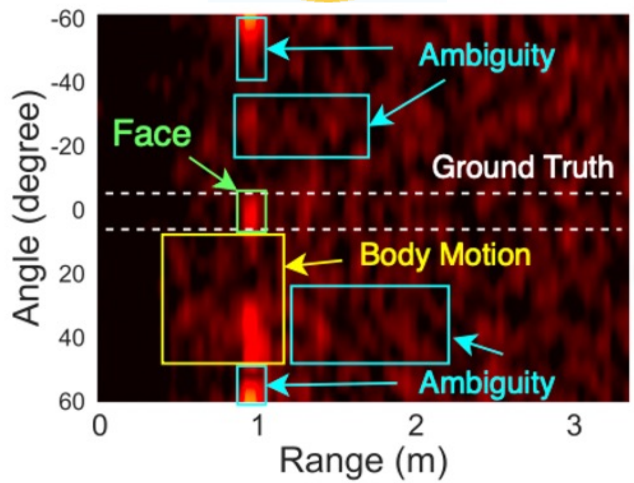
- Default point cloud approach fails to detect user's face due to **highly sparse point clouds** generated



(a)

- **Subtle facial movements:** facial muscle movements by expressions are in **in millimetre levels**

- **Massive ambient noise** contains in raw mmWave signals, *e.g., body motion, walking people, appliance, and ambient noise reflected by walls*



(b)

- **Limited mmWave dataset**: facial data collection is **costly** due to labelling efforts and **privacy concerns**

Key Ideas

- What if we could "**partially locate" user's face** for capturing subtle facial movements from **noisy raw mmWave signals**?

    - Step-1: using **unique biometric features** to locate users and **eliminate ambient noise**
    - Step-2: using **spatial facial features** to locate faces and **remove irrelevant body motions**

- What if we could use a public image FER dataset (i.e., large-scale) and its pre-trained models to **"transfer" knowledge** from image domain to mmWave domain to effectively enable the learning with **much less data collection**?

    - Using **cross-domain transfer learning** to enable optimal model performance with **small-scale mmWave dataset**

Our Contributions

- A **first-of-its-kind** mmWave radar based FER system that detects subtle facial muscle movements associated with raw mmWave signals for multimedia IoT applications

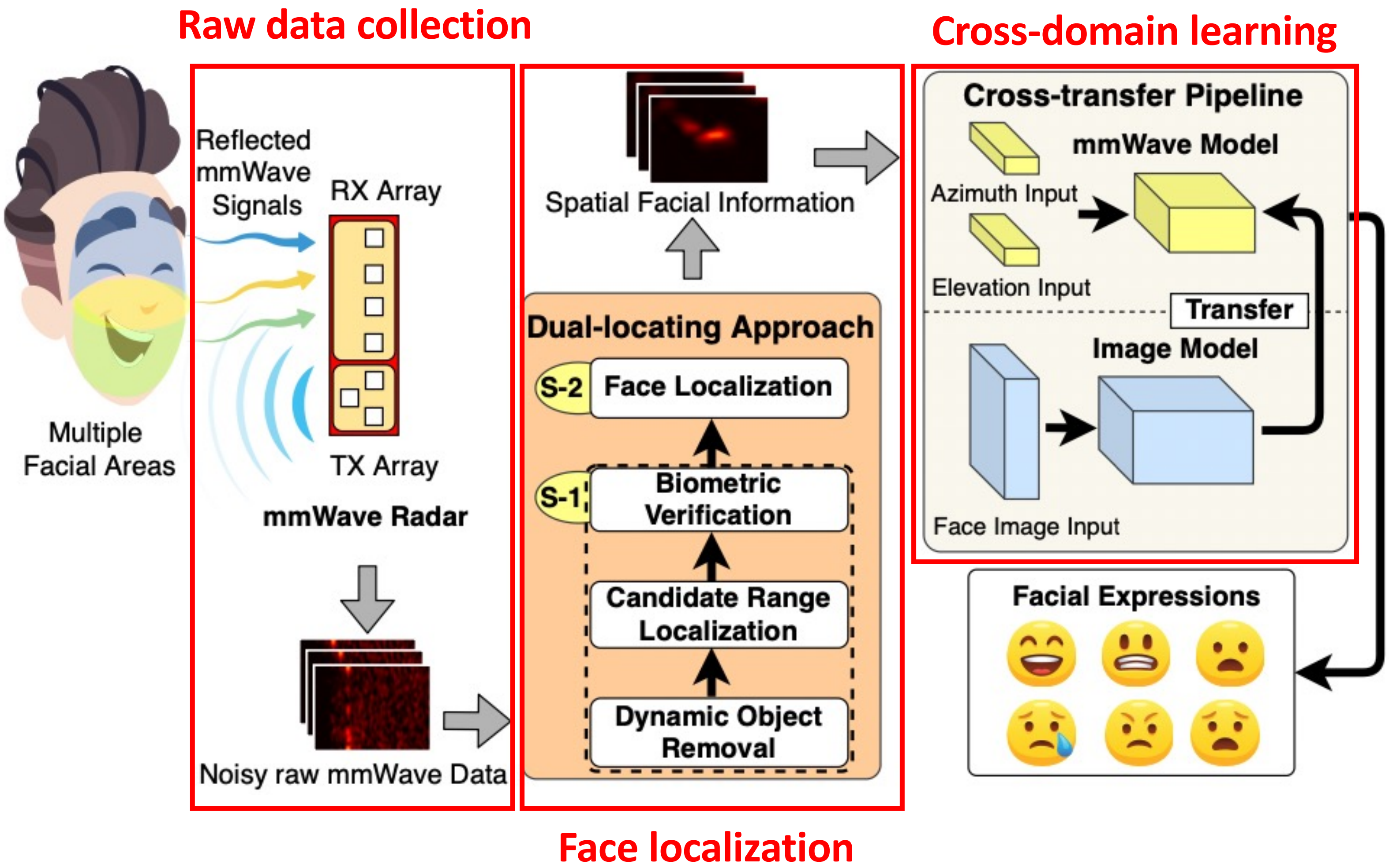
- A **novel dual-locating approach** to accurately locate on subjects' faces in space based on MIMO technology

