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Human Commuting Activity Recognition based on Mobility Natural Vibration on a Mobile Device

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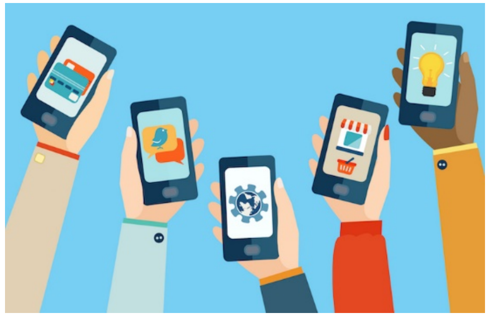
Background

- Commuting activity is an activity performed while people are commuting, such as walking and jogging for ambulation, subway, train, bus for public transportation, and car, bicycle, motorcycle for private vehicles [1].

- People show similar life patterns nowadays such as carrying smartphone while commuting. Smartphone can substitute the use of traditional wearable sensors embedding multimodal sensors. Detecting different kinds of commuting activities will let the stakeholders to understand better life pattern of the user, and provide health or convenience related services.

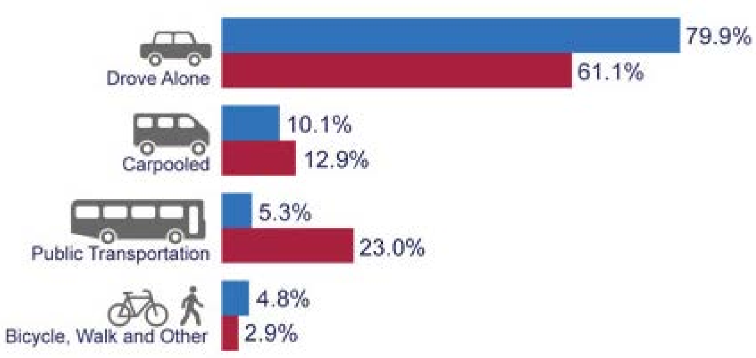


Smartphone has become a daily life device, **feasible for activity recognition**

Commuting activity data can be used to provide various services in the area of **health**, **convenience, and environment**

Background

- The advantage of automatic detection of commuting activity will be as follows
  - Statistical data of transportation usage can be acquired automatically, reducing the cost and time spent via manual survey [2]
  - User customized services or advertisements can be provided based on transportation just-in-time [3]
  - Monitoring health status, safety issues, and consumed calories can be provided for health care [4]
  - Carbon footprint can be estimated which is a unit of an object producing greenhouse gas. On foot will produce no gas, private vehicle will produce maximum gas, and public transportation will produce 1/n gas sharing people inside vehicles. Through this, one's impact on atmospheric environment can be found [5]



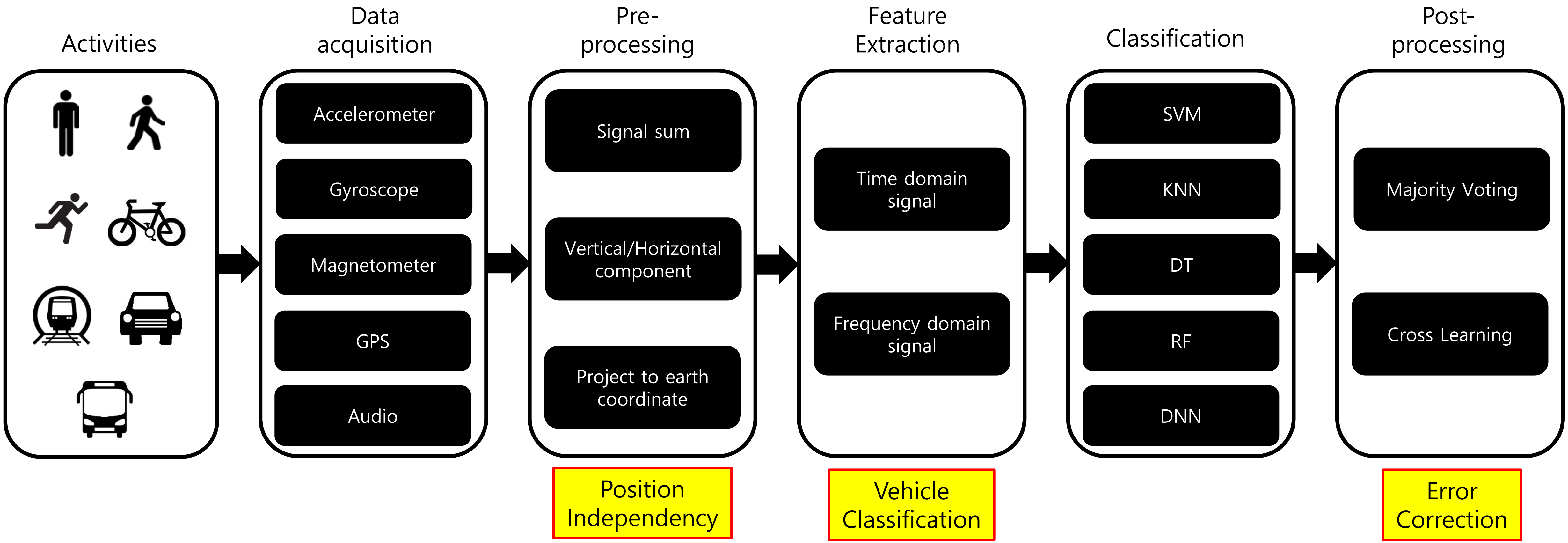
Statistical data of transportation usage can be acquired **automatically**

Monitoring health status such as consumed calorie can be provided for **health care**

Carbon footprint can be estimated figuring out of **impact to environment**

Motivation

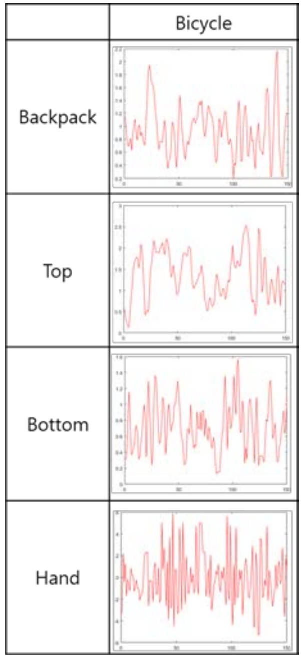
- General commuting activity recognition flow
  - General commuting activity recognition flow consists of data acquisition, pre-processing, feature extraction, and classification.
  - Following considerations are handled on following components
    - Pre-processing: Position independency
    - Feature extraction: Vehicle classification
    - Post-processing: Error Correction



