MU-ID: Multi-user Identification Through Gaits Using Millimeter Wave Radios

CSE870

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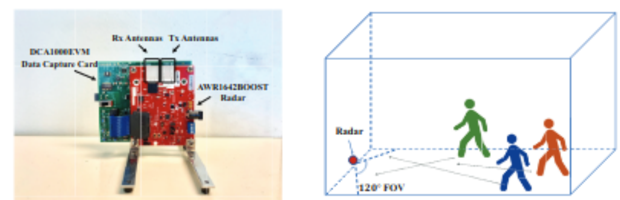
Objective

- MU-ID is the first work of performing multi-user identification based on lower limb movements using a single mmWave radar sensor
- Traditional WiFi-based gait recognition systems [1][2][3] identify the user based on the user's whole-body movements
- Recent studies rely on ambient CSI to identify single users according to their distinct gait patterns [1][2][3][4] as CSI is susceptible to the environmental changes which is restrictive.



(a) AWR1642BOOST radar paired with DCA1000EVM data capture card.

(b) Illustration of the radar displacement and possible walk paths.

Fig. 12: Illustration of the experimental setup.

[5]

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[1] https://dl.acm.org/doi/pdf/10.1145/2971648.2971670
[2] https://dl.acm.org/doi/10.5555/2959355.2959359
[3] https://ieeexplore.ieee.org/document/7536315/
[4] https://web.eecs.utk.edu/ jliu98/publications/shi2017smart.pdf
[5] https://web.eecs.utk.edu/ jliu/publications/yang2020muid.pdf

System Overview

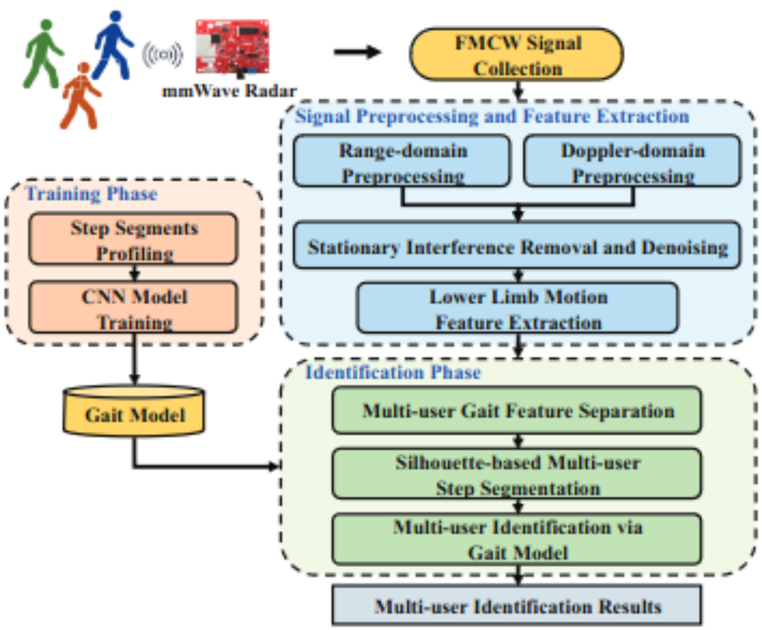

Fig. 2: Overview of MU-ID architecture.

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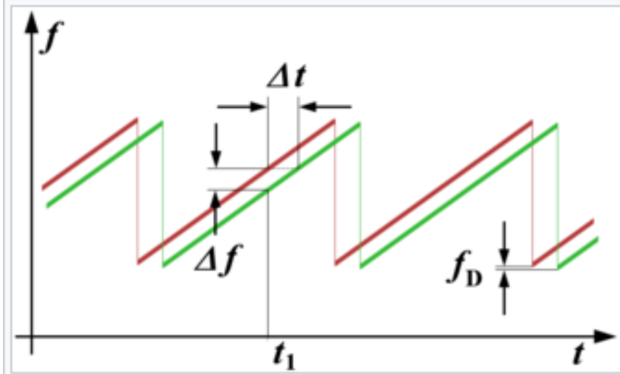
[1] Figure 2: https://web.eecs.utk.edu/ jliu/publications/yang2020muid.pdf

Frequency modulated continuous wave radar

- Radar device repeatedly transmits chirp signals linearly sweeping through frequency bandwidth (red)
- Range information is mixed with doppler information in return signal (green)
- Intermediate frequency (IF) signal is subtraction of transmitted and received signal



Ranging with an FM-CW radar system: if the error caused by a possible Doppler frequency f_D can be ignored and the transmitter's power is linearly frequency modulated, then the time delay (Δt) is proportional to the difference of the transmitted and the received signal (Δf) at any time.

