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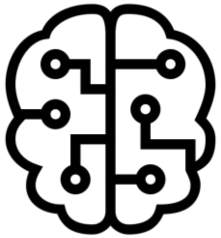
Novel Traffic Sensing Methods and Technologies for Non-Motorized Traffic Monitoring under Challenging Scenarios

Dr. Ziyuan Pu, Lecturer, Monash University, Civil Engineering

Prepared for Florida Atlantic University FMRI Webinar

February 23rd, 2022

Research Background



Artificial Intelligence

CAV

Smart City

Edge Computing

Interpretability
Sustainability
Safety

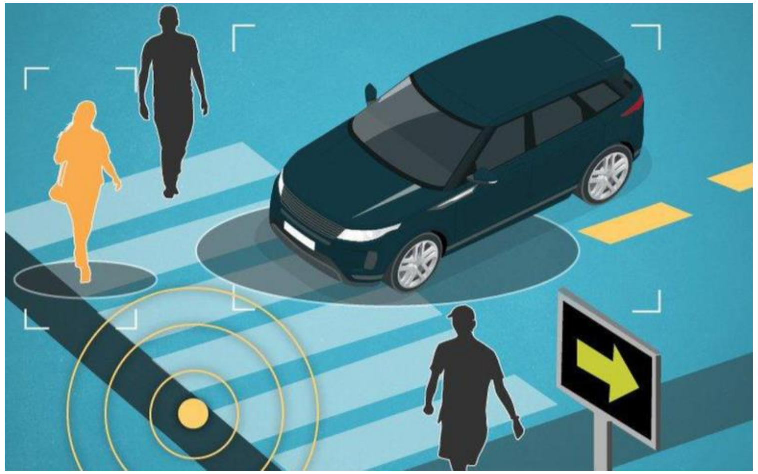
Traffic Data

Reliability
Efficiency
Accuracy

Transportation Systems

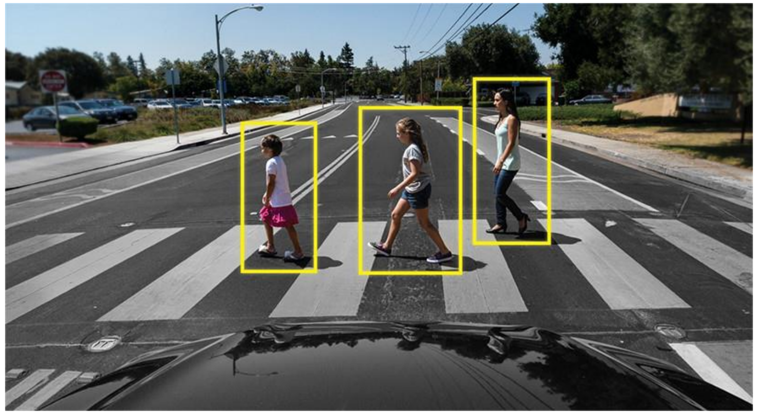
Non-Motorized Traffic Sensing

- Accurate, efficient, and reliable non-motorized sensing is needed
- Wrong detection results could cause traffic accidents



Smart Infrastructure

Wrong Detection Caused Crashes

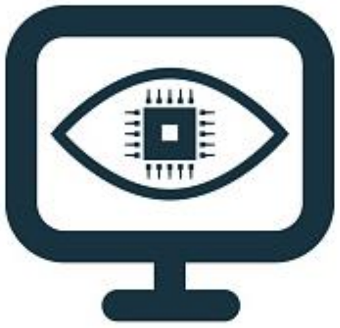


Automated Vehicles

Pictures from Google Images

Existing Sensing Methods and Technologies

- On-board Unit (OBU), and Road-Side Unit (RSU)
- Loop detector, LiDAR, infrared-based sensing, computer vision, wireless sensing
- Vision-based is the most effective due to affluent information, and cost-effective features



Computer Vision

LiDAR

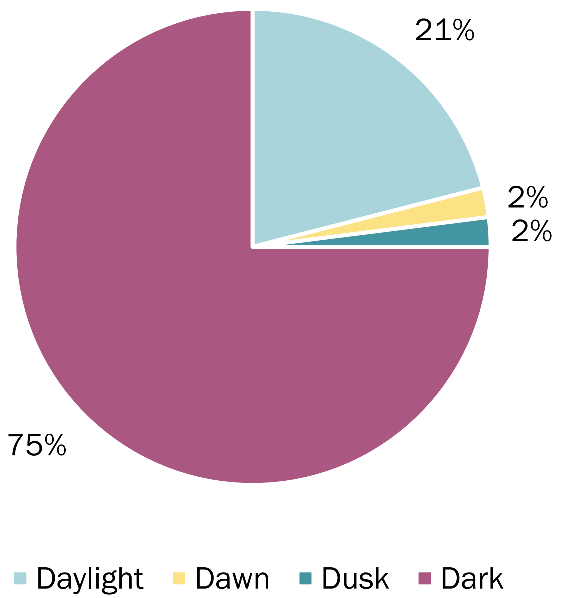
Infrared-based sensing

Wireless Sensing

Pictures from Google Images

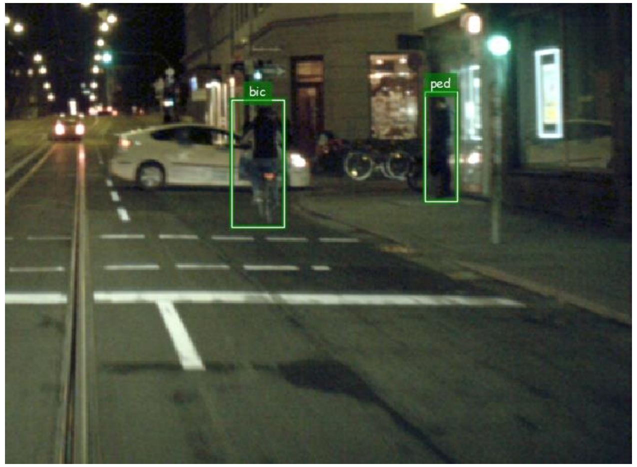
Non-Motorized Traffic Sensing with Low-Illumination

- Most pedestrian deaths occur at non-intersection locations, and at **night** (NHTSA).
- Vision-based sensing with Low-Illumination : 1) scarce texture information; 2) low contrast



Percentage of Pedestrian Fatalities

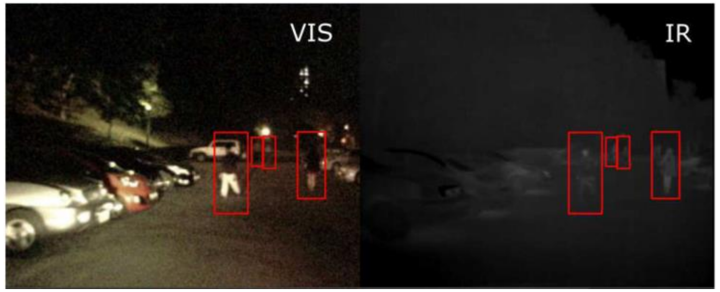
Vehicle Detection in Foggy Environment



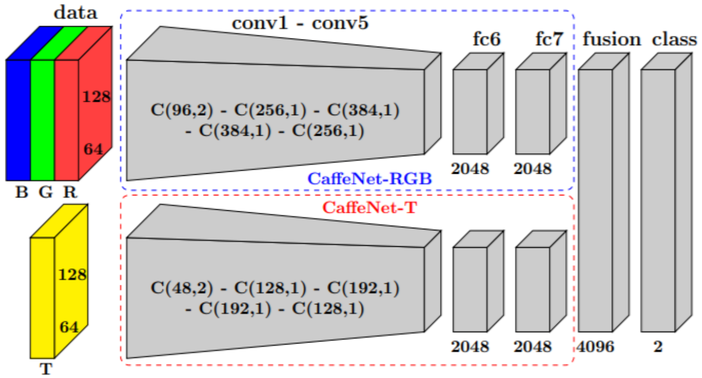
Non-Motorized User Detection with Low-Illumination

Non-Motorized Traffic Sensing with Low-Illumination

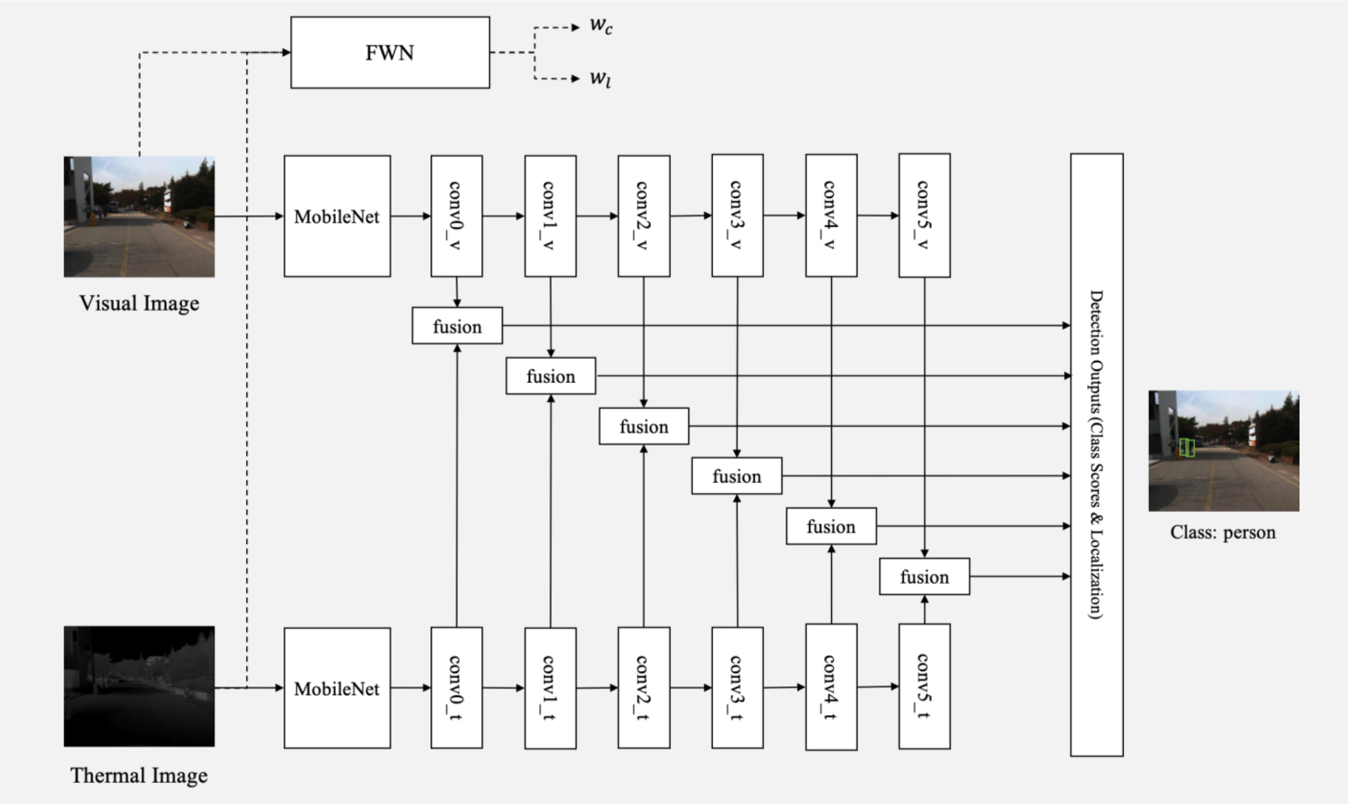
- System Design - Illumination and Temperature-Aware Multispectral Network (IT-MN)



Visible-Light and IR Image Fusion



Multispectral Object Detection Framework



Zhuang, Yifan, Ziyuan Pu*, Jia Hu, and Yinhai Wang. "Illumination and Temperature-Aware Multispectral Networks for Edge-Computing-Enabled Pedestrian Detection." *IEEE Transactions on Network Science and Engineering* (2021). https://ieeexplore.ieee.org/abstract/document/9667310/

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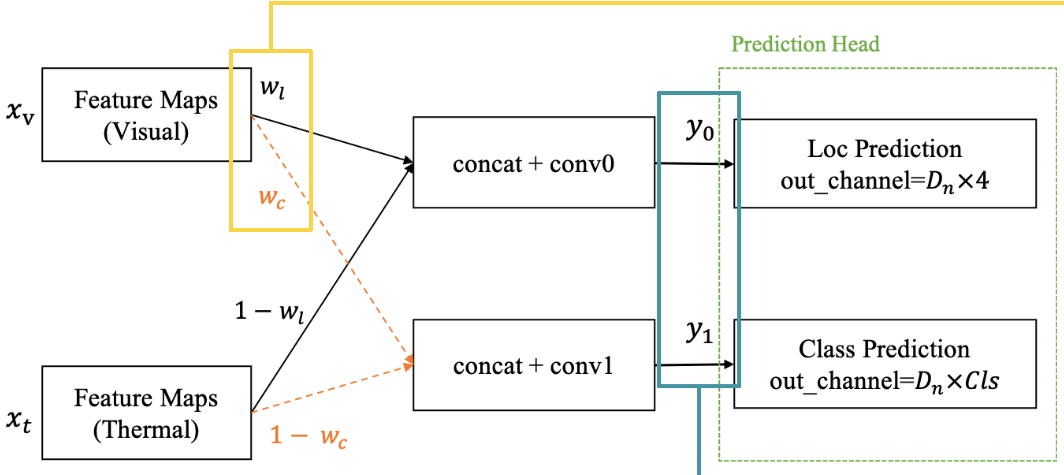
Non-Motorized Traffic Sensing with Low-Illumination