- A **novel cross-domain transfer pipeline** to enable an effective and safe model knowledge transformation for mmWave-based FER model learning

- An off-the-shelf mmWave radar based implementation with extensive experiments

- This pioneering system **mitigates concerns** over privacy concerns and lighting constraints, and **has strong adaptability** to fit a number of real-world scenarios with high accuracy

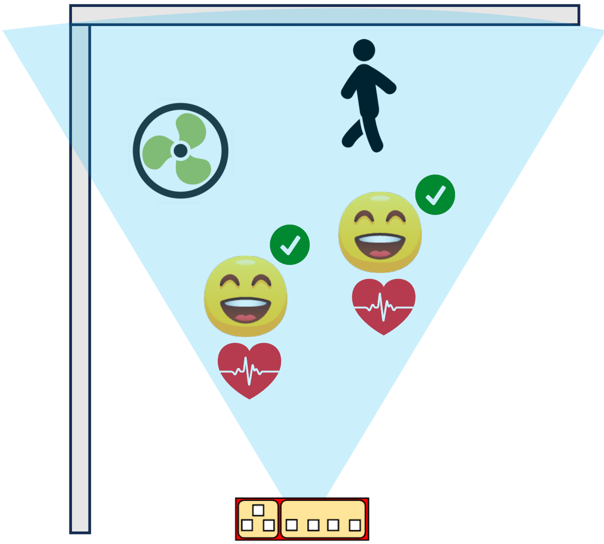
System Working Flow



Main Technique 1: Dual-locating Approach

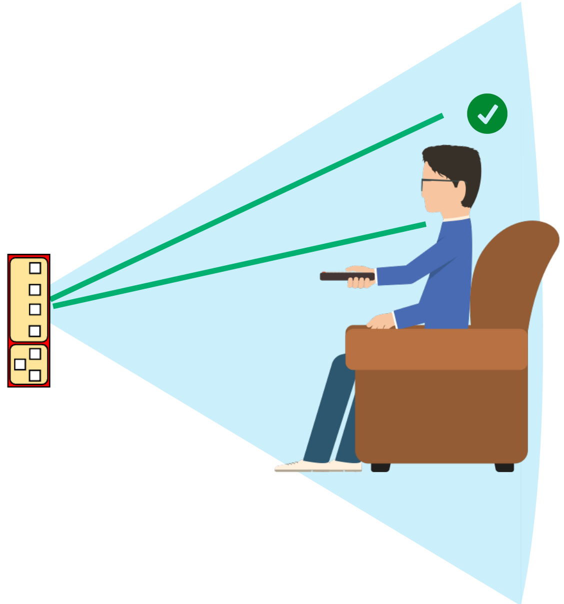
Step-1: eliminating ambient noise

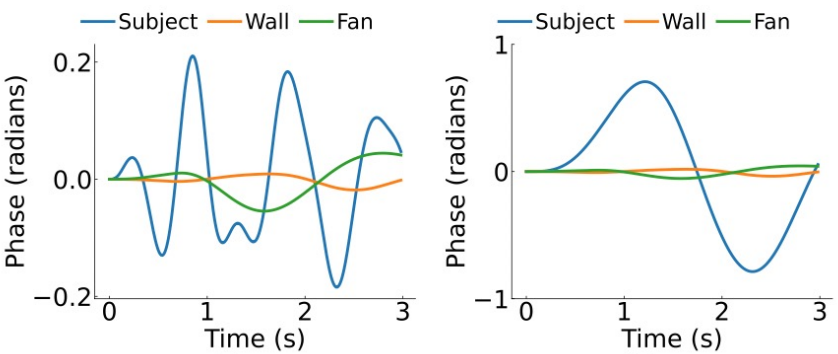
Noise removal pipeline (3-process)



Step-2: removing body motions

Face-matching mechanism
using Gaussian Mixture Model (GMM)