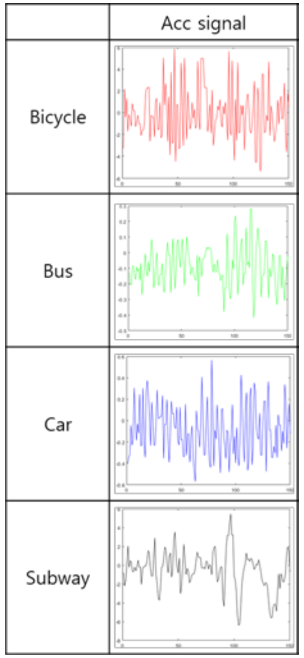
Motivation

Commuting activities such as vehicles are not well classified, in different positions, and cannot handle real world scenario only with machine learning method

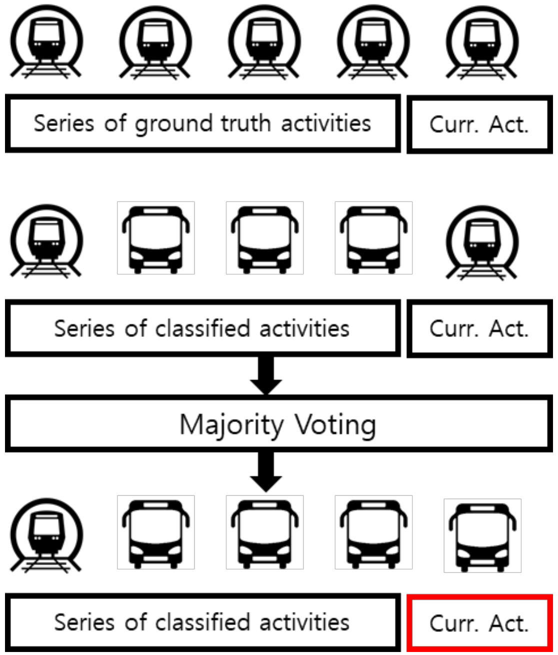
- Position independency
  - Not guaranteed on vehicles due to small signal change with no pattern



- Indifferent features
  - General features are hard to classify vehicles due to no pattern or difference



- Post-processing
  - Machine learning based post-processing cannot well reflect real world scenario



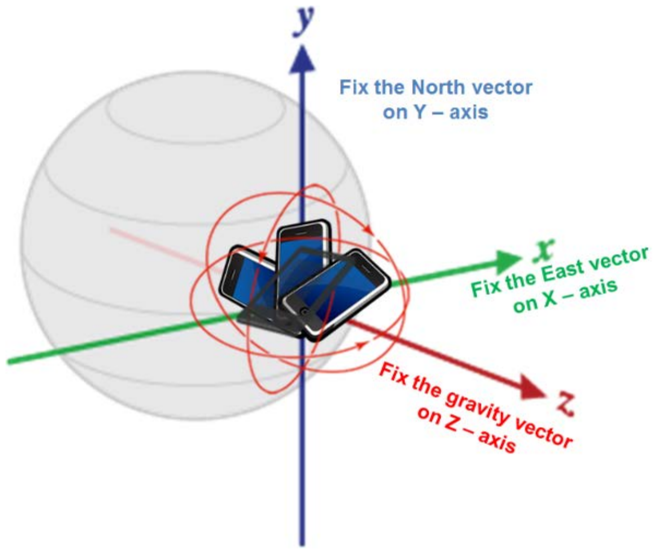
Related works

Category	Research	Sensors	Activities	Technique	Limitations
Position independency	Sztyler et al. 2017 [6]	Acc	Stair, Jump, Lie, Sit, Run, Walk	• Cross learning among positions and users are applied	• Got low accuracy
	Yang et al. 2016 [7]	Acc, Gyro	Stair, Stand, Run, Walk	• Get vertical and horizontal acc data using gravity	• Got general accuracy
	Coskun et al. 2015 [8]	Acc	Stair, Stand, Run, Walk, sit, bus	• Change Acc signal based on earth coordinate	• Overall accuracy is poor while stair and bus are worst
Commuting activity recognition	Lee et al. 2017 [9]	Acc, Audio	Walk, Bus, Subway, Taxi	• Use Acc for locomotion and then use audio for vehicle classification	• Low accuracy on sound based classification
	Jeyakumar et al. 2018 [10]	Acc, Gyro, Mag	Still, Walk, Run, Bike, Car, Bus, Train, Subway	• Input raw signal data to CNN with LSTM	• Subway shows low accuracy
	Ashqar et al. 2018 [11]	Acc, Gyro, GPS	Bike, Car, Walk, Run, Bus	• Used all of the frequency energy as features with RF	• Bus and car are confused with low accuracy
	Dabiri et al. 2018 [12]	GPS	Walk, Bike, Bus, Car, Train	• GPS trajectory data is fit to CNN	• Low accuracy compared using other data
	Lorintiu et al. 2016 [13]	Acc, Gyro, GPS	Still, Walk, Run, Bike, Road, Rail, Plane	• Frequency band is set in all area	• Vehicle is not separated in detail
	Yu et al. 2014 [14]	Acc, Gyro	Still, Walk, Run, Bike, Vehicle	• Peak frequency is selected from frequency signal	• Vehicle is not separated and poor accuracy
Post-processing	Wang et al. 2019 [15]	Audio	Still, Walk, Run, Bike, Car, Bus, Train, Subway	• Activity is updated by majority voting looking 1 minute duration due to continuous activity	• Long duration should be referred causing inefficiency
	Grzeszick et al. 2017 [16]	Acc, Gyro, Mag	Walk, Search, Pick, Carry	• Activity is updated with majority voting in predefined duration	• When equal result from majority voting, no updates

Related works

- Position independency methods
  - Existing position independency methods extract vertical-horizontal signal, remove gravity factor or combine signal into a single magnitude [6-8]
  - And then they extract ordinary features or extract correlation features
  - It is no good to be applied on vehicles that these does not show big variation of signal. The correlation would be the lowest.
  - [6] have done cross learning by exchanging data among positions and users, but didn't show meaningful result

Cross learning among positions and users



Project acceleration signal to earth coordinate

Related works

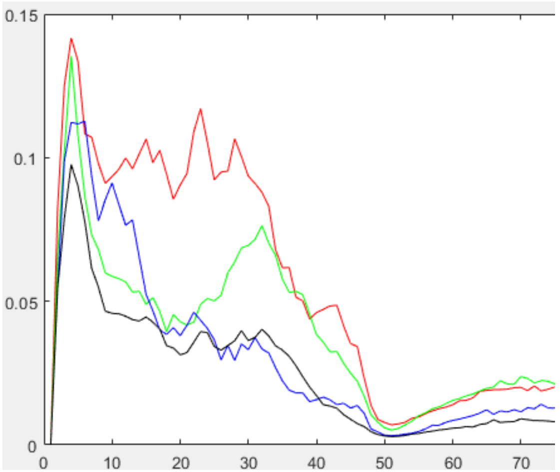
Features from frequency signal

- Except time domain signal, research extracting features [11, 13, 14] from frequency signal can be summarized as follows.