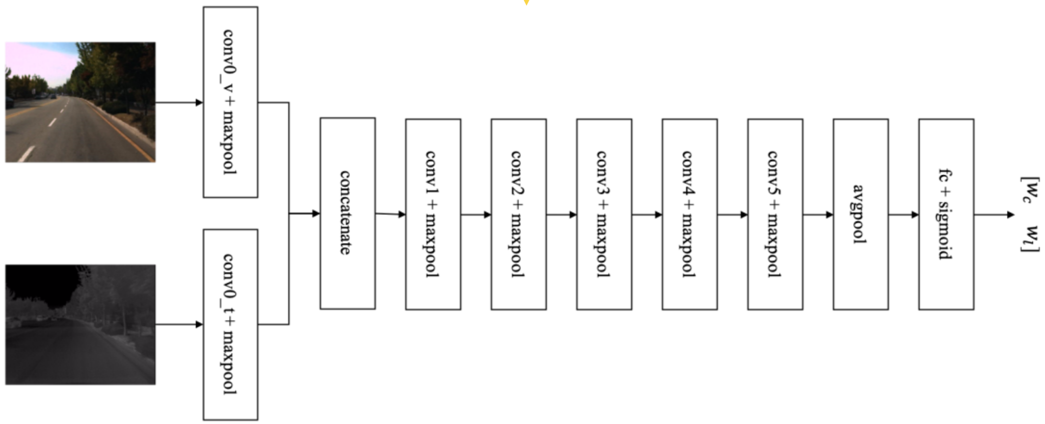
- Feature Fusion and Fusion Weight Computation



Framework of Localization and Classification Fusion

$$y_0 = f_0(w_l x_v + (1 - w_l)x_t)$$

$$y_1 = f_1(w_c x_v + (1 - w_c)x_t)$$



Framework of FWN (Fusion Weight Computation Network)

Zhuang, Yifan, Ziyuan Pu*, Jia Hu, and Yinhai Wang. "Illumination and Temperature-Aware Multispectral Networks for Edge-Computing-Enabled Pedestrian Detection." *IEEE Transactions on Network Science and Engineering* (2021).
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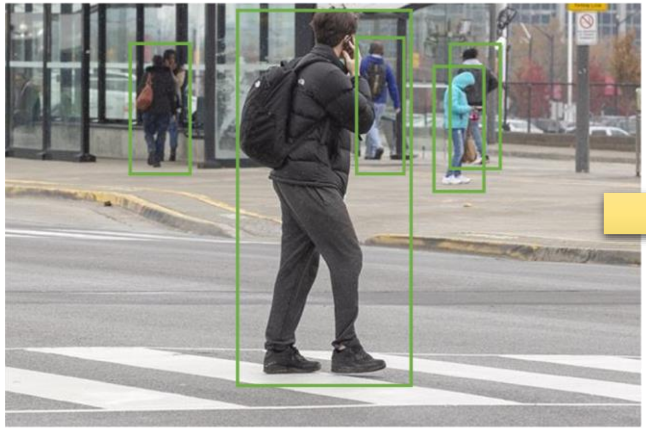
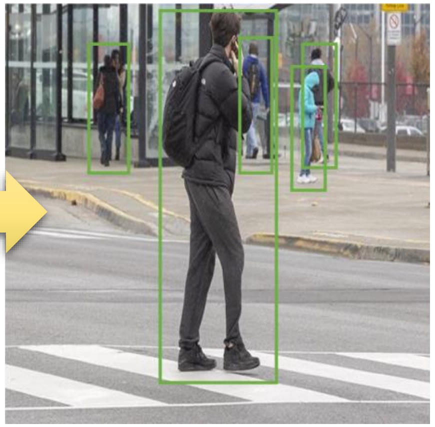
Non-Motorized Traffic Sensing with Low-Illumination

- Default Box Generation

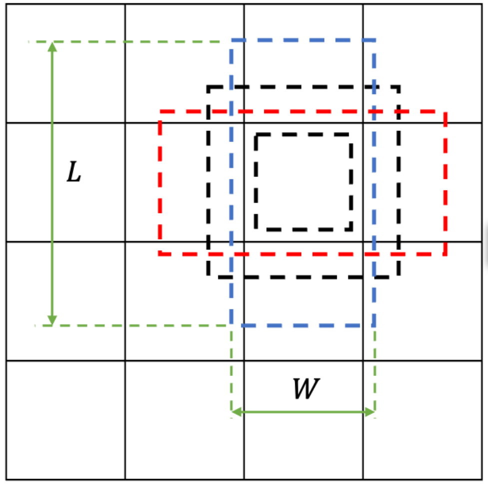
One straightforward solution to decrease the computing complexity is reducing the default box (anchor) number.



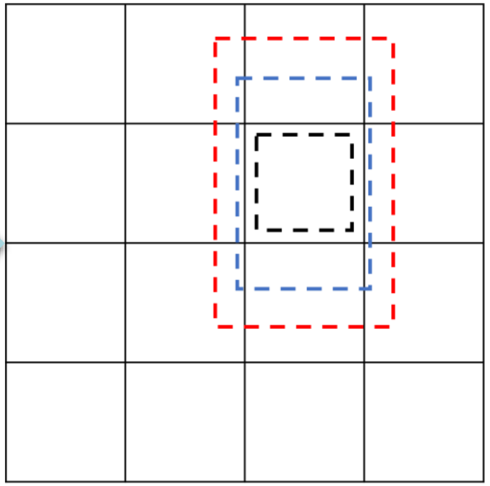
Pedestrian Image of Original Dimension



Pedestrian Image of Resized Dimension



Original Default Box



Optimized Default Box

In order to fit the model, the input image is resized to a square size.

Original box aspect ratios: 1, 2, 3, 1/2, 1/3

Optimized box aspect ratios: 1, 1/2, 1/3

Zhuang, Yifan, Ziyuan Pu*, Jia Hu, and Yinhai Wang. "Illumination and Temperature-Aware Multispectral Networks for Edge-Computing-Enabled Pedestrian Detection." *IEEE Transactions on Network Science and Engineering* (2021). https://ieeexplore.ieee.org/abstract/document/9667310/

Non-Motorized Traffic Sensing with Low-Illumination

- Performance Evaluation

Comparison of Mean MR, All Day, Daytime and Nighttime

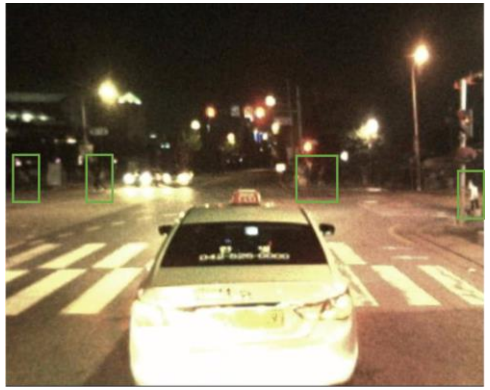
	L-SSD	IATDNN	MLF-CNN	IT-MN	Q. IT-MN
MR (All)	43.06%	29.62%	25.65%	14.19%	14.55%
MR (Day)	50.73%	30.30%	25.22%	14.30%	14.67%
MR (Night)	35.38%	26.88%	26.60%	13.98%	14.29%

Comparison of Inference Time on GPU and Raspberry Pi
(Unit: Second per Frame)

	L-SSD	IATDNN	MLF-CNN	IT-MN	Q. IT-MN
Speed (CPU)	0.03	0.25	0.15	0.03	-
Speed (GPU)	0.38	2.60	1.60	0,40	0.21

Day Road (Visible Light)

Day Road (Thermal)



Night Road (Visible Light)

Night Road (Thermal)

Zhuang, Yifan, Ziyuan Pu*, Jia Hu, and Yinhai Wang. "Illumination and Temperature-Aware Multispectral Networks for Edge-Computing-Enabled Pedestrian Detection." *IEEE Transactions on Network Science and Engineering* (2021).
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Too Much Data for Analysis

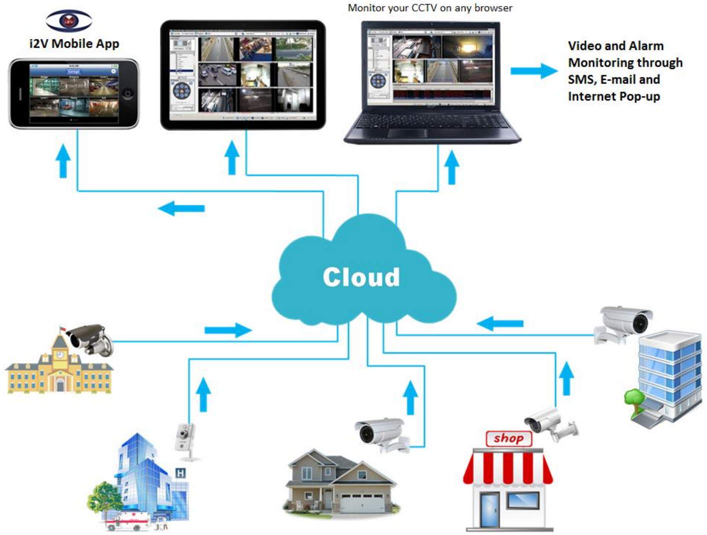
Large-scale sensor network

Multiple surveillance cameras

Multiple sensing tasks

Three “**More**”: more locations, more sensors, more sensing tasks

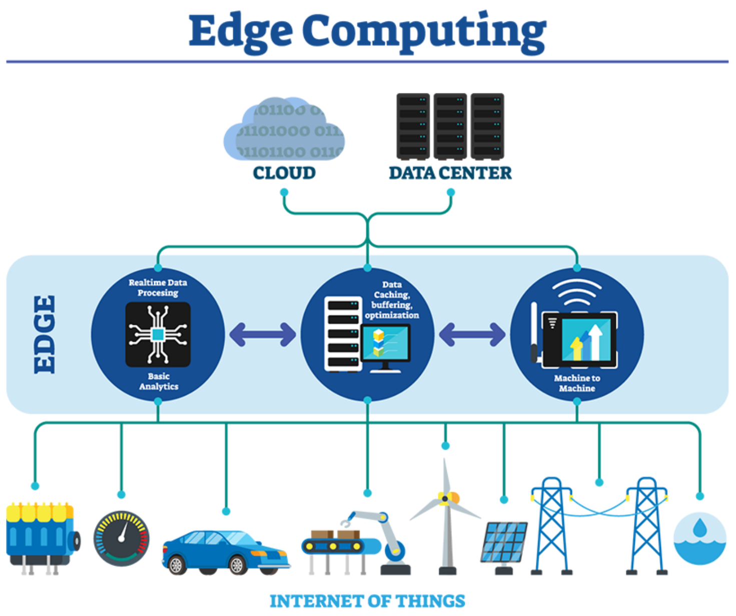
Cloud computing: All data collected at the frontend will be transmitted to the server for **processing** and **storage**.