[1]

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[1] https://en.wikipedia.org/wiki/Continuous-wave_radar

FMCW range estimation

Apply FFT and use fd-IF signal to calculate distance to target

$$d = \frac{f_{IF} * c * T}{2B}$$

Where f_{IF} is the average frequency of the IF signal over time window T and B is the chirp sweep bandwidth

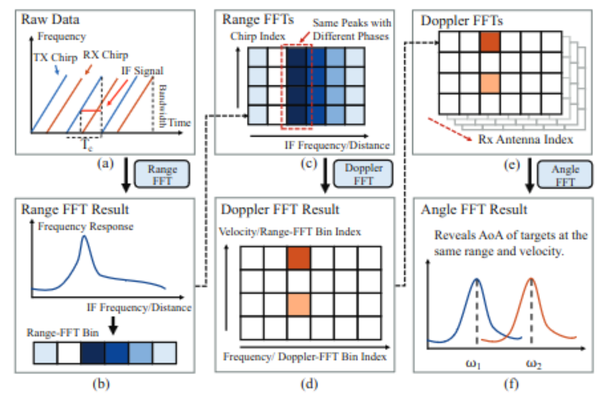

Fig. 1: Illustration of FMCW radar signal processing techniques.

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[1] https://web.eecs.utk.edu/ jliu/publications/yang2020muid.pdf

FMCW velocity estimation

Use phase difference of td-IF signal to calculate distance to target

$$v = \frac{\lambda * \omega}{4\pi T}$$

Where ω is the phase difference of the IF signal over time window T

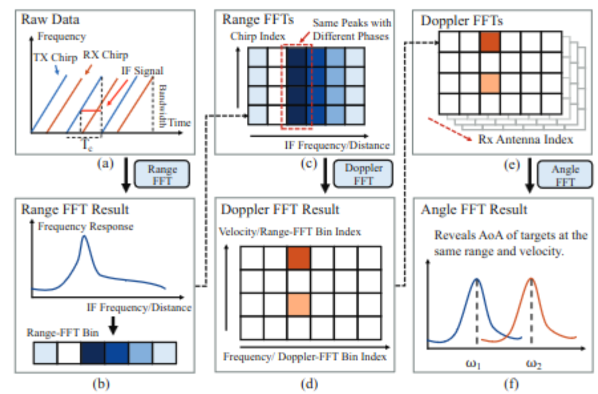

Fig. 1: Illustration of FMCW radar signal processing techniques.

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[1] https://web.eecs.utk.edu/ jliu/publications/yang2020muid.pdf

FMCW AoA estimation

Use phase difference of td-IF signal to calculate AoA for multi-target differentiation. Uses single-path model with linear antenna array.

$$\theta = \sin^{-1}\frac{\lambda * \omega}{2\pi\delta}$$

Where δ is the inter-antenna spacing.

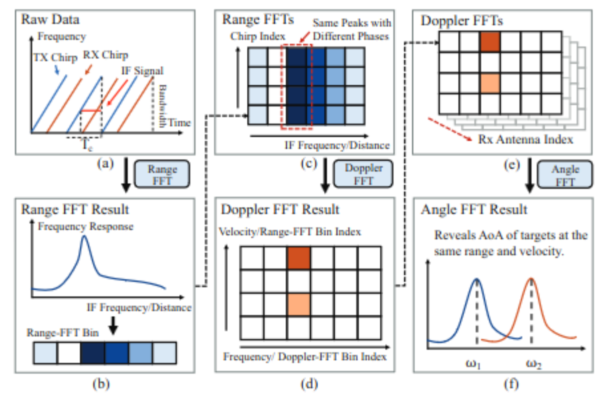

Fig. 1: Illustration of FMCW radar signal processing techniques.

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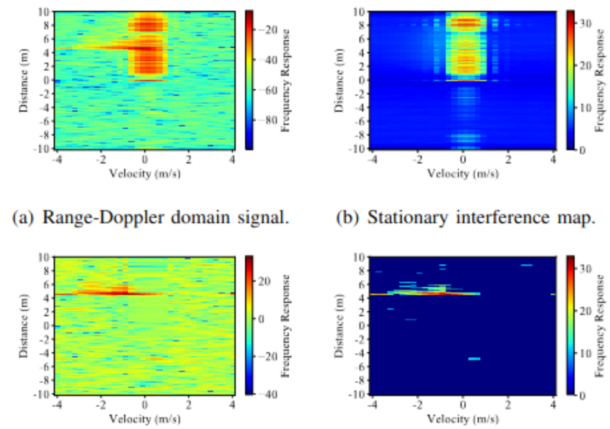
[1] https://web.eecs.utk.edu/ jliu/publications/yang2020muid.pdf

FMCW stationary interference removal and denoising

The frequency / velocity response associated with stationary objects is constant over time, so can be estimated as the average response in the range-doppler domain. This is calculated over a sliding window then subtracted from the recieved signal.