Heart rate (left) and respiration (right) verification

Located facial mmWave raw data

mmFER Demo

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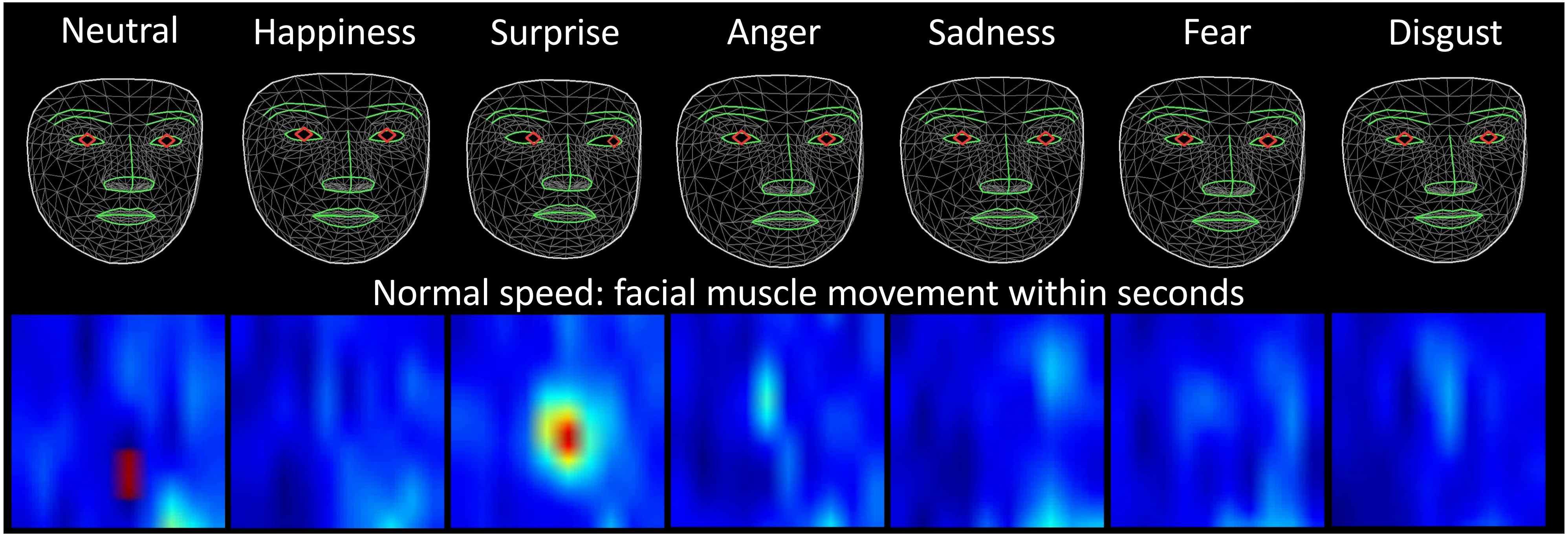
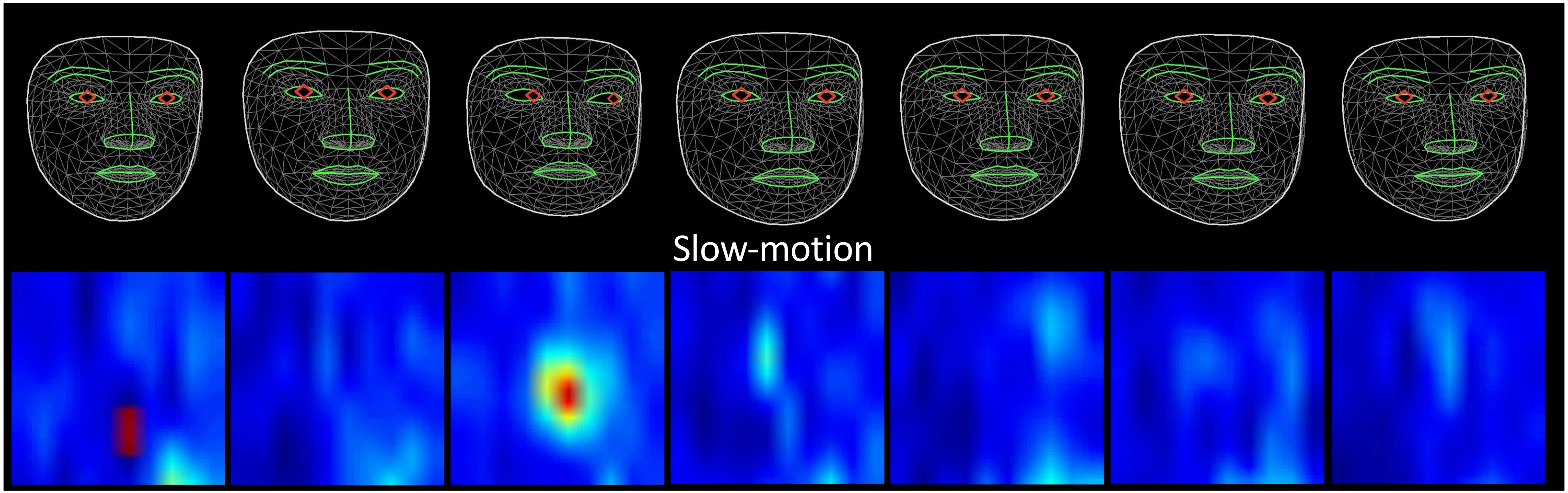
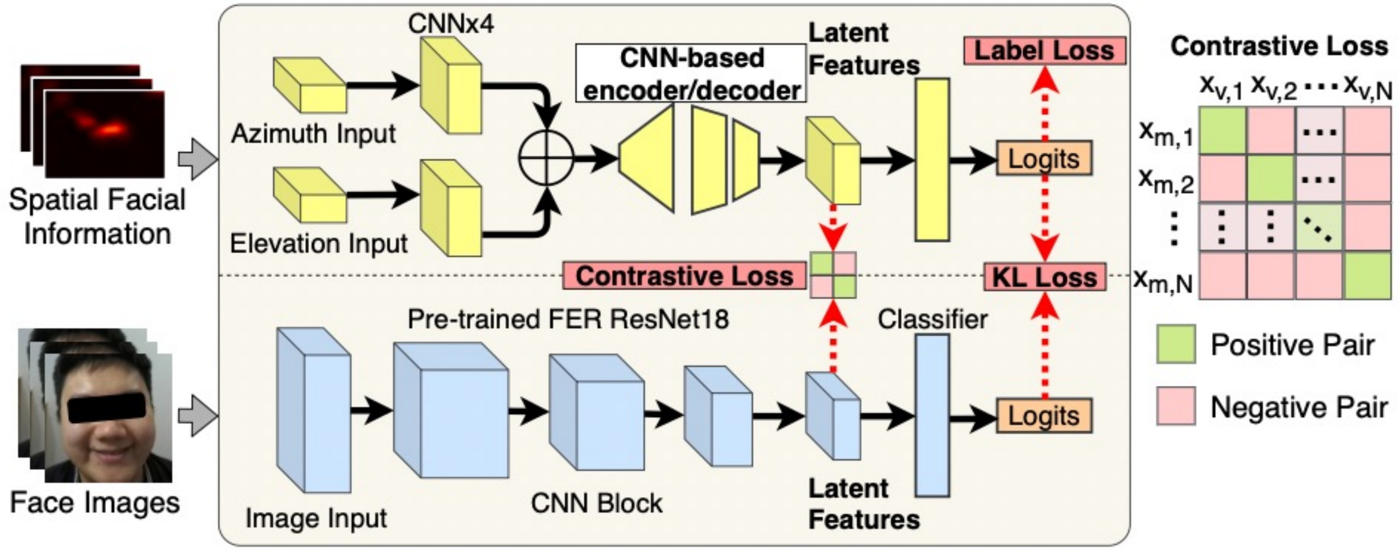