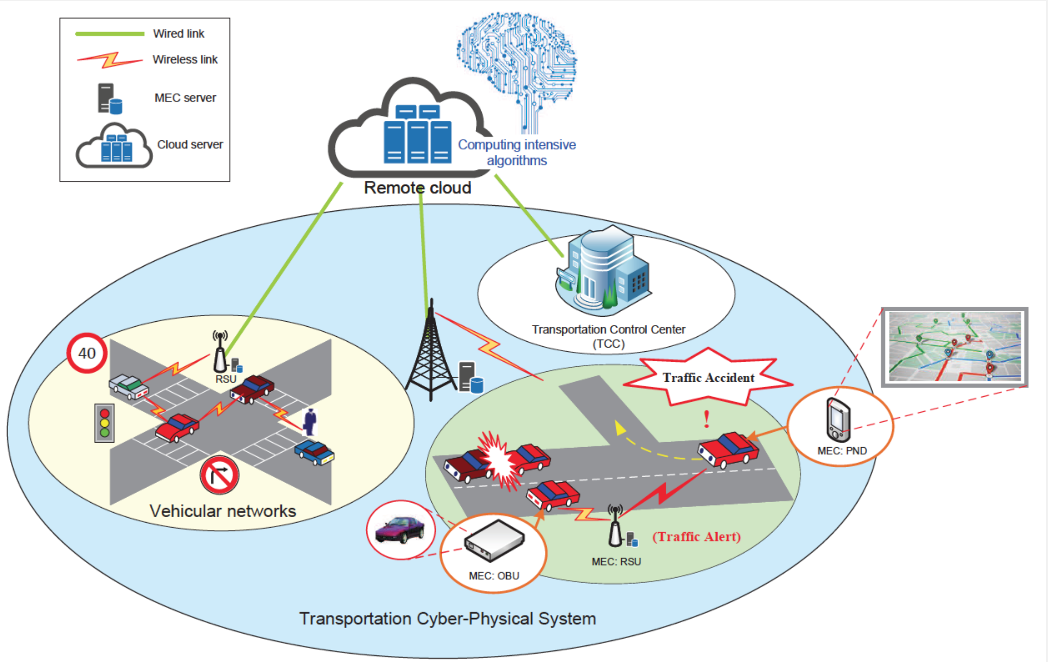
Cloud Computing Framework

Edge Computing

- Edge computing is a **distributed computing paradigm** that brings computation and data storage closer to the **sources of data**



The Edge Computing Infrastructure



Edge Computing in ITS

Advantages of edge computing:

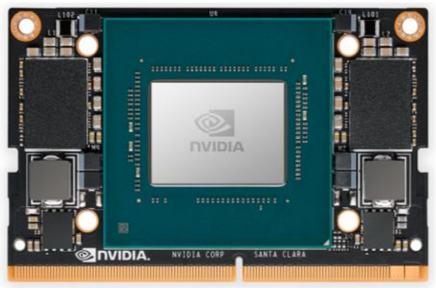
1) Short latency in large scale network
2) Strong scalability for deployment
3) High privacy, i.e., facial and speech information

Edge Computing

- Challenges of edge computing:

1) Weak computing power or low computing resources

Edge Device, e.g.,
Nvidia Jetson Xavier NX
(21 TOPS)



Cloud / Server GPU, e.g.,
Nvidia A100 (**624 TOPS**)

How to improve model efficiency?

1) Simplify model structure or select a smaller model

Example: Separable convolution:

$$12 \times 12 \times 3 \rightarrow 12 \times 12 \times 256$$

Traditional convolution ($5 \times 5 \times 3 \times 256$): **1,228,800**

Separable convolution ($5 \times 5 \times 1 \times 1$ and $1 \times 1 \times 3 \times 256$): **53,952**

2) Compress models, e.g., model quantization and pruning

Model quantization: reducing the parameter precision

Model pruning: reducing connections between neurons

Bit Mask

1	0	1
1	0	1
1	0	1

$\otimes$

Weight

.7	.2	.1
-.2	.8	.9
.2	.1	.3

$=$

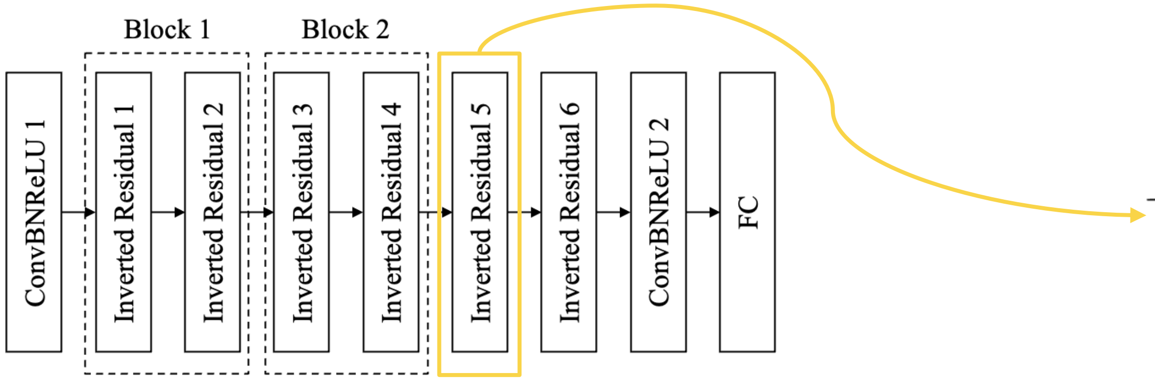
Pruned

.7	0	1
-.2	0	1
.2	0	1

Pruning Strategy

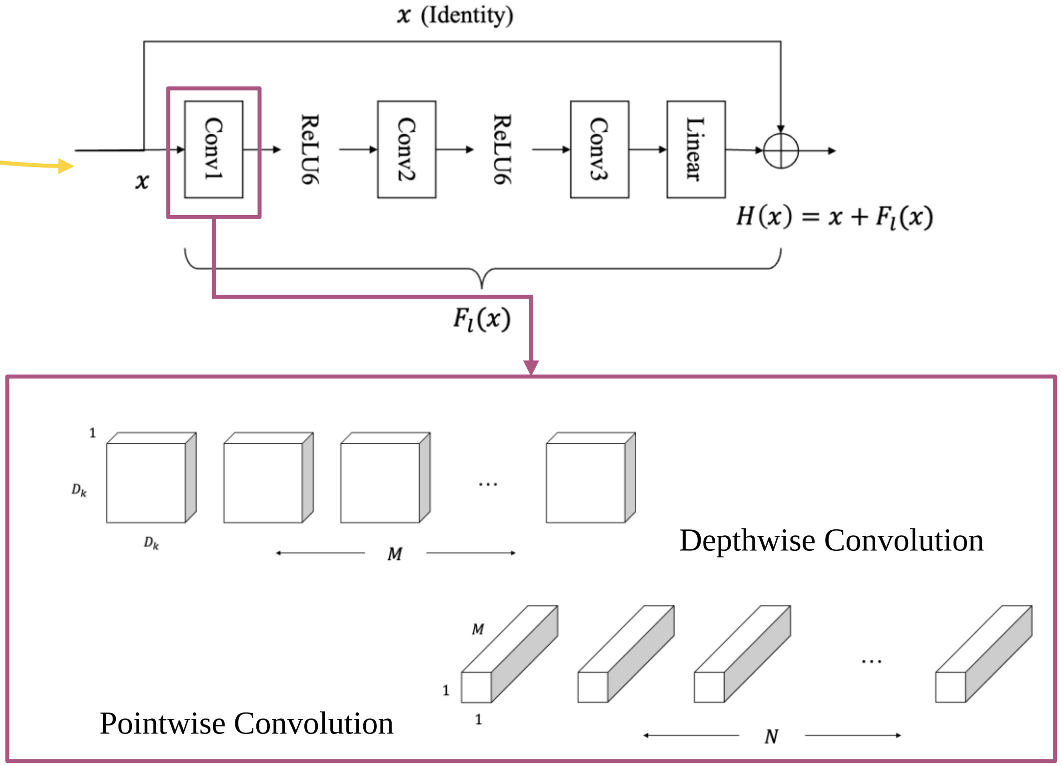
Quantized Neural Network for Crowd Estimation

- Model Framework and Quantization

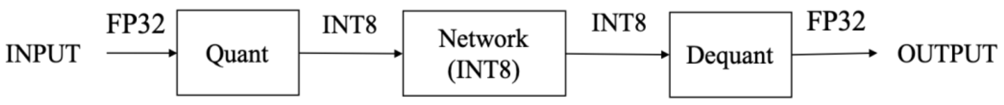


Framework of Detection Model

Framework of Residual Module



$$Q(x) = \lfloor x/s + z \rceil$$



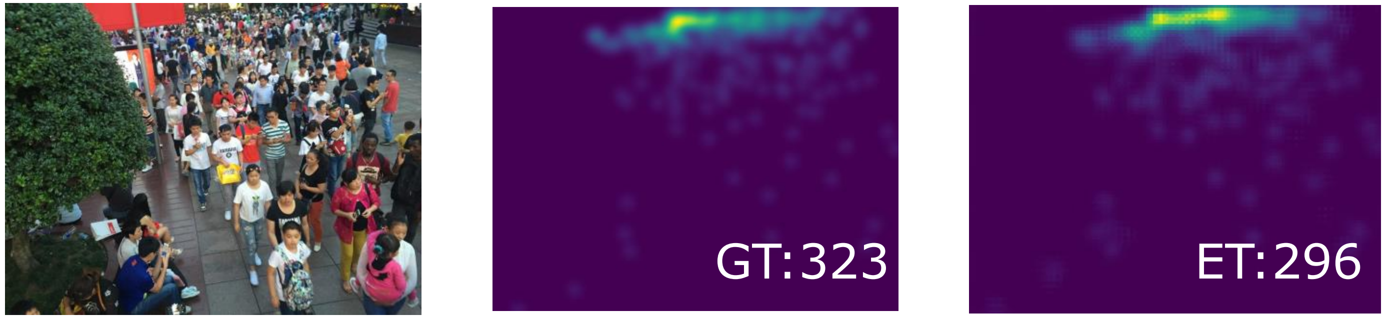
Framework of Quantization and Dequantization

Wang, Shuo, Ziyuan Pu*, Qianmu Li, Yaming Guo, and Meng Li. "Edge Computing-Enabled Crowd Density Estimation based on Lightweight Convolutional Neural Network." In *2021 IEEE International Smart Cities Conference (ISC2)*, pp. 1-7. IEEE, 2021.
https://ieeexplore.ieee.org/abstract/document/9562877

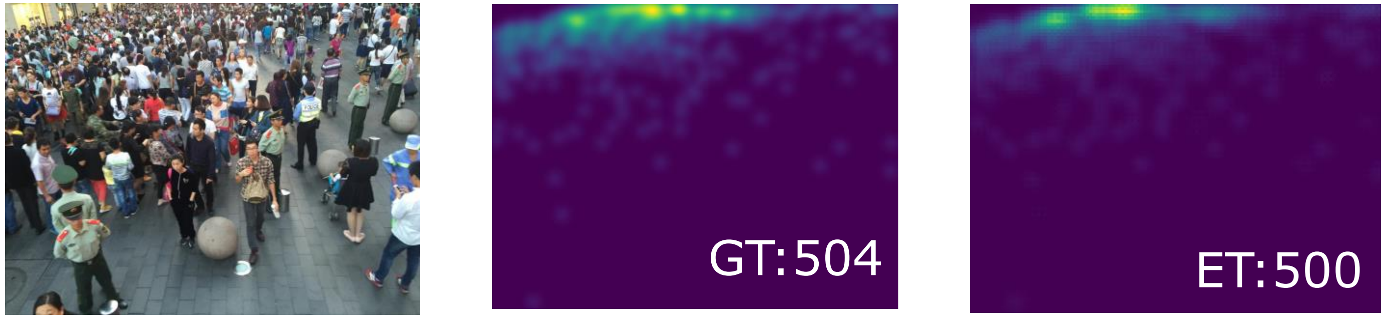
Quantized Lightweight CNN for Crowd Estimation

- Public Datasets: ShanghaiTech PartB
- 12 SOTA models for the comparison
- Highly improve efficiency without losing accuracy

Model	MAE	RMSE	Parameters(M)
DR-RESNET	14.5	21	0.028
MCNN	26.4	41.3	0.13
Switching CNN	21.6	33.4	15.11
CSRNet	10.6	16.0	16.2
MRCNet	10.3	18.4	20.3
OUR MODEL	11	17.6	10.07



(d) Density maps of D4 level



(e) Density maps of D5 level

Wang, Shuo, Ziyuan Pu*, Qianmu Li, Yaming Guo, and Meng Li. "Edge Computing-Enabled Crowd Density Estimation based on Lightweight Convolutional Neural Network." In *2021 IEEE International Smart Cities Conference (ISC2)*, pp. 1-7. IEEE, 2021.
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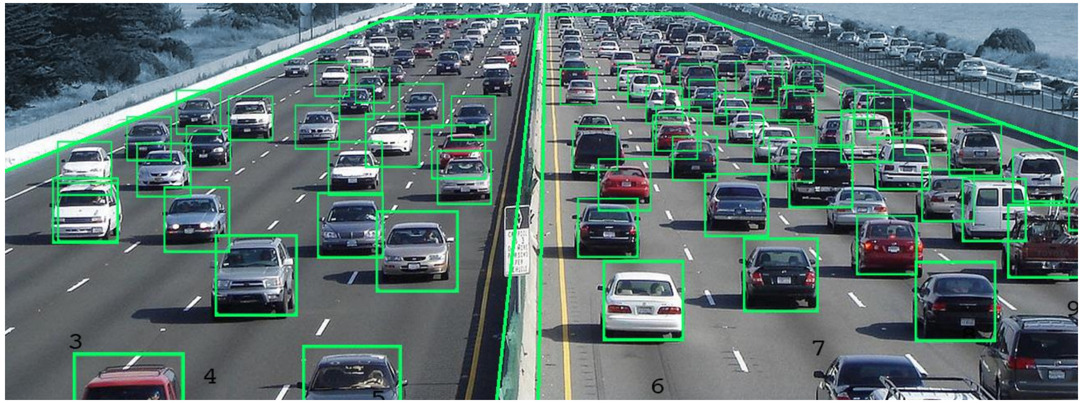
Traffic Sensing Theory