Noise is removed using a high-pass filter.



(a) Range-Doppler domain signal.

(b) Stationary interference map.

(c) Interference removal result.

(d) Denoised range-Doppler signal.

Fig. 3: Illustration of interference removal and denoising.

[1]

[1] https://web.eecs.utk.edu/ jliu/publications/yang2020muid.pdf

Example preprocessed range-doppler signal

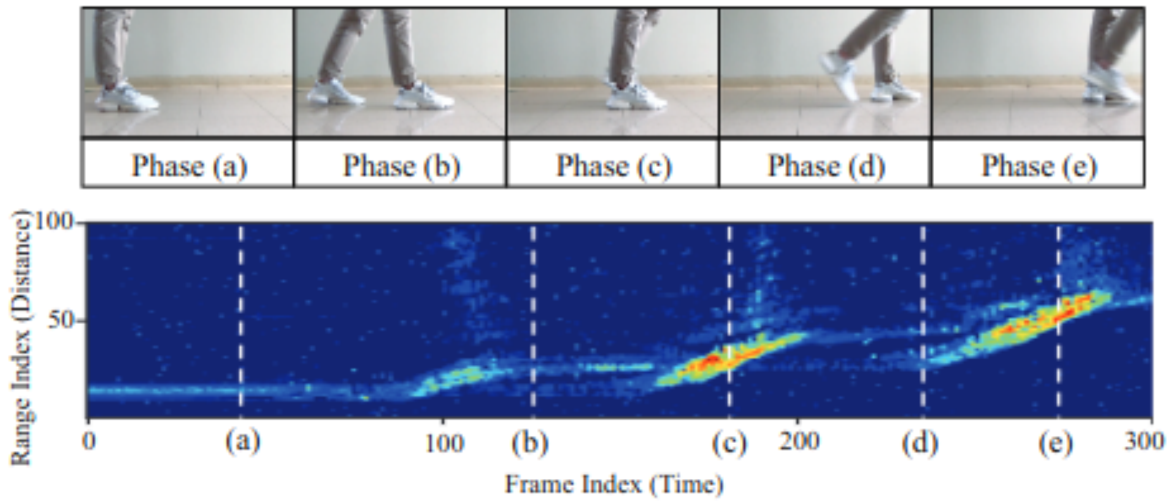


Fig. 5: Correspondence between the actual step and lower limb feature map.

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[1]https://web.eecs.utk.edu/ jliu/publications/yang2020muid.pdf

User detection and separation

- Areas with high frequency in range-doppler signal are turned into (x, y) coordinates using range and AoA estimation
- K-Means clustering is used to detect and separate users for multiple values of K
- Number of users is chosen as K which minimizes Calinski-Harabasz index

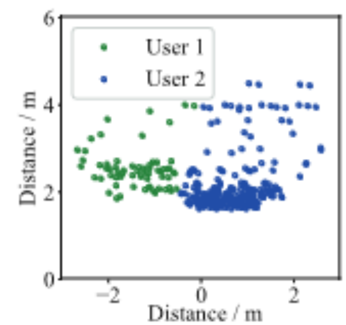


Fig. 7: Scatters of two abreast users in the spatial domain.

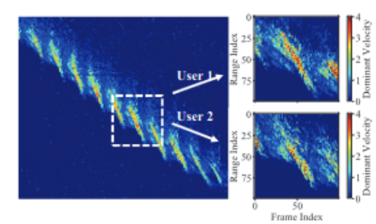
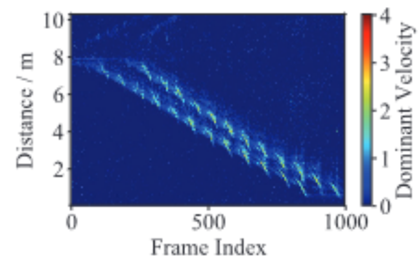


Fig. 8: Mixed steps of two abreast users (left), and separation results (right). [1]

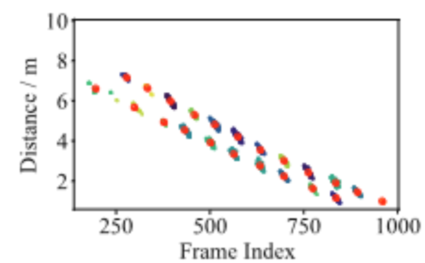
[1] https://web.eecs.utk.edu/ jliu/publications/yang2020muid.pdf

Step segmentation

- Individual steps are identified as clusters using DBSCAN
- Steps are segmented by squares centered over step-cluster centroids



(a) Lower limb motion map of two users walking towards the radar.