Main Technique 2: Cross-transfer Pipeline



- Inspired by the principle of cross-domain transfer learning, uniquely using **a pre-trained FER image model** to **"teach"** training our mmWave model

- Proposing **an autoencoder based feature alignment mechanism** to reduce the impact of data heterogeneity of image to mmWave data

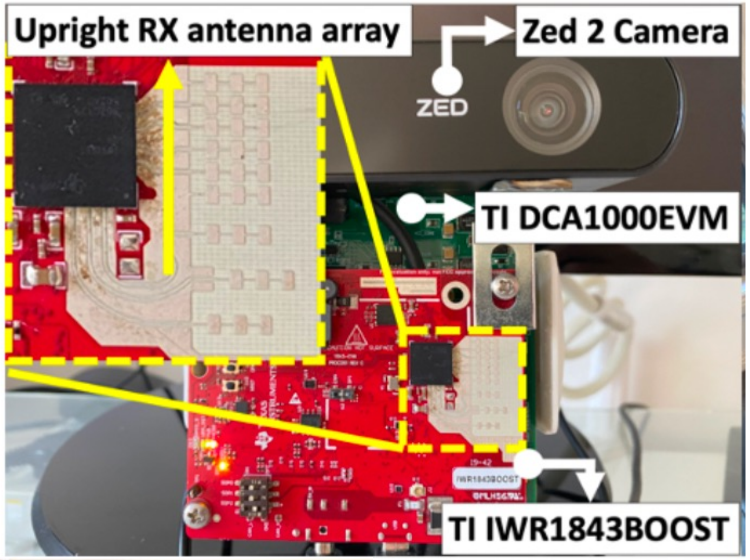
- Proposing **a hybrid learning loss function:**
  1) A supervised loss;
  2) A Kullback–Leibler (KL) divergence loss;
  3) A contrastive loss based on positive-negative correlation, largely improve model performance