❑Traffic Sensing Theory



Point Detection

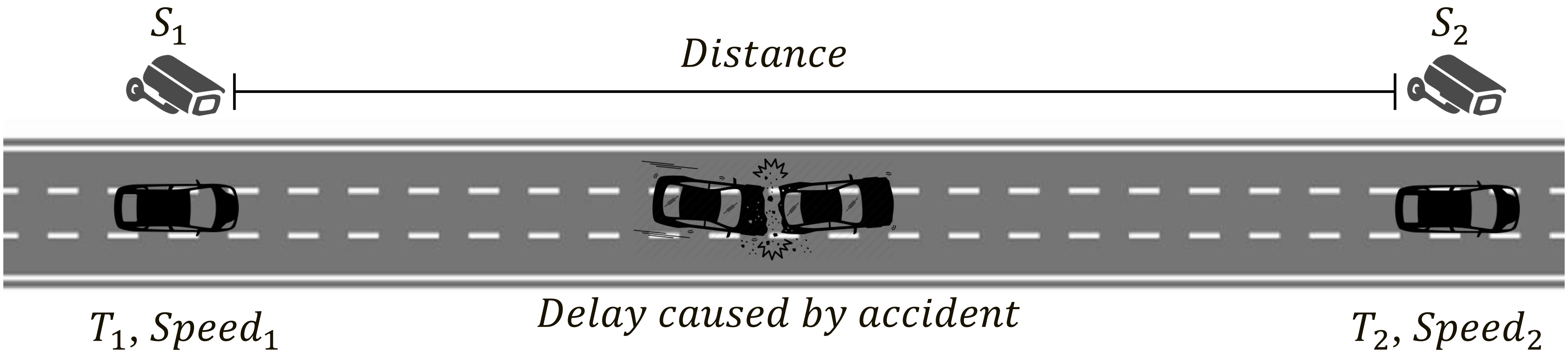
Re-Identification

Traffic Parameters: Traffic volume, localized traffic parameters
Sensing Technologies: Loop detectors, microwave sensors, radar sensors, etc.

Traffic Parameters: Traffic volume, localized traffic speed, travel time, trip trajectory
Sensing Technologies: Video-based sensing, etc.

Pictures from Google Images

Traffic Sensing Theory

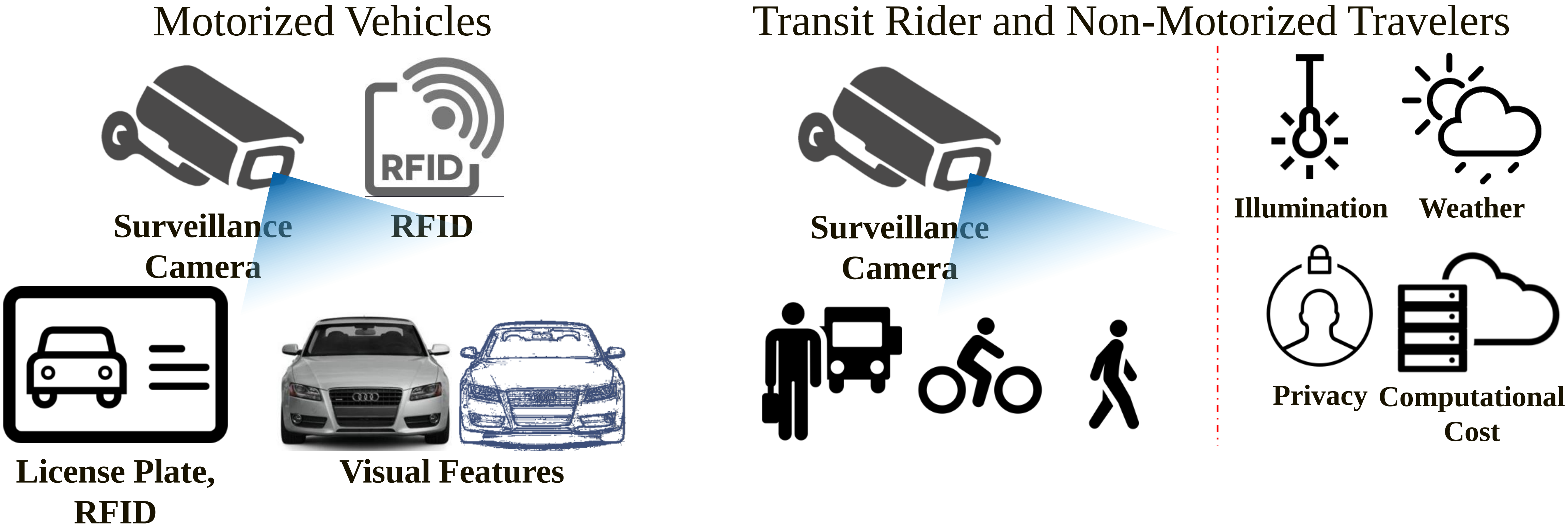


$$Average\ Speed^{S_1 - S_2}_{Point\ Detection} = average(Speed_1, Speed_2)$$

$$Average\ Speed^{S_1 - S_2}_{Re-Identification} = \frac{Distance}{T_2 - T_1}$$

Pictures from Google Images

Limitations in Re-Identifying Non-Motorized Travelers



Pictures from Google Images

Device-Based Wireless Sensing

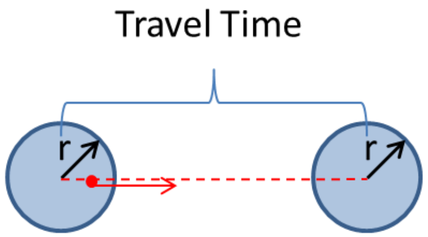
- Capture Media Access Control (MAC) address of Wi-Fi and Bluetooth devices.
- A device is discoverable if Wi-Fi or Bluetooth is active and no connections yet.
- The detection range depends on the type of antenna being used.
- Typically, Wi-Fi 50-80 meters, Bluetooth 20-30 meters

Pictures from Google Images

Limitations in Device-Based Wireless Sensing

- Traffic Mode Uncertainty

- Localized Spatial Uncertainty



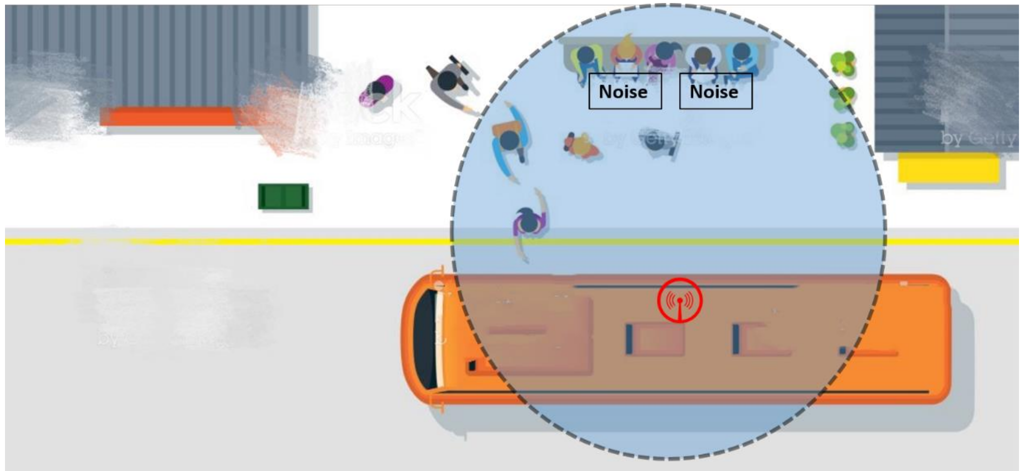
- Population Uncertainty

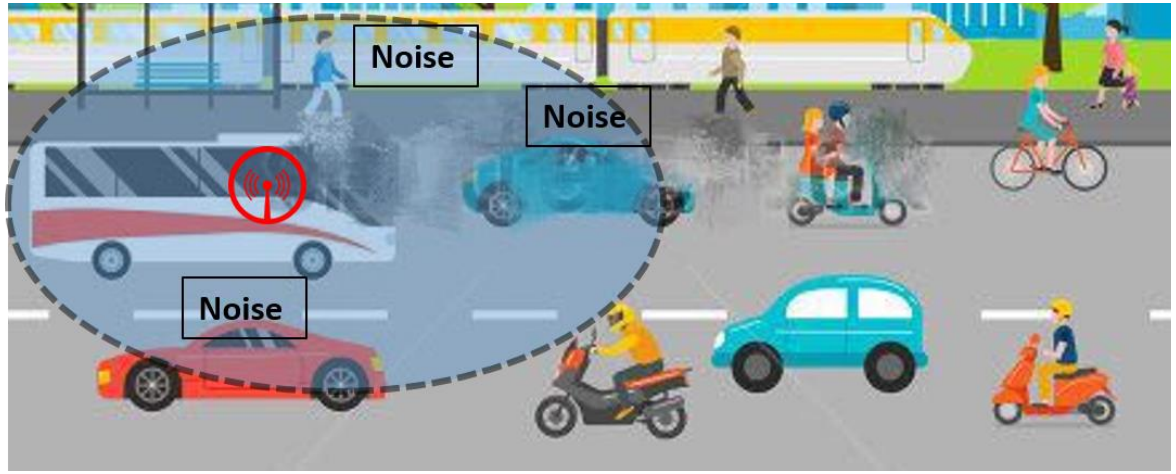
Discoverable Indiscoverable

Proposed Method – Transit Rider

- Challenges

- Traffic Mode Uncertainty (Passenger & Non-Passenger)



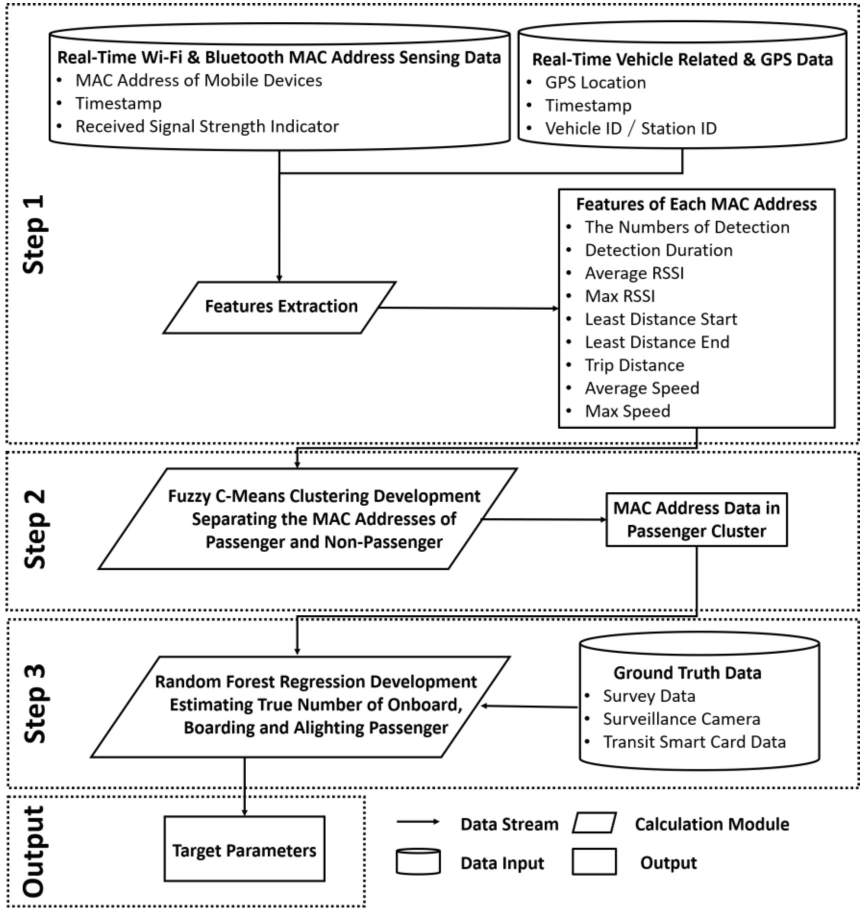


- Population Uncertainty (Partial passengers carry discoverable mobile devices)

Pu, Z., Zhu, M., Li, W., Cui, Z., Guo, X., & Wang, Y. (2020). Monitoring public transit ridership flow by passively sensing Wi-Fi and Bluetooth mobile devices. *IEEE Internet of Things Journal*, *8*(1), 474-486.
https://ieeexplore.ieee.org/abstract/document/9149951/

Proposed Method – Transit Rider

- **Traffic Mode Uncertainty** (Passenger & Non-Passenger) (Step 1 - 2)
  - Extracting features of each MAC address
  - Separating passenger and non-passenger MAC addresses based on Fuzzy C-means clustering
- **Population Uncertainty** (Step 3)
  - Estimating population ridership flow based on clustered passenger MAC addresses