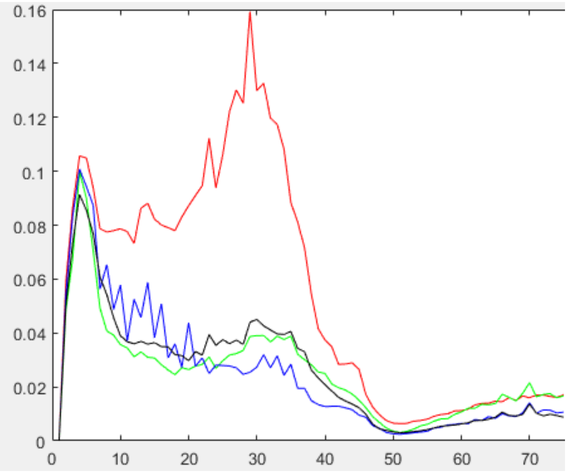
Feature	Description	Limitation
Mean	Returns average of all frequency in segment window	Statistical method cannot be applied where each frequency has different dimension
Standard deviation	Returns standard deviation of all frequency in segment window	Statistical method cannot be applied where each frequency has different dimension
All of the frequency energy	Returns each of the energy value of each frequency	All of frequency data is used causing inefficiency
Energy proportion	Returns proportion of energy in different frequency bands	Frequency band is selected heuristically
Peak frequency energy	Returns the maximum energy among all frequency	Peak frequency will keep changing
2^{nd} peak frequency energy	Returns the 2^{nd} maximum energy among all frequency	Peak frequency will keep changing

(a)

(b)



(c)

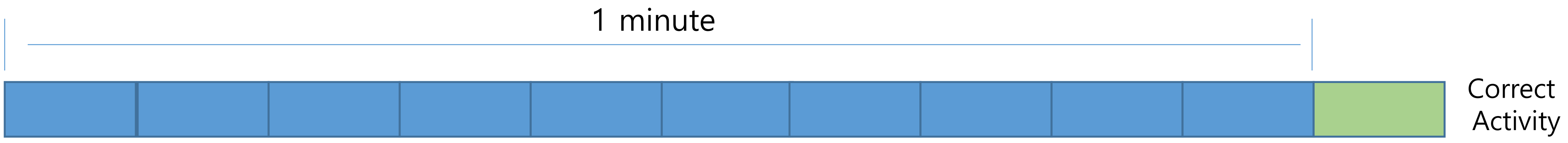


Different states of signal from intercity bus ((a) stop, (b) low speed, (c) high speed) with different positions
Red: Hand, Green: Backpack, Blue: Top, Black: Bottom

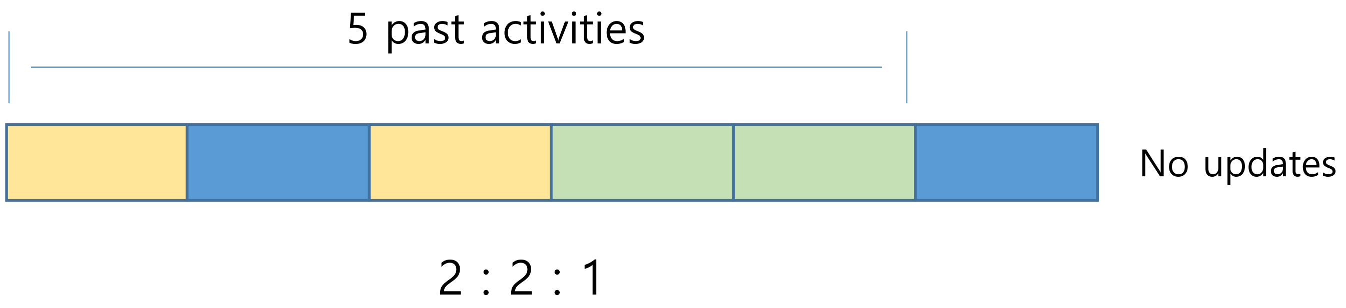
Related works

- Post-processing methods
  - Existing post-processing methods utilize majority voting referring pre-defined length of duration [15, 16]
  - Inefficient referring multiple windows and has problem when equal result for voting is concluded

  - [15] sets one minute duration to refer past activities for majority voting. They have set this because vehicle is a continuous long-term repetitive activity. Performance is good having lots of data to refer, but is inefficient



  - [16] sets five past activities to refer. The problem comes when majority voting shows equality. In this case, they haven't updated current activity



Limitation & Solution

Limitation 1: Position IND

- Not appropriate to be applied to static activities such as vehicles

Limitation 2: Features

- Cannot reflect characteristic of vehicle

Solution 1

- Natural vibration features from frequency domain signal

Objectives

- Extract natural vibration features based on frequency domain on different vehicles and positions

Limitation 3: Post-processing

- Inefficient referring multiple windows
- No updates when equal result from voting

Solution 2

- Activity correction after classification

Objectives

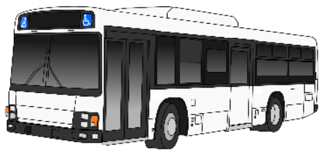
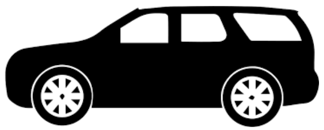
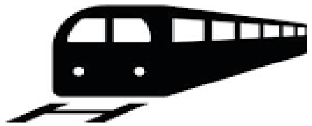
- GPS coordinate based ground subway classification
- State transition rule
- Activity correction based on temporal correlation

Natural vibration

- Considering natural vibration (frequency)
  - Natural vibration where every object has their own, is the frequency at which a system tends to oscillate in the absence of any driving or damping force
  - Vehicle's natural vibration comes from suspension such as spring stiffness, shock absorber damping force, and tire vertical stiffness. It is also affected by road condition, speed, weight, and engine vibration [17]
  - Natural vibration features will be extracted from different vehicle conditions

Body part	Natural frequency (Hz)
The whole body	7.5
Body torso	7–13
Head	8–12
Thoracic cavity	4–6
Heart	5
Abdominal cavity	6–9
Spine	10–12
Pelvic	6