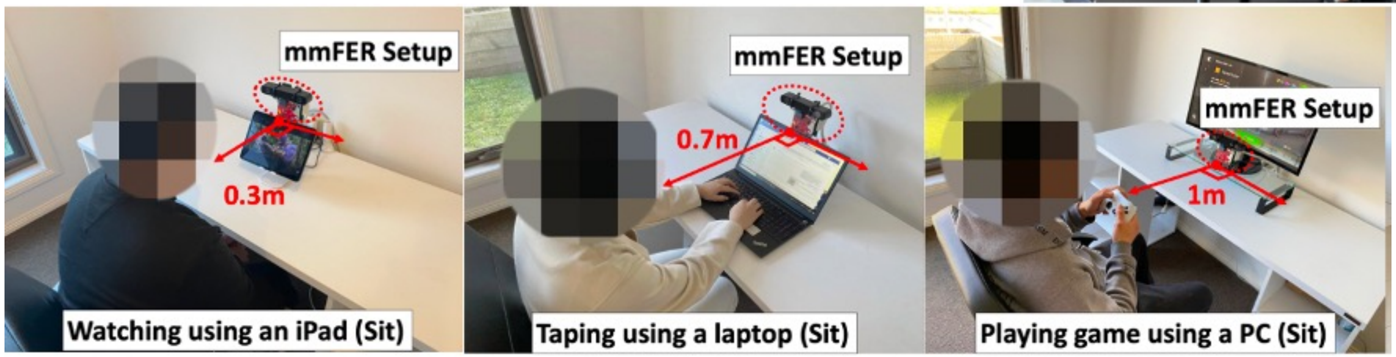
System Implementation and Setup

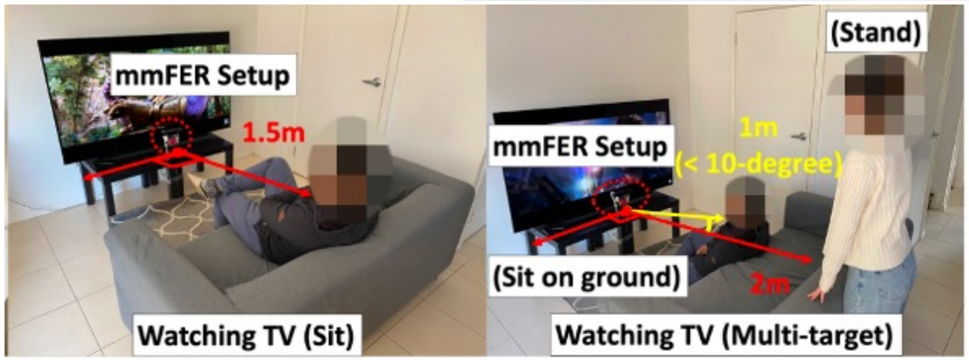
- **Setup**: TI IWR1843BOOST sensor board operating at 77-81GHz ($299) and a TI DCA1000EVM data capture board ($599)