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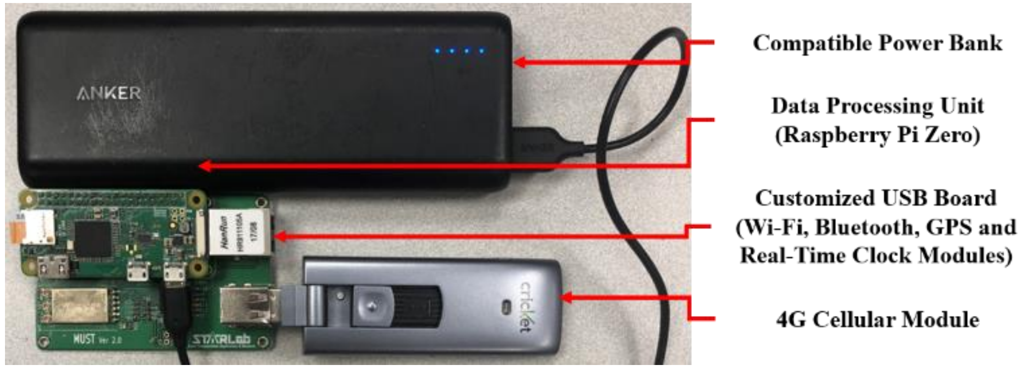
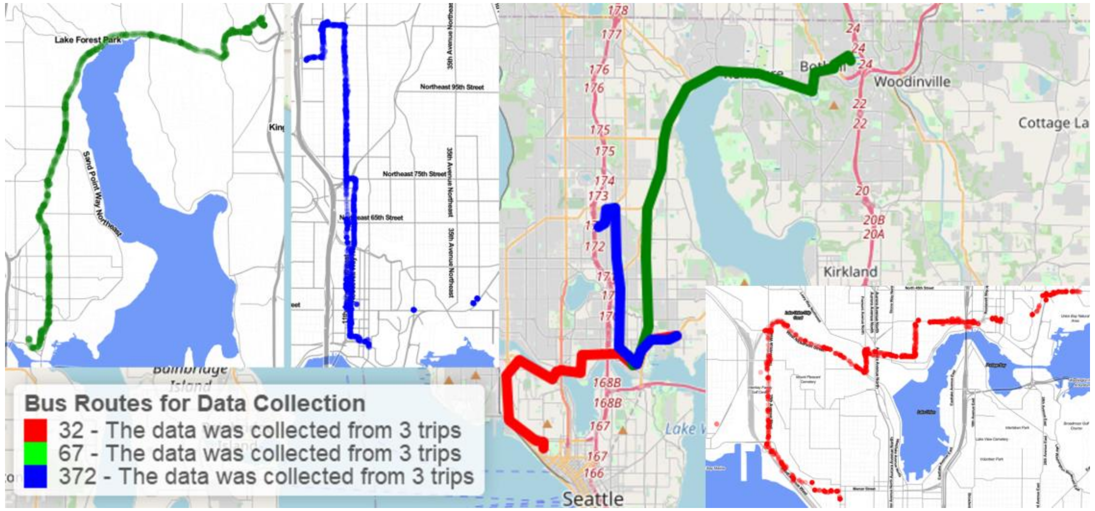
Proposed Method – Transit Rider

- **Customized Wireless Sensor**
  - Passive sensing Wi-Fi and BT Device
  - Recording high-resolution GPS
  - Transmitting data by cellular data
- **Data Collection**
  - 3 transit routes (32, 372, and 67)
  - 9 trips (3 for each)
  - Manually collect Ground truth



Customized Wireless Sensor



Study Site

Pu, Z., Zhu, M., Li, W., Cui, Z., Guo, X., & Wang, Y. (2020). Monitoring public transit ridership flow by passively sensing Wi-Fi and Bluetooth mobile devices. *IEEE Internet of Things Journal*, *8*(1), 474-486. https://ieeexplore.ieee.org/abstract/document/9149951/

Proposed Method – Transit Rider

- Results
  - On-board, boarding and alighting riders
  - The proposed method outperformed other baseline models
  - Accuracy is about 85%

Boarding \ Alighting	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Total Boarding MAC	Total Ground Truth Boarding	Total Estimated Boarding
1	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	2	2	3
2		0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	2	0
3			0	1	0	1	0	0	0	0	0	0	0	0	0	2	1	2
4				0	0	0	0	0	0	1	0	0	0	0	0	1	0	1
5					0	1	0	0	0	0	0	0	0	0	0	1	1	1
6						0	1	0	0	0	0	0	0	0	0	1	1	1
7							0	3	1	0	0	0	0	0	0	4	2	3
8								0	0	0	0	0	0	0	0	0	1	3
9									0	0	0	0	2	0	0	2	0	2
10										0	1	1	0	0	0	2	2	1
11											0	1	0	0	0	1	0	0
12												0	0	0	1	1	1	2
13													0	1	0	1	0	3
14														0	0	0	3	2
15															0	0	0	0
Total Alighting MAC	0	0	0	1	0	2	1	3	1	1	1	2	2	3	2	19 \ 19		
Total Ground Truth Alighting	0	0	0	0	1	2	1	0	1	0	1	0	2	2	6		16 \ 16	
Total Estimated Alighting	0	0	1	1	1	2	1	1	2	2	1	2	3	2	5			24 \ 24

Stops	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Ground Truth Onboard Passenger	2	4	5	5	5	4	5	6	5	7	6	7	5	6	6
Onboard MAC of Each Stop	2	3	5	5	6	5	8	5	6	7	7	6	5	2	0
Estimated Onboard Passenger	2	4	5	5	5	6	6	4	4	5	5	5	4	3	1

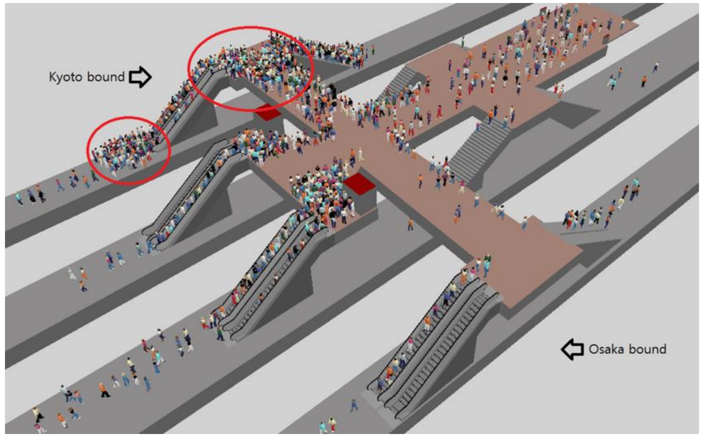
Pu, Z., Zhu, M., Li, W., Cui, Z., Guo, X., & Wang, Y. (2020). Monitoring public transit ridership flow by passively sensing Wi-Fi and Bluetooth mobile devices. *IEEE Internet of Things Journal*, *8*(1), 474-486. https://ieeexplore.ieee.org/abstract/document/9149951/

Proposed Method – Multi-Modal Traffic Speed

❑Introduction

- Non-motorized traffic information is important

Multi-Modal Traffic Signal Control



Non-Motorized Traffic Management

Proposed Method – Multi-Modal Traffic Speed

❑Methodology Overview

- **Localized spatial uncertainty** – correct traffic speed based on RSSI measurements

- **Traffic mode uncertainty** – identify traffic mode of each MAC trip based on extracted features using semi-PCM clustering (detection times, duration, and time difference)

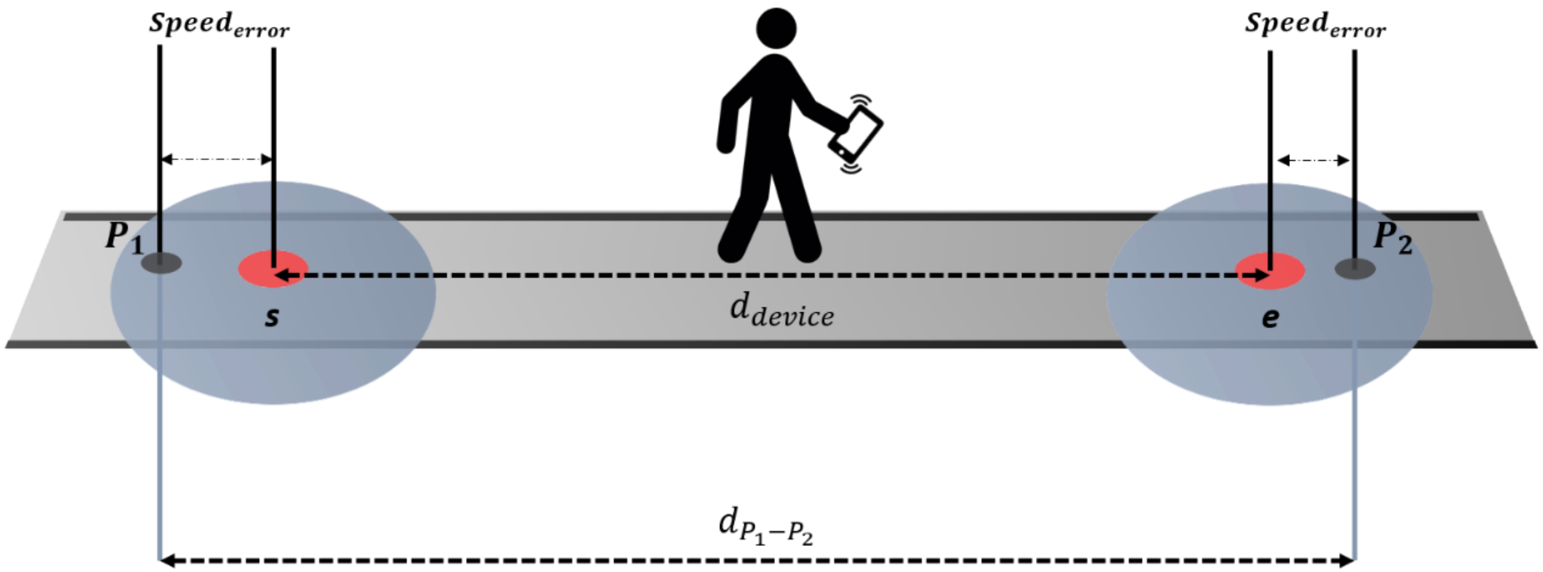
Algorithm: Real-Time Multi-Modal Traffic Speed Estimation

Initialization: start time t_0, time interval Δt
for road segments i in $\{1, \dots, N\}$ **do**:
  Extract all MAC trips M within time interval $[t_0, t_0 + \Delta t]$
  for MAC trip j in $\{1, \dots, M\}$ **do**:
    Correct traffic speed based on RSSI
    Extract features vector v_j of MAC Trip j
  end for
  Identify travel modes for all MAC trips M using Semi-PCM
end for
Output: average multi-modal traffic speed of all road segments for the time window $[t_0, t_0 + \Delta t]$

Pu, Z., Cui, Z., Tang, J., Wang, S., & Wang, Y. (2021). Multi-Modal Traffic Speed Monitoring: A Real-Time System Based on Passive Wi-Fi and Bluetooth Sensing Technology. *IEEE Internet of Things Journal*.
https://ieeexplore.ieee.org/abstract/document/9653682

Proposed Method – Multi-Modal Traffic Speed

- Localized Spatial Uncertainty



$$Speed_{estimated} = \frac{d_{device}}{TT_{P_1-P_2}}$$

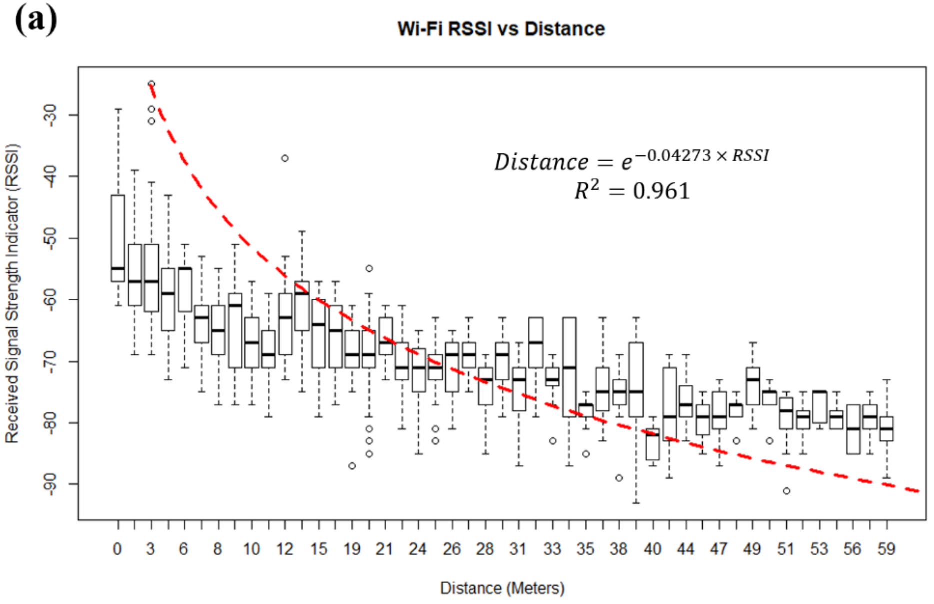
$$Speed_{error} = \frac{\left|d_{device} - d_{P_1-P_2}\right|}{TT_{P_1-P_2}}$$