Natural vibration of human body part (ISO 2631)

	Type 1	Type 2
Bus	 Intercity Bus	 City Bus
Car	 Diesel Car	 Gasoline Car
Subway		
Bicycle		

Different types of vehicle data are collected

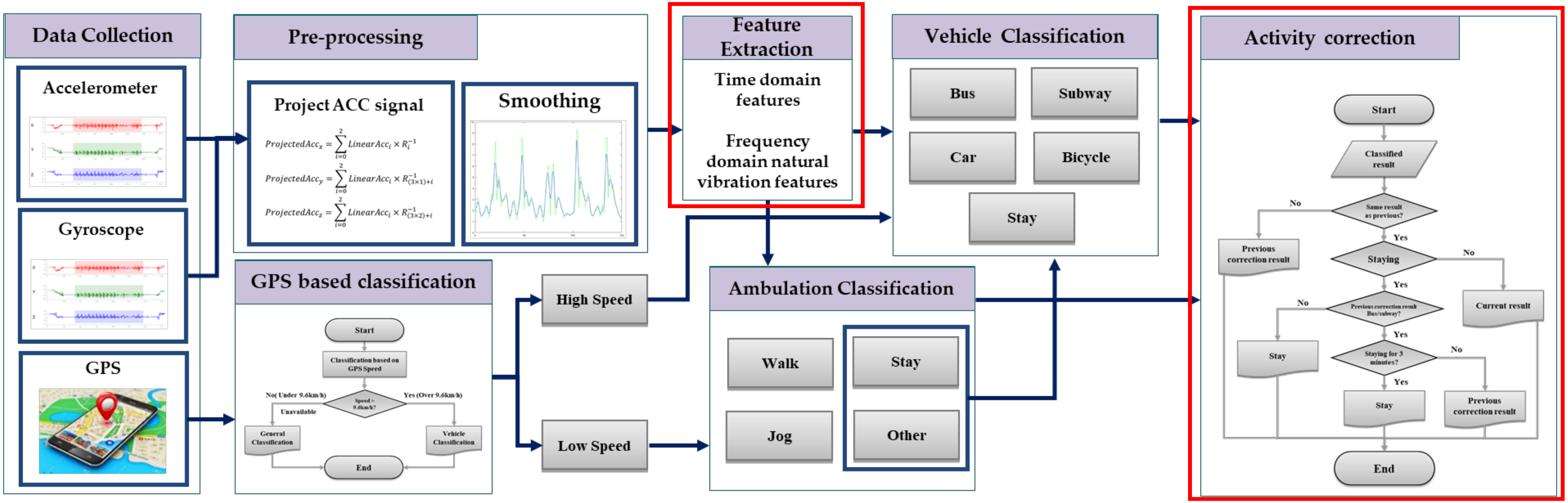
Thesis overview

Goal

- Develop a commuting activity recognition based on smartphone position independency with activity correction

Challenges

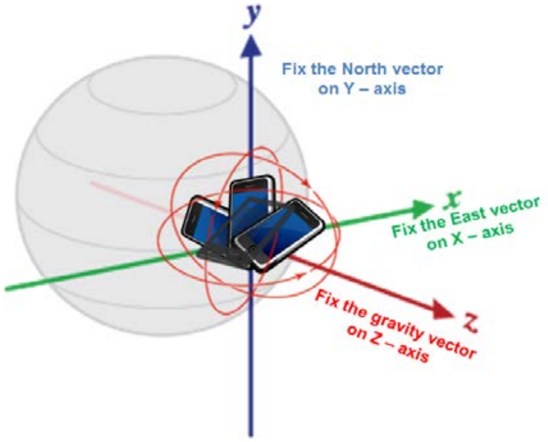
- What kind of features and methods can well distinguish vehicles in different positions
- How to correct the classification error considering real-world environment



Preprocessing for position independency

- **Project linear acceleration to earth coordinate**
  - To get gravity axis for natural vibration feature extraction, linear acceleration signal is projected based on earth coordination to exclude gravitational factors
  - Rotation matrix (R) is used using geomagnetic and acceleration data as follows where ϕ=azimuth, θ=pitch, and ψ=roll.[fang]

$$R = \begin{bmatrix} cos\phi cos\psi - sin\phi sin\psi sin\theta & sin\phi cos\theta & cos\phi sin\psi + sin\phi cos\psi sin\theta \\ -(sin\phi cos\psi + cos\phi sin\psi sin\theta) & cos\phi cos\theta & -sin\phi sin\psi + cos\phi cos\psi sin\theta \\ -sin\psi cos\theta & -sin\theta & cos\phi cos\theta \end{bmatrix}$$



$$ProjectedAcc_x = \sum_{i=0}^{2} LinearAcc_i \times R_i^{-1}$$

$$ProjectedAcc_y = \sum_{i=0}^{2} LinearAcc_i \times R_{(3\times1)+i}^{-1}$$

$$\boxed{ProjectedAcc_z = \sum_{i=0}^{2} LinearAcc_i \times R_{(3\times2)+i}^{-1}}$$

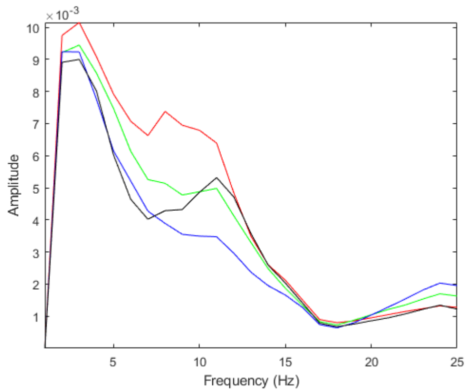
  - 3D axis acceleration signal sum is used to discard the orientation attribute [13]

$$Magnitude_i = \sqrt{Signal_{x_i}^2 + Signal_{y_i}^2 + Signal_{z_i}^2}$$

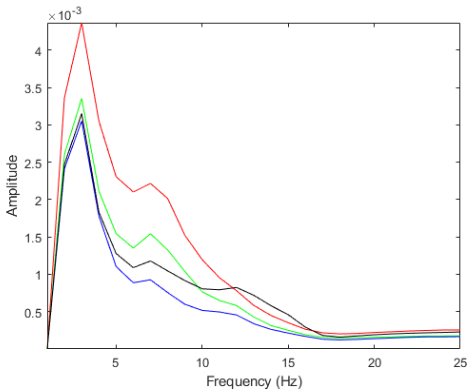
Feature extraction – Solution 1: Natural vibration features

Setting bandwidth to extract natural vibration

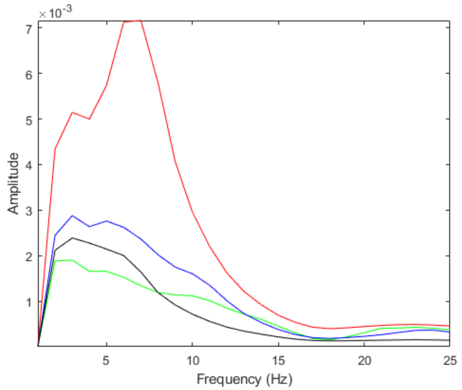
- From the average distribution of different vehicles on different positions in frequency domain signal, it is clear that different frequency band can be set as follows.
  - Low frequency band (1-5hz): First and maximum frequency occurs.
  - Mid frequency band (5-18hz): Bandwidth having second peak.
  - High frequency band (18-25hz): Third peak occurred on some vehicles.