- **Upright RX antenna array** in elevation for face localization

- **Data collection**: recruiting 10 subjects

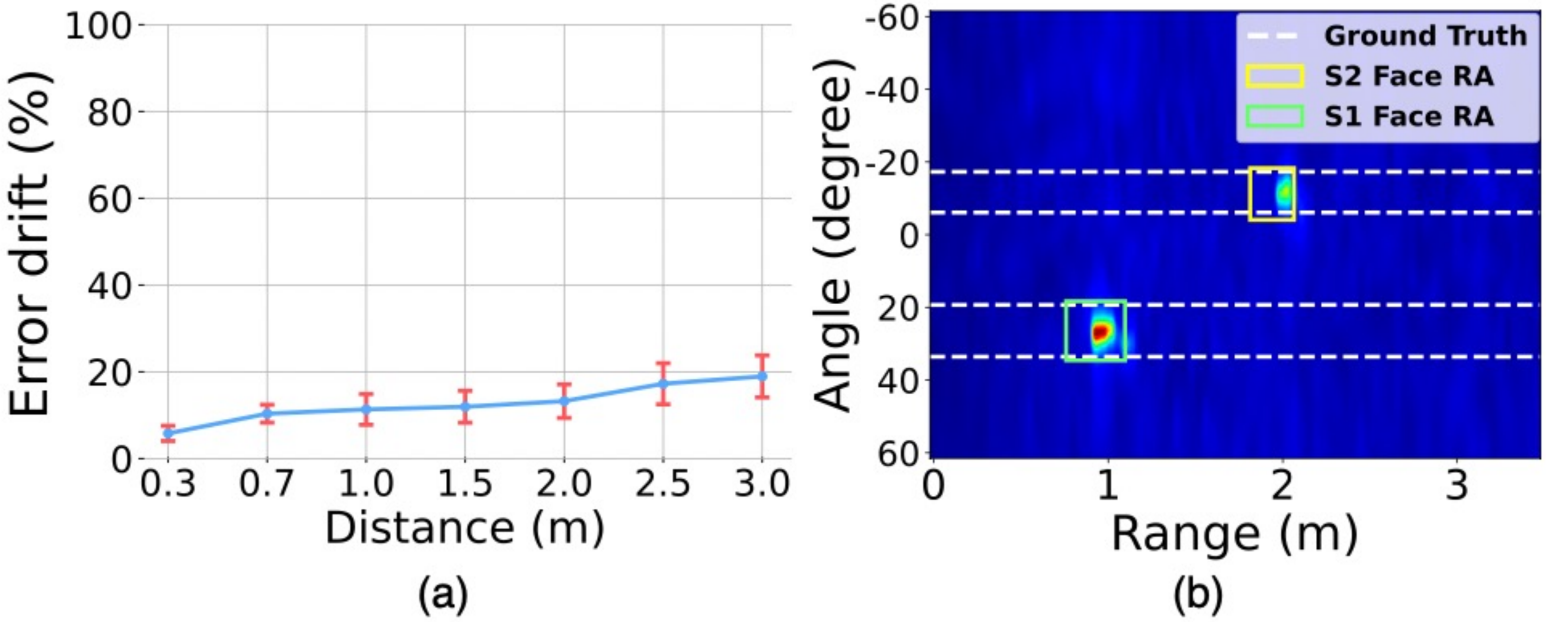






- **Use scenario**: tested in different scenarios with different noise setup, e.g., *body motions, postures, subject-to-radar distance, face orientation, wearable accessories*

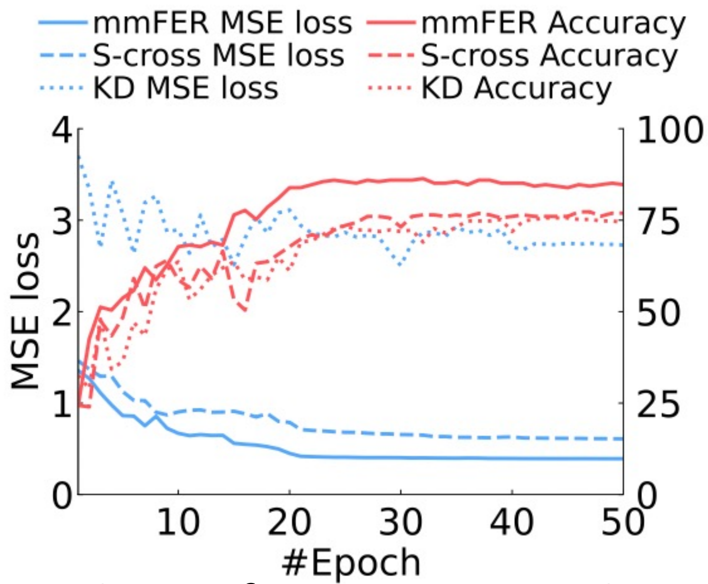
Evaluation: Dual-locating Performance



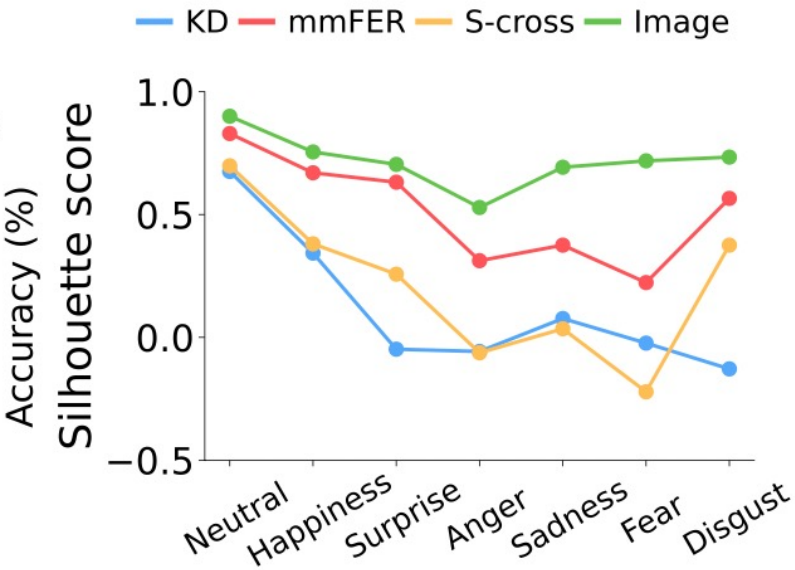
- Fig. (a) shows that our approach can effectively enable face localization at different subject-to-radar distances with **minor error drift**

- Fig. (b) shows that our approach can locate face accurately for **multiple targets** by removing ambient noise