Pu, Z., Cui, Z., Tang, J., Wang, S., & Wang, Y. (2021). Multi-Modal Traffic Speed Monitoring: A Real-Time System Based on Passive Wi-Fi and Bluetooth Sensing Technology. *IEEE Internet of Things Journal*.
https://ieeexplore.ieee.org/abstract/document/9653682

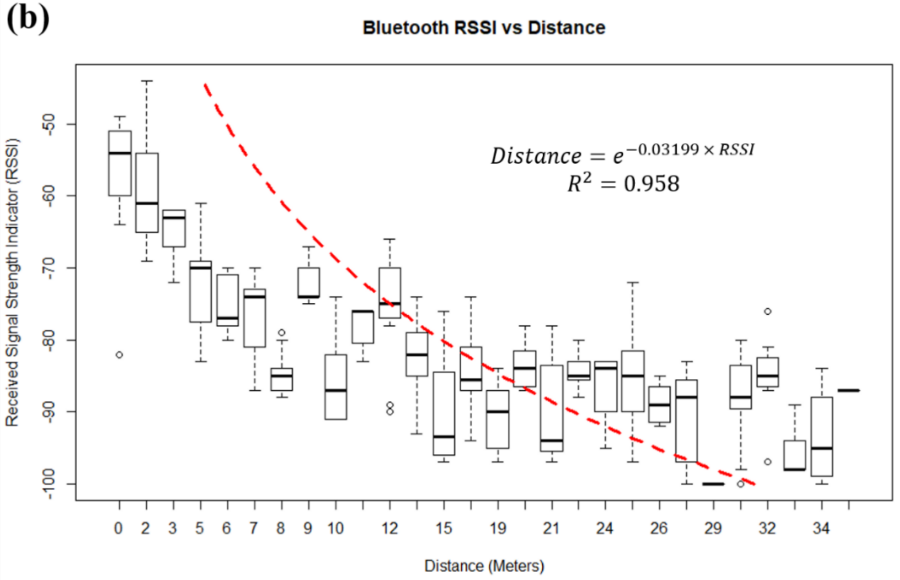
Proposed Method – Multi-Modal Traffic Speed

- Localized Spatial Uncertainty

(a)



(b)



$$d_{Wi-Fi} = e^{-0.04273 \times RSSI}$$

$$d_{Bluetooth} = e^{-0.03199 \times RSSI}$$

Pu, Z., Cui, Z., Tang, J., Wang, S., & Wang, Y. (2021). Multi-Modal Traffic Speed Monitoring: A Real-Time System Based on Passive Wi-Fi and Bluetooth Sensing Technology. *IEEE Internet of Things Journal*.
https://ieeexplore.ieee.org/abstract/document/9653682

Proposed Method – Multi-Modal Traffic Speed

❑Localized Spatial Uncertainty

- Correct traffic speed based on RSSI measurement and relative position to sensors
- Using all detected points to correct traffic speed for one trip

$$Corrected\ Speed_{s-e} = \begin{cases} \dfrac{d_{device} - d_s + d_e}{TT_{s-e}}, if\ P^s = \{P_n^s | n \in (min, n]\}\ and\ P^e = \{P_n^e | n \in (min, n]\} \\ \dfrac{d_{device} + d_s - d_e}{TT_{s-e}}, if\ P^s = \{P_n^s | n \in [1, min)\}\ and\ P^e = \{P_n^e | n \in [1, min)\} \\ \dfrac{d_{device} + d_s + d_e}{TT_{s-e}}, if\ P^s = \{P_n^s | n \in [1, min)\}\ and\ P^e = \{P_n^e | n \in (min, n]\} \\ \dfrac{d_{device} - d_s - d_e}{TT_{s-e}}, if\ P^s = \{P_n^s | n \in (min, n]\}\ and\ P^e = \{P_n^e | n \in [1, min)\} \end{cases}$$

$$Corrected\ Speed_{trip} = \frac{\sum_i^{\boldsymbol{S}} \sum_j^{\boldsymbol{E}} Corrected\ Speed_{i-j}}{\boldsymbol{S} \times \boldsymbol{E}}$$

Pu, Z., Cui, Z., Tang, J., Wang, S., & Wang, Y. (2021). Multi-Modal Traffic Speed Monitoring: A Real-Time System Based on Passive Wi-Fi and Bluetooth Sensing Technology. *IEEE Internet of Things Journal*. https://ieeexplore.ieee.org/abstract/document/9653682

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Proposed Method – Multi-Modal Traffic Speed

❑Traffic Mode Uncertainty

- Randomly initialization will result in local optimal for a dataset

- Initializing hyper-parameters by a small set of labelled data

$$u_{ij} = \frac{1}{1 + \left(\frac{d_{ij}^2}{\eta_i}\right)^{\frac{1}{m-1}}}$$

$$\eta_i = K \frac{\sum_{j=1}^{N} u_{ij}^m d_{ij}^2}{\sum_{j=1}^{N} u_{ij}^m}$$

$$\eta_i = \frac{\sum_{x_j \in (labelled)}^{n_{labelled}} d_{ij}^2}{n_{labelled}}$$

Algorithm: Semi-Supervised PCM Clustering

Initialization:

The number of clusters C

The maximum number of iterations L

The fuzzification parameter m

Calculate the center of each cluster in labelled data $v_i^{(0)}$

Initialize η_i using Equation

Initialize $U^0 \in R^{C \times N}, u_{ij}^0 = U^0(i,j) \in [0,1]$ using Equation

Repeat:

Update U^t, and Increment L

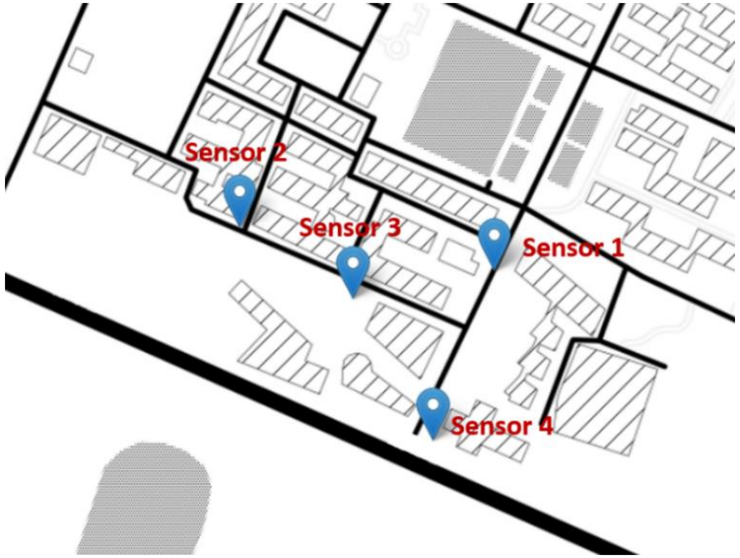
Until: $\|U^t - U^{t-1}\| \leq \varepsilon$ or $t \geq L$

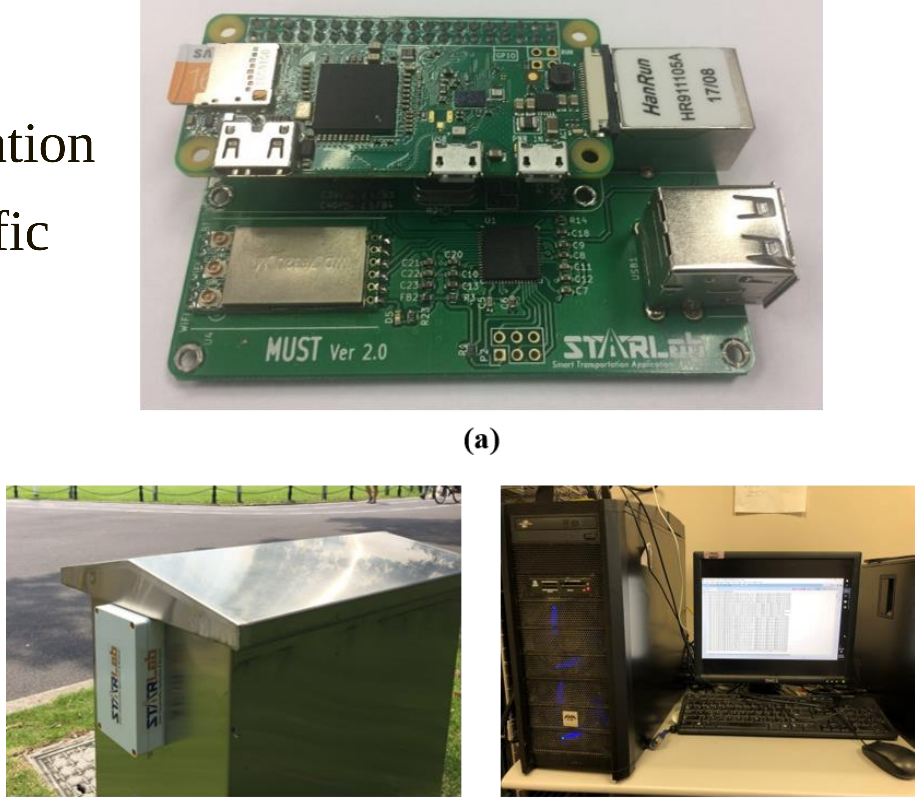
Pu, Z., Cui, Z., Tang, J., Wang, S., & Wang, Y. (2021). Multi-Modal Traffic Speed Monitoring: A Real-Time System Based on Passive Wi-Fi and Bluetooth Sensing Technology. *IEEE Internet of Things Journal*.
https://ieeexplore.ieee.org/abstract/document/9653682

Proposed Method – Multi-Modal Traffic Speed

❑System Deployment and Data Collection

- Collect data by four customized wireless sensors for validation
- Ground truth data is collected by surveillance camera (traffic mode, traffic speed for different modes)





(a)

(b)

(c)

Pu, Z., Cui, Z., Tang, J., Wang, S., & Wang, Y. (2021). Multi-Modal Traffic Speed Monitoring: A Real-Time System Based on Passive Wi-Fi and Bluetooth Sensing Technology. *IEEE Internet of Things Journal*. https://ieeexplore.ieee.org/abstract/document/9653682

Proposed Method – Multi-Modal Traffic Speed

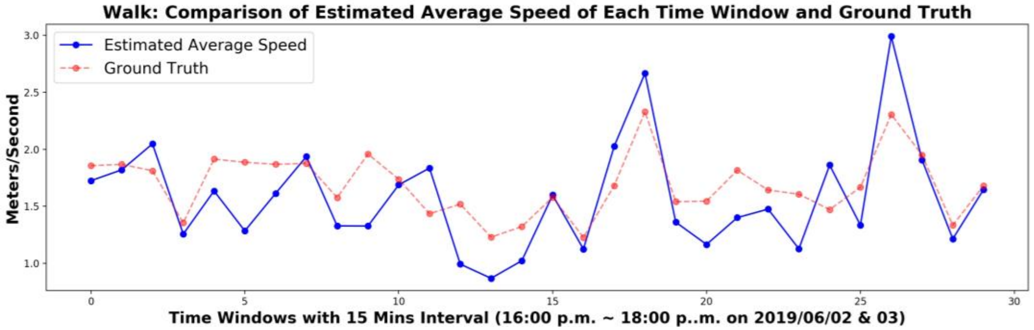
❑Results – Multi-Modal Traffic Speed

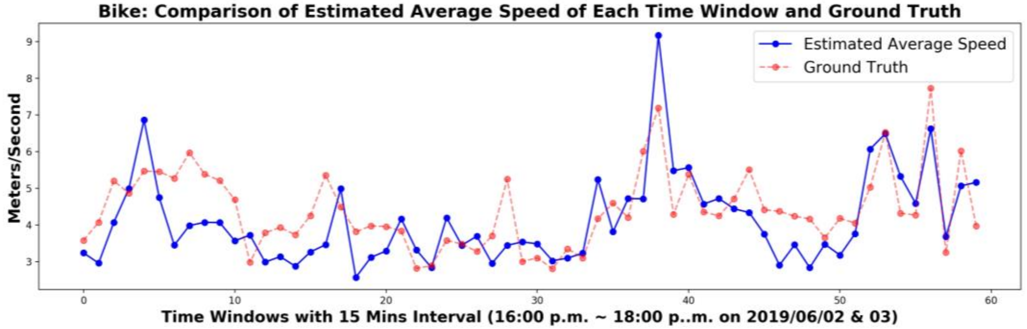
- Overall traffic speed estimation accuracy is about 85%