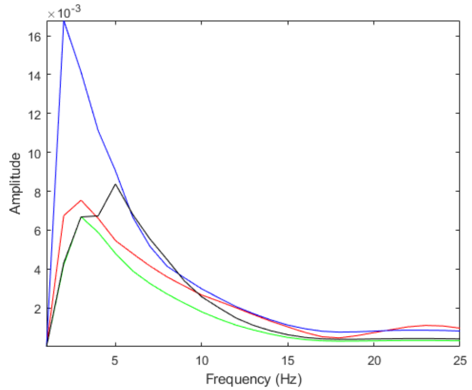
(a) Bus



(b) Subway



(c) Car



(d) Bicycle

Average distribution of different vehicles on different positions in frequency domain signal
Red: Hand, Green: Backpack, Blue: Top, Black: Bottom

Feature extraction – Solution 1: Natural vibration features

Acquiring natural vibration

- Based on each frequency bandwidth, natural vibration frequency is acquired
  1. Get average from whole data on each frequency
  2. Get average frequency on each bandwidth
  3. Get standard deviation on each bandwidth
  4. Set the natural frequency band by adding and subtracting standard deviation from average

Get Natural Vibration Frequency

Input : *A* – Acceleration data of gravity axis

Output : *N* –Natural vibration frequency band

F = Frequency
B = Frequency band

for each frequency $\mathbf{F_i}$
    $\mathbf{FA_i}$ = getAverage
end

for each frequency band $\mathbf{B_i}$
    $\mathbf{BA_i}$ = getAverageFrequency
    $\mathbf{BS_i}$ = getStandardDeviation
    $\mathbf{NB_i}$ = getBandofNaturalVibrationFrequency
end

Natural vibration frequencies

Vehicles	Section 1		Section 2		Section 3	
	Natural Frequency	Deviation	Natural Frequency	Deviation	Natural Frequency	Deviation
Bus	3	2	9	4	24	4
Subway	3	2	8	5	25	4
Car	3	2	8	5	25	4
Bicycle	4	2	7	6	24	3

Feature extraction – Solution 1: Natural vibration features

- **Feature extraction using time + frequency domain signal**
  - Not only natural vibration features but all features are used to extract features

	Time domain	Frequency domain
Features	Mean(8), Standard deviation(8), Max(8), Min(8), Zero crossing(6), Mean crossing(8), Range(8), Interquartile Range(8), Median(8), Median Abs(8), Median Abs deviation(8), Skewness(8), Kurtosis(8), Covariance(6), Cross Correlation(6), Correlation Coefficient(6)	Energy of each frequency in the range of natural vibration in section 1 (each 1~5Hz) (5), section 2 (each 5~18Hz) (9), section 3(each 18~25Hz) (7), Energy sum of frequency range in section 1 (1~5Hz, 2~5Hz) (2), section 2 (5~13Hz) (1), section 3 (20~25Hz, 21~25Hz) (3), Energy sum of section 1 (1), section 2 (1), section 3 (1), Spectral Entropy (X, Y, Z) (3)
Target sensor	Accelerometer, Gyroscope	Accelerometer
Number of features	128	32
Total numbers	160	

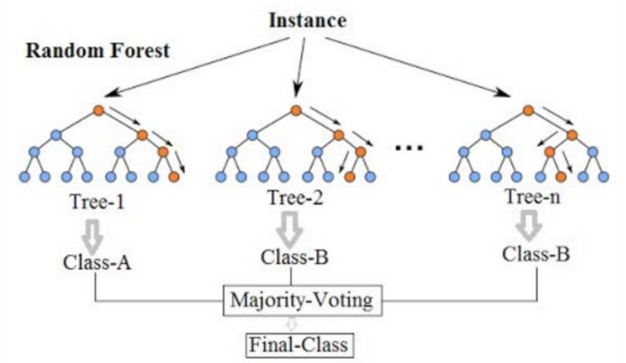
Classification

Random forest classifier

- To find the best classifier working well for proposed method, comparison has been made with well-known classifiers using the whole dataset.
- Random forest showed the best result and was chosen. Other research prefers RF for vehicle detection [11, 19]
- It can well handle overfitting problems by dividing random data into bunch of decision trees

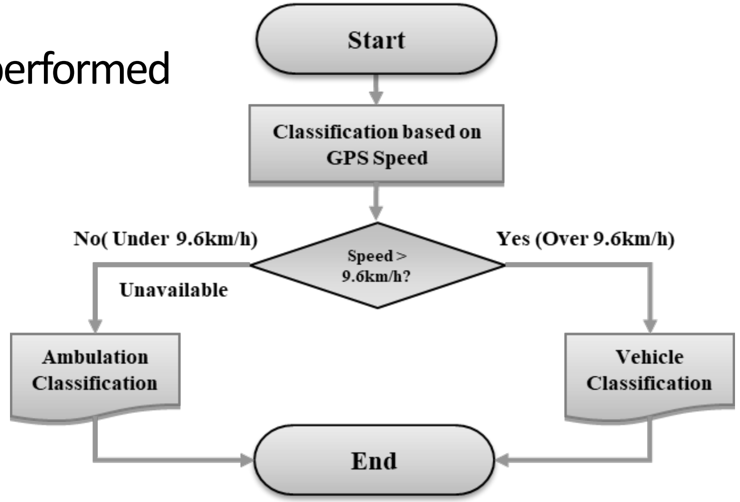
GPS speed based classification

- The first classification is made based on GPS speed according to average jogging speed defined as 6miles/h (9.6km/h) [18]
- If the speed is over 9.6km/h, vehicle classification is performed.
- If the speed is under 9.6km/h or no GPS signal is captured, Ambulation classification is performed