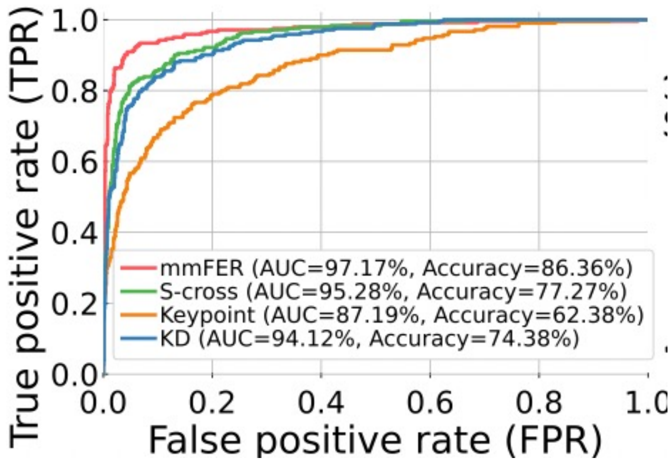
Evaluation: Cross-transfer Performance



Learning performance comparison



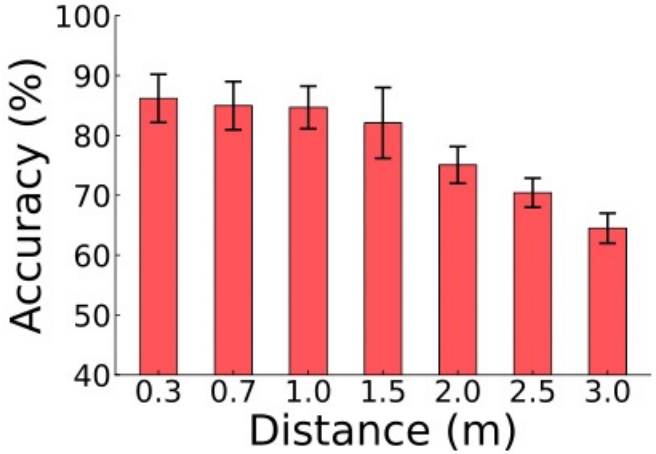
Transferability performance comparison



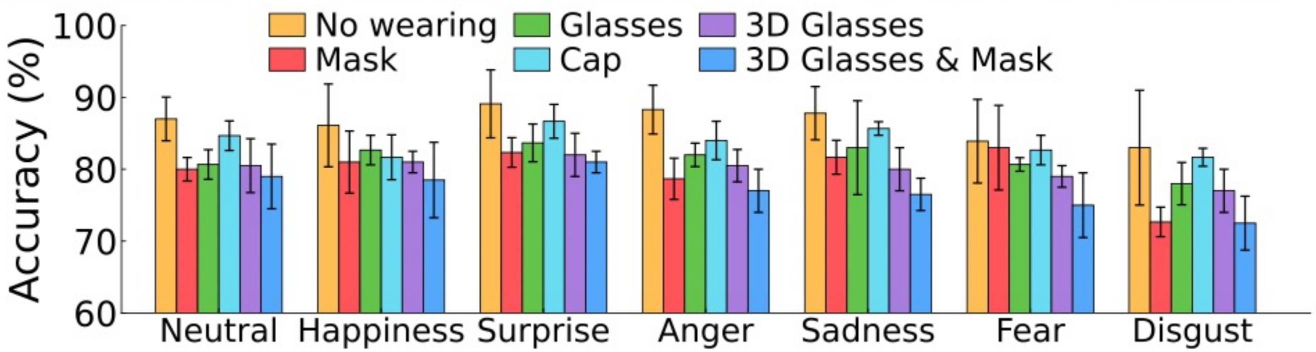
Training ROC curve

- Comparing to **3 baselines**:
    - Knowledge distillation (KD)
    - Facial landmark based image-to-sensing transformation (Keypoint)
    - Unsupervised cross learning approach (S-cross)
- Our approach outperforms baselines, **achieving highest accuracy**

Evaluation: Overall Performance



- **84.48% accuracy** in a subject-to-radar distance between **0.3 and 1.5m**
- **80.57% accuracy** when distance increases to **2.5m**
- No major accuracy drop in a scenario with **wearing accessories**



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Thank you!
Questions

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