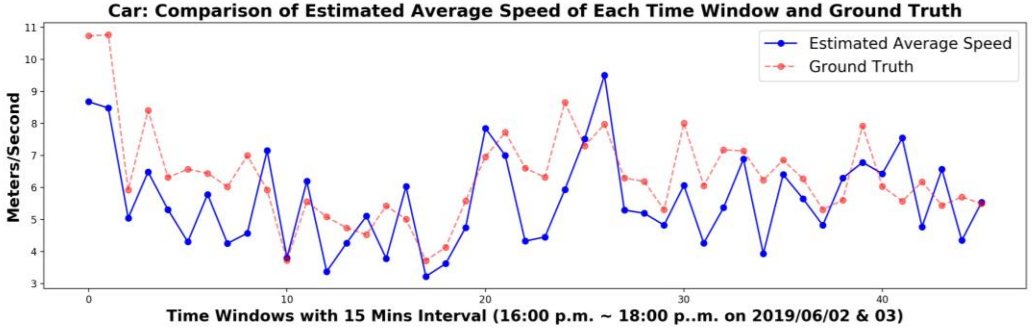
- Car and walk modes got better performance than bike mode

Mode	Car		Bike		Walk	
	Original Speed	Corrected Speed by RSSI	Original Speed	Corrected Speed by RSSI	Original Speed	Corrected Speed by RSSI
MSE	2.2898	1.5235	1.0612	0.6867	0.1383	0.0943
MAE	1.2768	1.0507	0.8688	0.7094	0.3258	0.2537
MAPE	0.2001	0.1594	0.1926	0.1606	0.1947	0.1519

"Multi-Modal Traffic Speed Monitoring: A Real-Time System Based on Passive Wi-Fi and Bluetooth Sensing Technology." *IEEE Internet of Things Journal*







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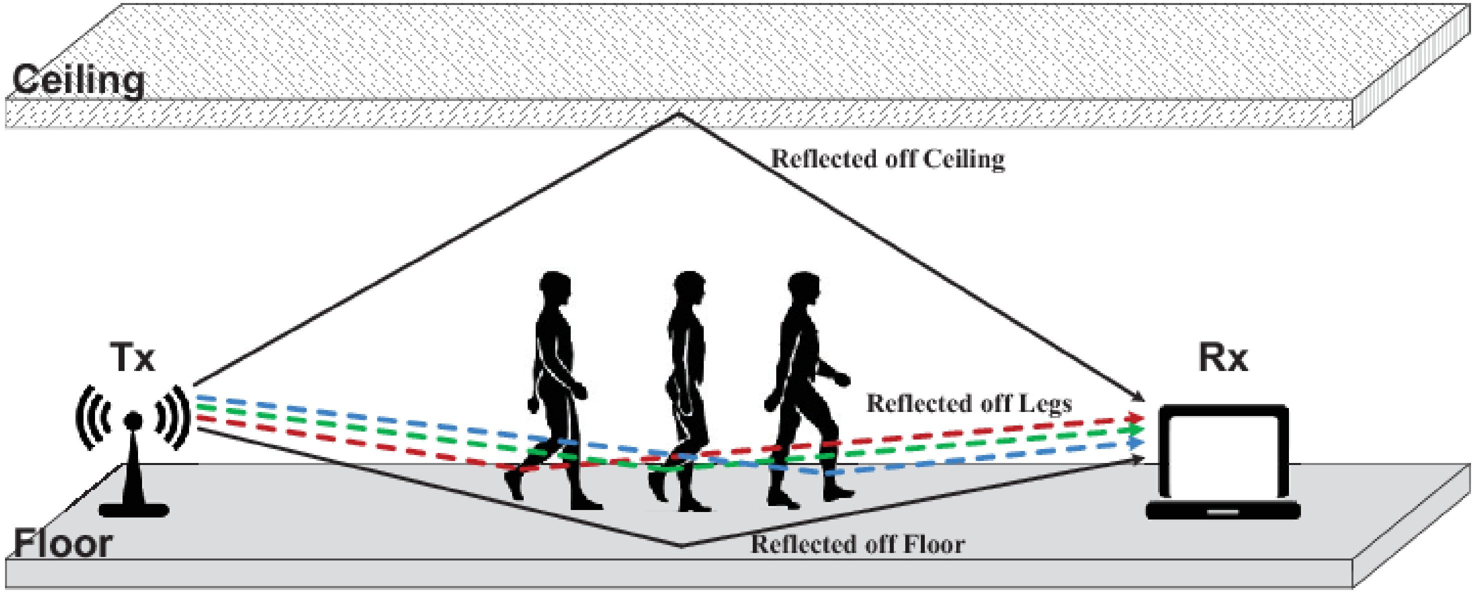
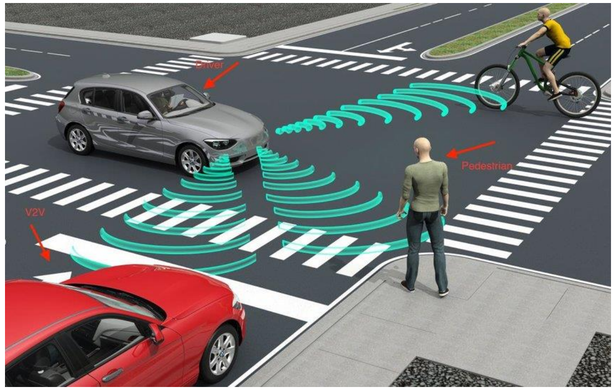
Proposed Method – Pedestrian

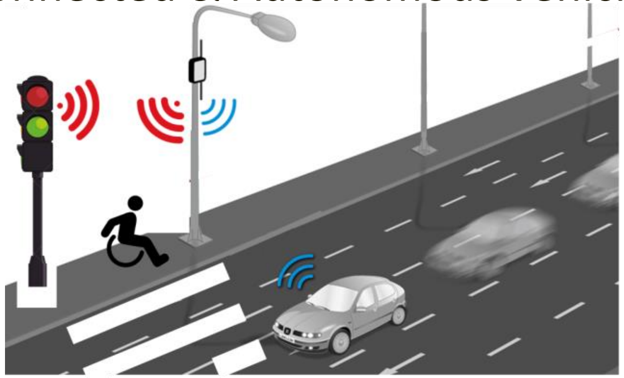
❑Population Uncertainty – Device-Free Wireless Sensing

- Utilizing Wi-Fi Channel State Information (CSI)
- Detecting pedestrian existence, moving direction and moving speed.





Connected & Autonomous Vehicle



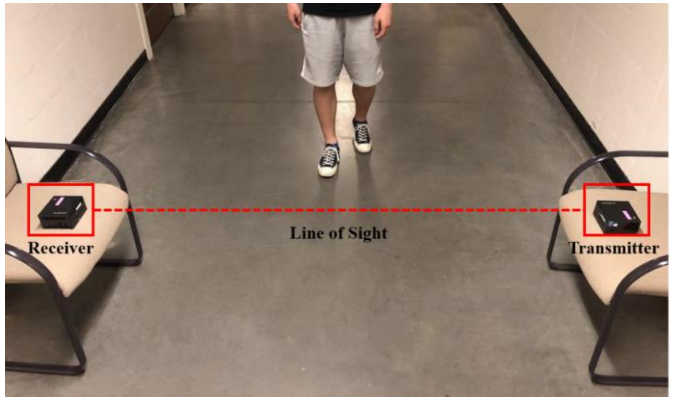
Pedestrian Crossing Signal System

Pictures from Google Images

Proposed Method – Pedestrian

❑Equipment Development and Experiment Design

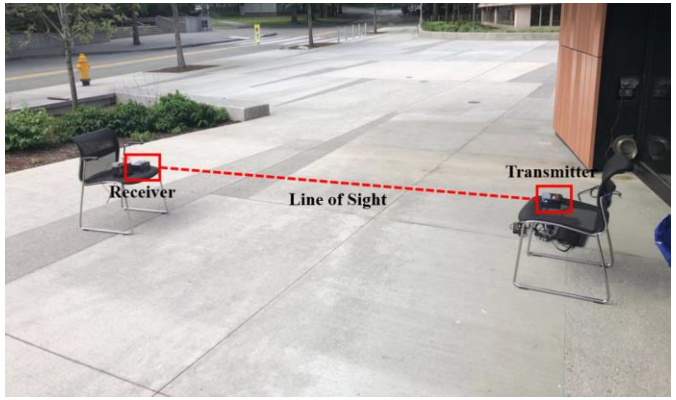
- Conducting experiment in indoor and outdoor environment
- Investigating impacts of different sampling ratios and antennas



Indoor Environment

Sensing Equipment

Omni-directional and directional



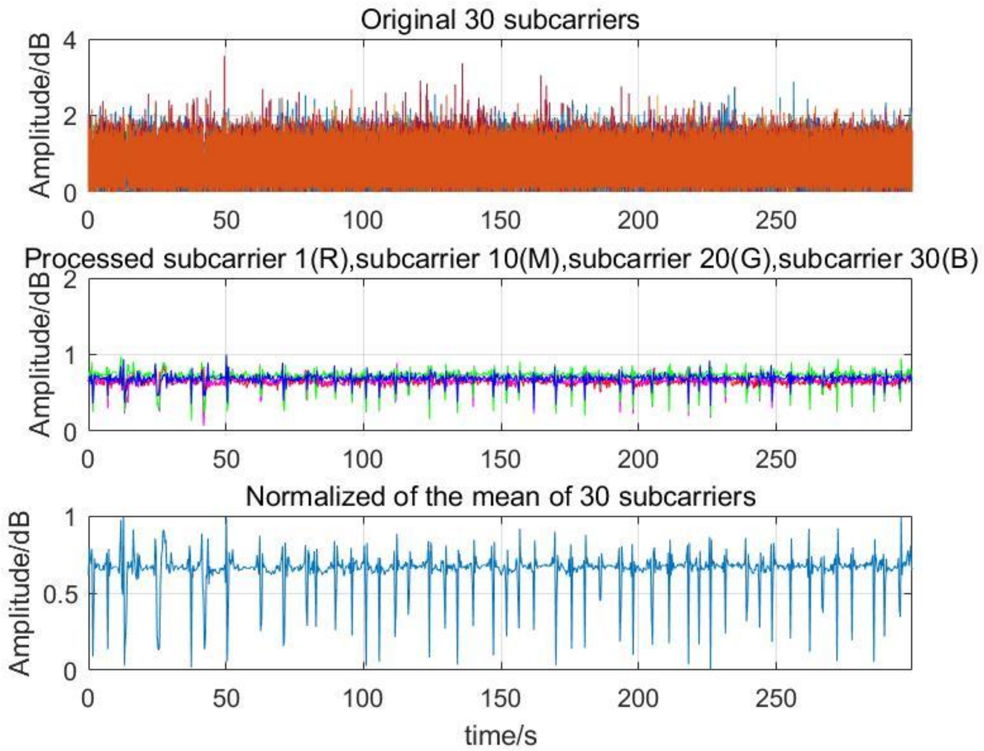
Outdoor Environment

Pu, Z., Zhang, Q., Zhuang, Y., Lv, Y., & Wang, Y. (2020, August). A device-free Wi-Fi sensing method for pedestrian monitoring using channel state information. In *International Conference on Transportation and Development 2020* (pp. 207-220). Reston, VA: American Society of Civil Engineers. https://ascelibrary.org/doi/abs/10.1061/9780784483138.019

Proposed Method – Pedestrian

❑Wi-Fi CSI Pre-processing

- Filtering outliers using Hampel Identifier
- Imputing lose packets using Linear Signal Interpolation
- Smoothing CSI signal using Kalman Filter
- Denoising CSI signal using Wavelet Transform



Pre-processing Results of CSI Signal collecting by 100 Hz in Outdoor

Pu, Z., Zhang, Q., Zhuang, Y., Lv, Y., & Wang, Y. (2020, August). A device-free Wi-Fi sensing method for pedestrian monitoring using channel state information. In *International Conference on Transportation and Development 2020* (pp. 207-220). Reston, VA: American Society of Civil Engineers. https://ascelibrary.org/doi/abs/10.1061/9780784483138.019

Proposed Method – Pedestrian

❑Pedestrian Existence Detection

▪A parameter is calculated to represent the level of fluctuation of normalized average CSI amplitude at each timestamp

$$diff = \max\left(x(i:i+T)\right) - \min\left(x(i:i+T)\right)$$

▪A predefined threshold is used to determine whether a pedestrian is passing or not

$$threshold = \mu - p * \sigma$$

Sampling Ratio	Environment	# Pedestrian	# Detection	Accuracy
100Hz	Indoor-Omni	130	128	**98.46%**
	Outdoor-Omni	154	147	95.45%
	Outdoor-Di	99	98	**98.99%**
500Hz	Indoor-Omni	49	46	93.88%
	Outdoor-Omni	51	48	94.12%
	Outdoor-Di	102	100	98.04%
800Hz	Indoor-Omni	24	10	41.67%
	Outdoor-Omni	27	13	48.15%
	Outdoor-Di	96	90	93.75%