SVM	KNN	DT	RF
78.363	83.794	85.400	93.203
LSTM	CNN 1D	CNN 2D	
89.963	91.948	92.351	

Comparison result with different classification methods

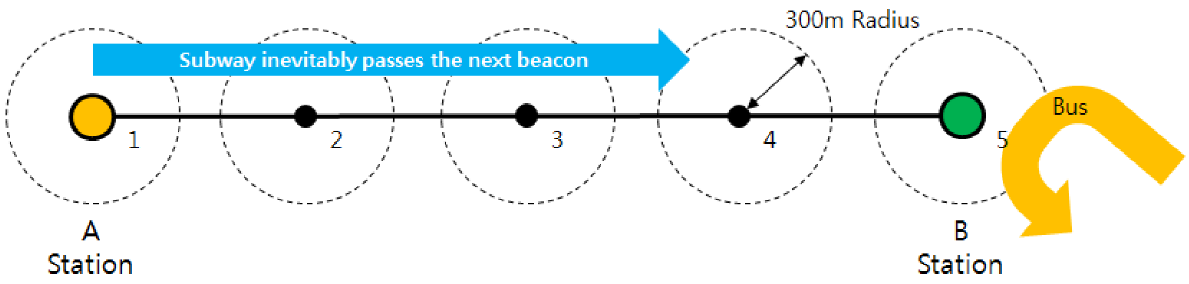


GPS speed based classification

Post-processing – Solution 2: Activity Correction

GPS coordinate based correction

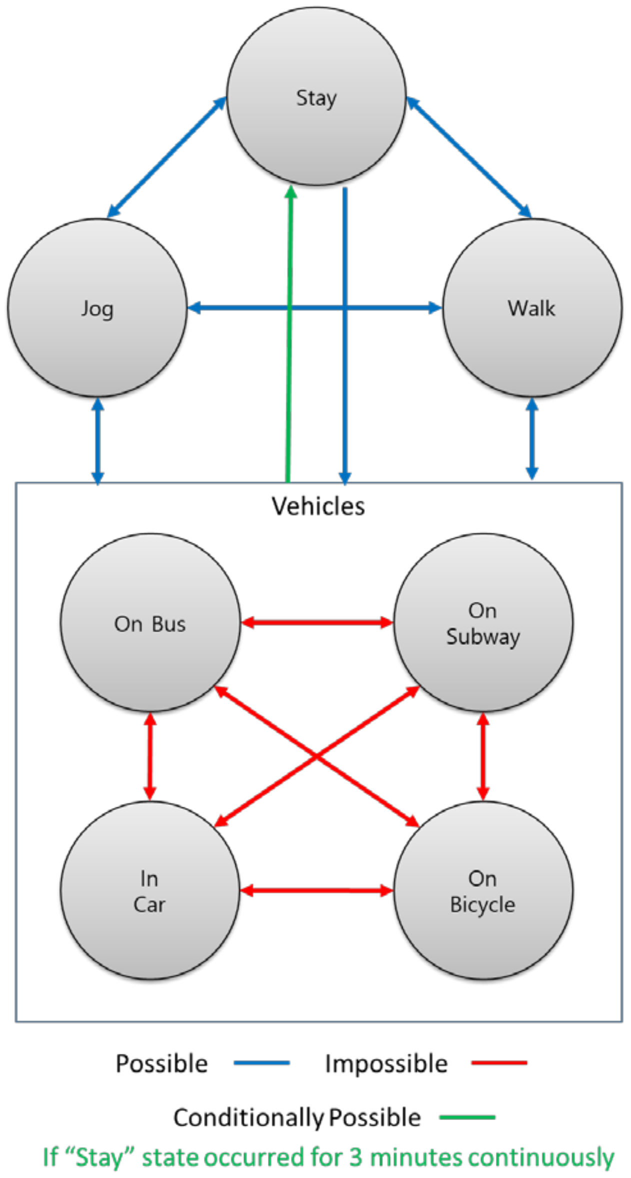
- Basically subway cannot receive GPS signal. But it may receive while running ground level section
- To differentiate subway from others, 5 beacons between two stations are set
- Generally one station to another takes about 2-3 minutes
- If the user passes within the radius of 300m of each beacon within 30 seconds, we assume that user is on the subway.



Coordinate based Classification of ground level subway and road vehicles

State transition rule

- Based on temporal correlation in real-world situation, some of the activities cannot be switched to another
  - Ex) While on Bus, the state cannot be changed to other vehicles. The user is at lest required to walk for other vehicle.



State transition rule

Post-processing - Solution 2: Activity Correction

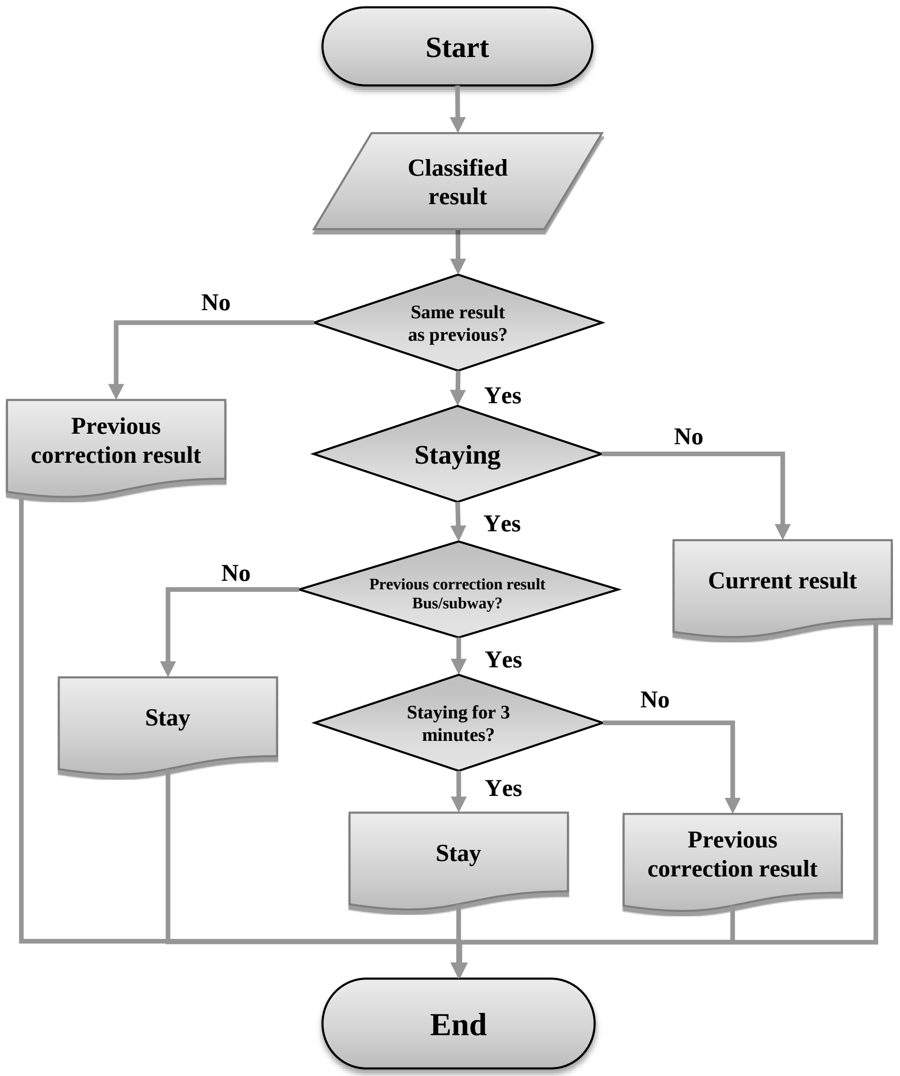
- **Activity correction based on temporal correlation**
  - Current activity is compared with previously recognized activity and previously corrected activity
  - Basically, it does not change the activity directly to prevent miscorrection
  - For some occasions that vehicle has stopped due to traffic or station, activity remains to related vehicle but changes to stay after 3 minutes which is average maximum time of stopping