(b) Step segmentation clustering result with step center marked as red.

[1]

[1] https://web.eecs.utk.edu/ jliu/publications/yang2020muid.pdf

Gait Profiling

- Segmented steps are classified using CNN
- Model is trained in supervised setting

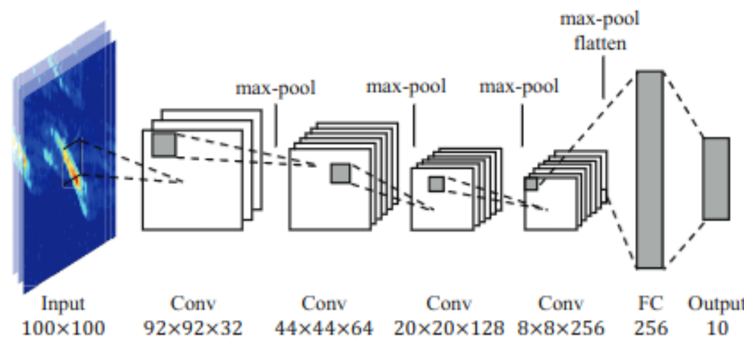


Fig. 10: Illustration of the proposed CNN structure.

[1]

[1] https://web.eecs.utk.edu/ jliu/publications/yang2020muid.pdf

Results: single-user

- Average single-step ID accuracy: 97.7%

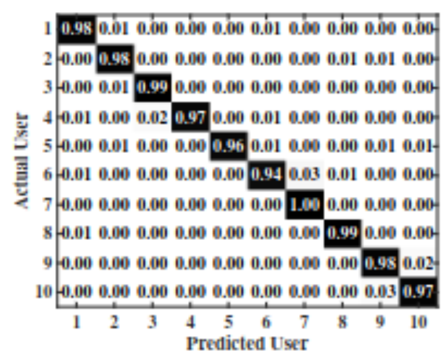


Fig. 13: Confusion matrix of single-user identification.

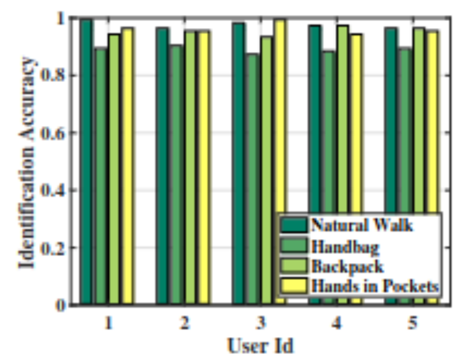


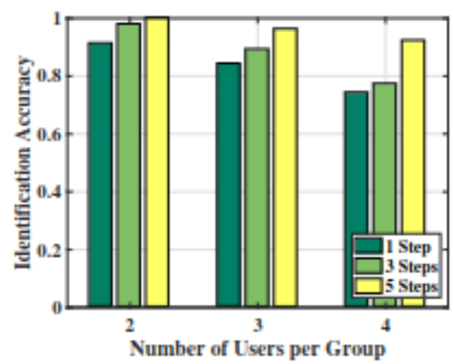
Fig. 17: Identification accuracy with different upper limb behaviors.

[1]

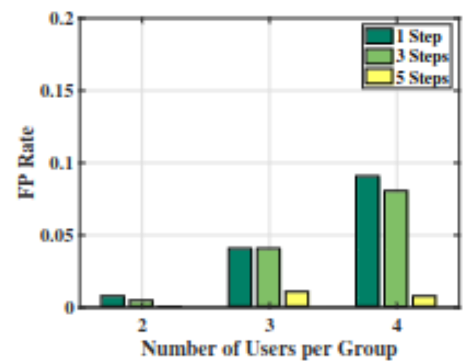
[1] https://web.eecs.utk.edu/ jliu/publications/yang2020muid.pdf

Results: multi-user

- Average single-step ID accuracy (3 users): 84%
- Average 5-step ID accuracy (3 users): 96%



(a) Average accuracy of 1, 3, and 5-step identification.



(b) Average FP rate of 1, 3, and 5-step identification.

Fig. 15: Performance of multi-user identification.

[1]

[1] https://web.eecs.utk.edu/ jliu/publications/yang2020muid.pdf