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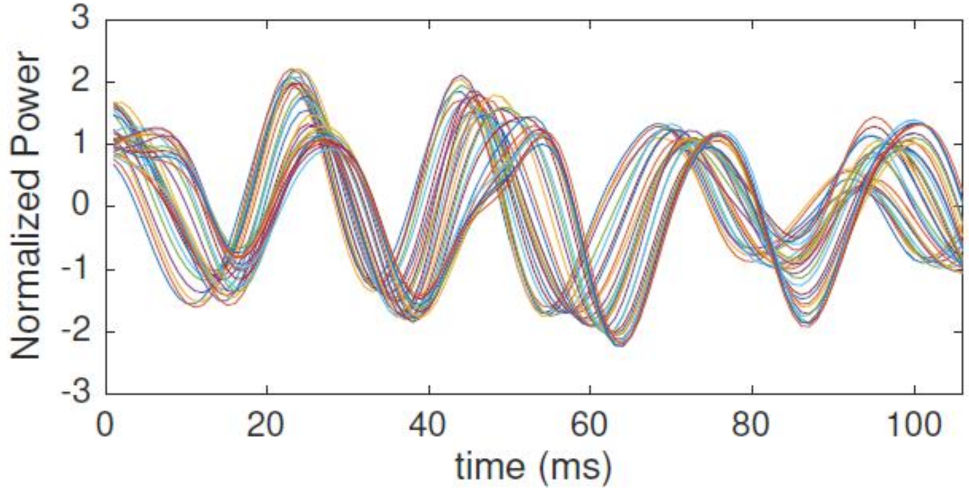
https://ascelibrary.org/doi/abs/10.1061/9780784483138.019

Proposed Method – Pedestrian

❑Identifying Moving Direction

- CSI signal with longer waveform is perturbed first
- Utilizing phase difference to identify moving direction

$$\Delta\rho = 2\pi(d_1 - d_0)\Delta f / c$$



Phase Difference

Detection Results

Environment	Direction 1			Direction 2		
	# Pedestrian	# Correct Detection	Accuracy	# Pedestrian	# Correct Detection	Accuracy
Indoor	65	65	100.00%	65	63	96.92%
Outdoor	77	71	92.21%	77	72	93.51%

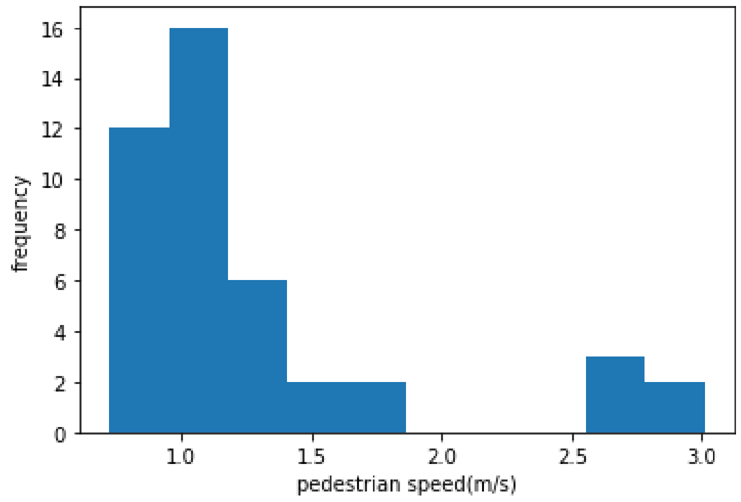
Pu, Z., Zhang, Q., Zhuang, Y., Lv, Y., & Wang, Y. (2020, August). A device-free Wi-Fi sensing method for pedestrian monitoring using channel state information. In *International Conference on Transportation and Development 2020* (pp. 207-220). Reston, VA: American Society of Civil Engineers. https://ascelibrary.org/doi/abs/10.1061/9780784483138.019

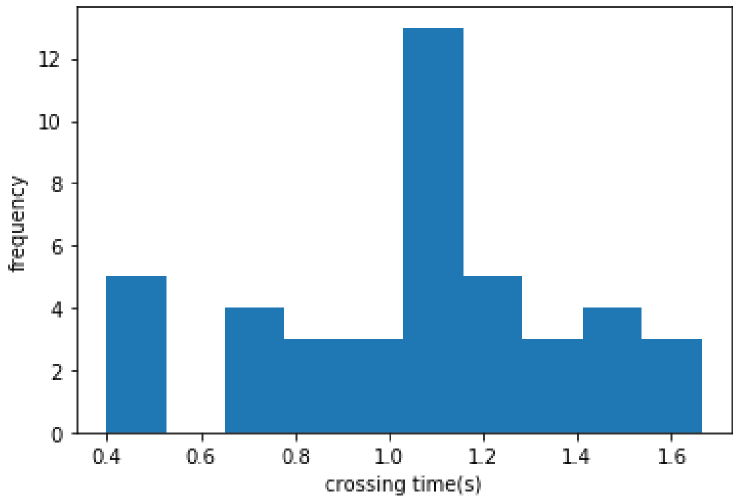
Proposed Method – Pedestrian

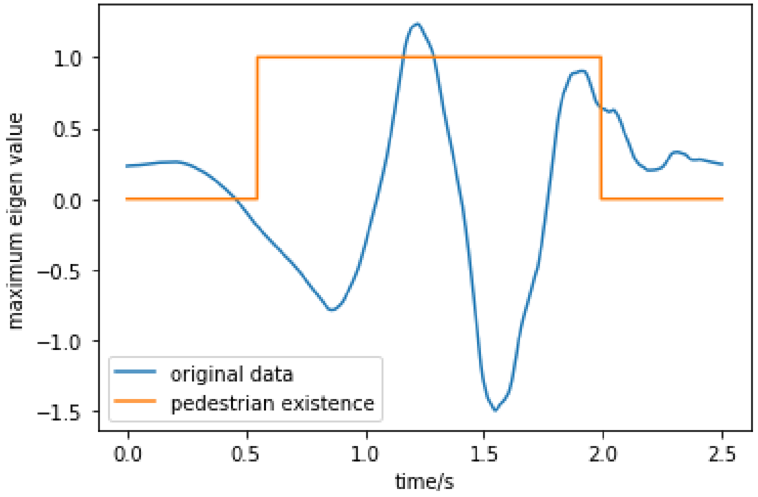
❑Estimating Moving Speed

▪The mean of speed is 1.29m/s with standard variation of 0.58m/s.

▪After eliminating outliers, mean values is 1.13m/s, and standard deviation is 0.34m/s.







Detecting start and end time of pedestrian existence

"A Device-Free Wi-Fi Sensing Method for Pedestrian Monitoring Using Channel State Information." *International Conference on Transportation and Development 2020*. https://ascelibrary.org/doi/abs/10.1061/9780784483138.019

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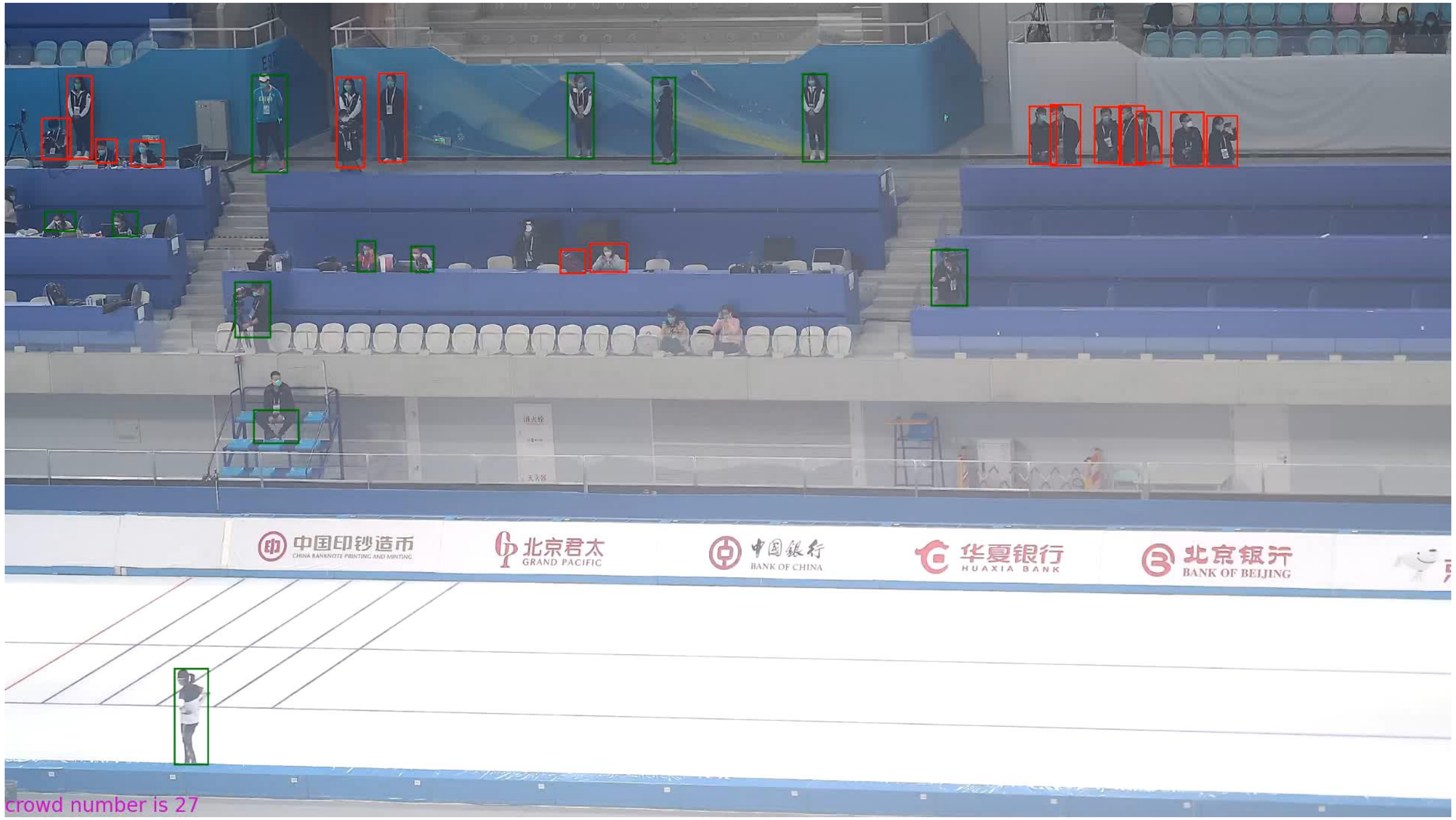
Implementations – Social Distancing Detection for 2022 Winter Olympic Games

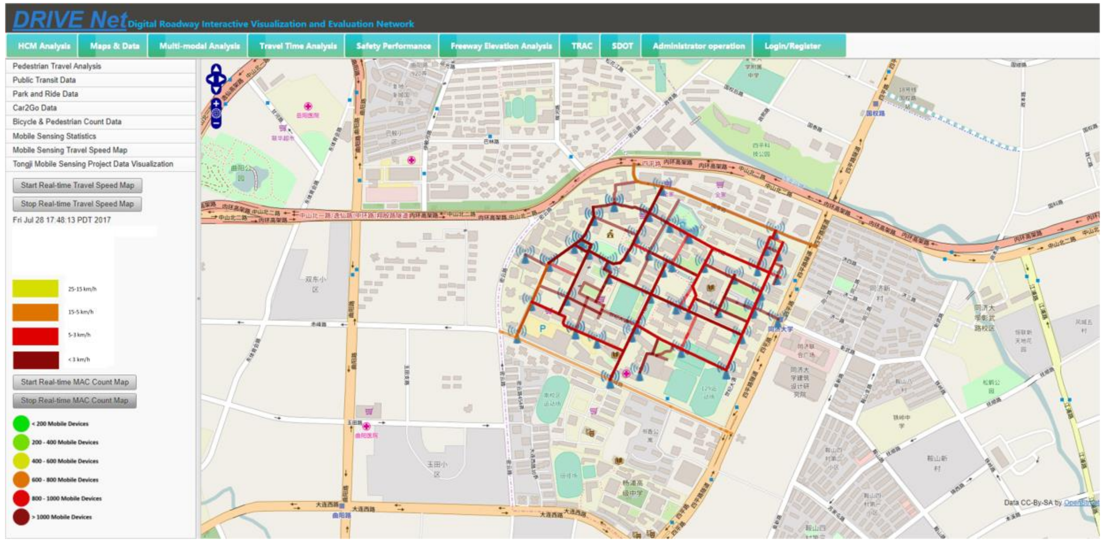
- Estimating crowd density
- Detecting the social distance among crowd
- Generating warnings if audience are too close



Implementations – Pedestrian Monitoring at Tongji University

- Tongji University, Shanghai
- Over 100 sensors, 2017 - present

Sensing Device and Remote Server



Pedestrian Travel Time

Pedestrian Point Volume in Peak Hour

Pictures from Google Images

Thanks for your time!

Q&A

MONASH University