Activity Correction

Input : *A* – Activity classified from RF

Output : *F* –Final activity

```
while 1 do
    if currentActivity == previouslyCorrectedActivity then
        if currentActivity != stay then
            F = currentActivity
        else
            if stay > 3 minutes then
                F = stay
           else
                F = previouslyCorrectedActivity;
            endif
        endif
    else
        F = previouslyCorrectedActivity;
    endif
endwhile
```



Activity correction

Experimental Environments

- **Collection device**
  - Four Galaxy S7
- **Collected sensor signals**
  - Linear acceleration (X, Y, Z) (Range: 8g, Frequency: 50hz)
  - Angular velocity
  - GPS (Speed, Latitude, Longitude)
- **Position and orientation of smartphone**
  - Top/Bottom pocket, backpack, hand
- **Collected activities**
  - 5 minutes: Stay (Sit, Stand), Walk, Jog, Bicycle
  - 10 minutes: Bus, Subway
  - 20 minutes: Car
  - Additional data for different types of bus and car

Dataset (Number of instances)

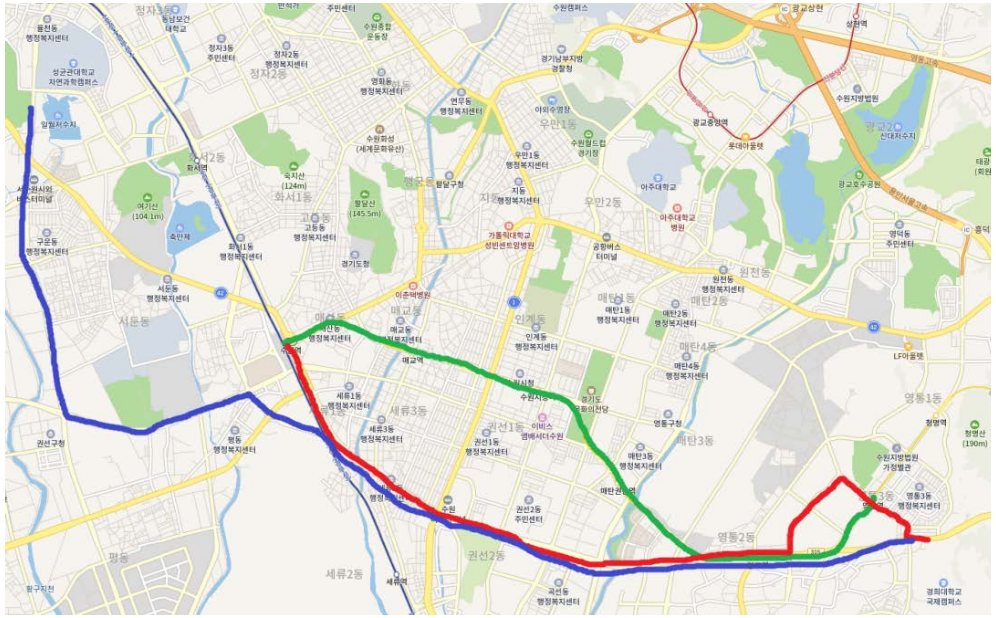
	Stay	Walk	Jog	Bus	Subway	Car	Bicycle	Total
Train	6,973	7,343	6,823	7,073	7,121	7,016	7,139	49,488
Test	618	360	80	3,865	2,492	4,047	388	11,848

Participants

No.	Age	Height (cm)	Weight (kg)
1	25	180	80
2	26	172	78
3	27	167	67
4	27	183	73
5	28	179	73
6	29	170	61
7	29	180	78
8	30	175	56
9	32	167	74
10	32	180	74
11	34	178	87
12	34	183	85
13	35	167	63
14	38	180	74
15	42	175	89
16	66	170	70
17	62	156	56
Average	35.06	174.24	72.82

Experimental Environments

- **Vehicle data collection route**
  - Subway: Bundang line (Yeongtong – Suwon STA)
  - Bus
    - Highway: 5100 (KHU – Gangnam)
    - City road: 310, 900, 7-2 (KHU – Suwon STA, All same route)
  - Car
    - Highway: Dongbu-daero (KHU – Osan city hall)
    - City road: KHU – SKKU

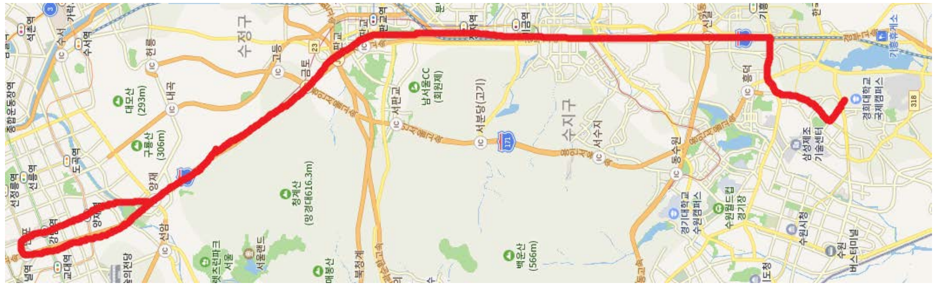


Subway, City road bus, City road car

Route for data collection

Bus Subway Car

Highway car

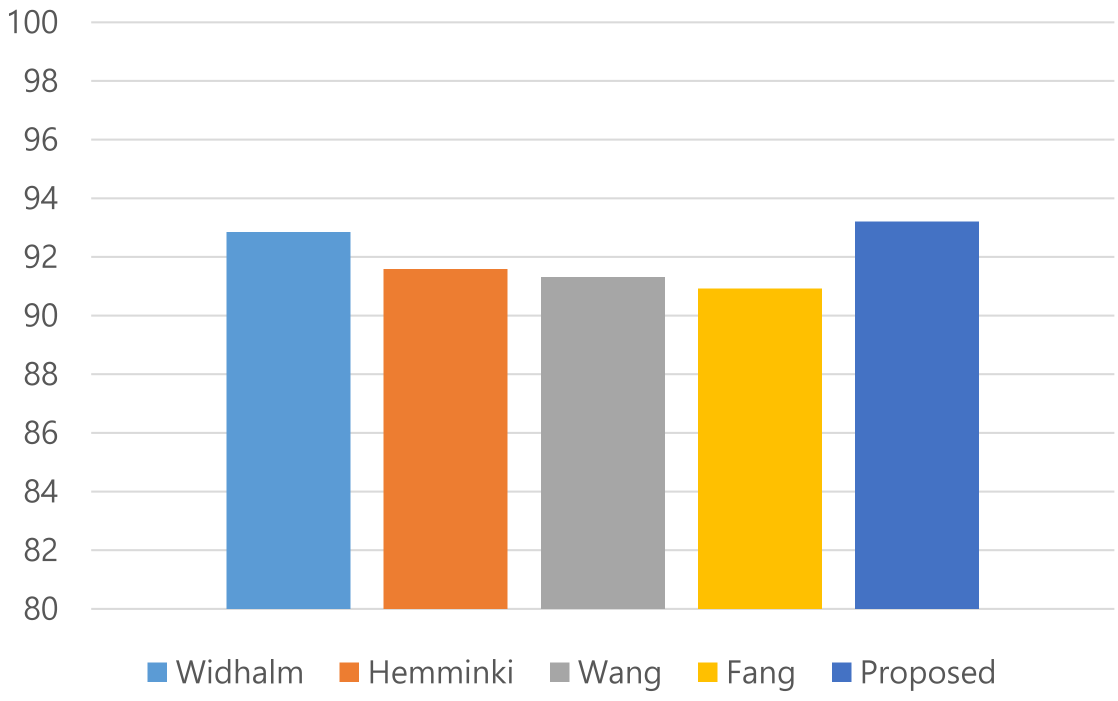


Highway bus

Experiment 1: Comparison with different research

Accuracy (%)

Widhalm et al. [21]	Hemminki et al. [22]	Wang et al. [23]	Fang et al. [24]	Proposed
92.846	91.591	91.308	90.927	93.203



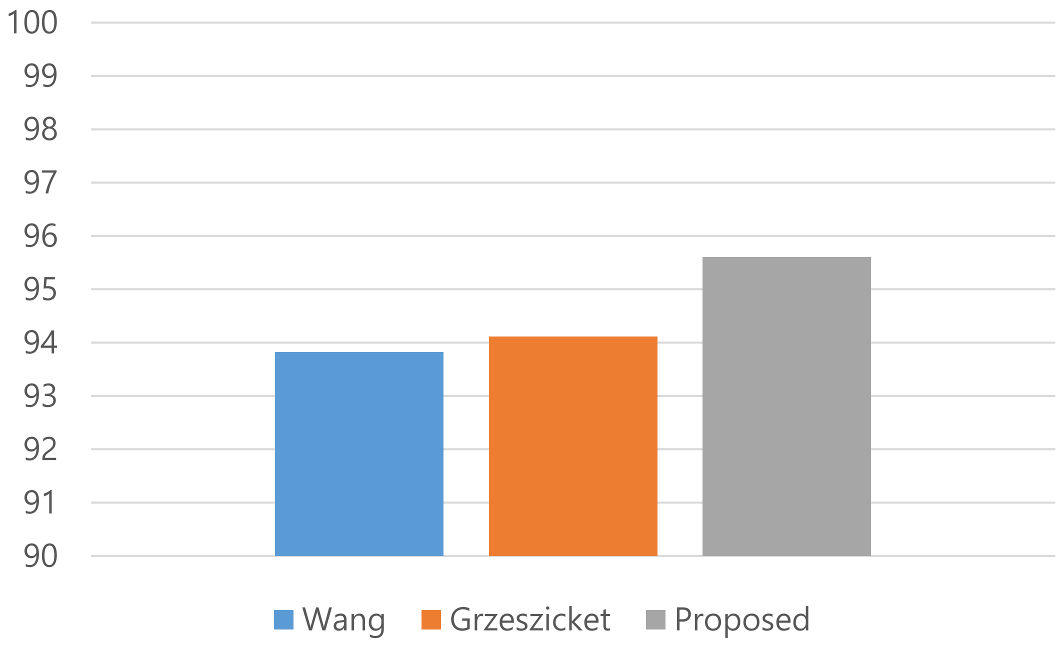
Higher is better

- Comparison evaluation method is conducted on our collected dataset. Only classification results are shown before applying activity correction.
- Proposed method showed the best accuracy of 93.203% among all.
- Widhalm et al. used all the frequency energy where each may have their own meaning. Wang and Fang method used low frequency band energy where vehicles show most energy in these area. Fang only used one which is the peak energy but still will have the value in low frequency band.
- From this result, we cannot say the proposed natural vibration feature outperforms the other feature extraction methods. But as it will be later shown, it has more generalization and overfitting prevention power than others.

Experiment 2: Comparison with different post-processing research

Accuracy (%)

Research	Before applying post-processing	After applying post-processing
Wang et al. [25]	93.203	93.821
Grzeszicket et al. [26]		94.109
Proposed		95.598



Higher is better

- From the experiment result, proposed method showed more increase in accuracy than other two methods.
- As expected, Wang's method increased most little and then Grzeszicket's method but still lower than proposed methods. This is because that sometimes tie happens by looking multiple activities.
- Meanwhile, proposed methods only refers previously recognized activity which may not have the problem aforementioned.

Conclusion & Future work

The thesis contributes to

- **Extracting natural vibration features to well distinguish vehicles guaranteeing different positions**
  - Natural vibration can successfully differentiate between static vehicles and also guarantees position independency on each vehicle
  - The results shows that natural vibration features can achieve higher accuracy than existing methods

- **Activity correction algorithm correcting final activity**
  - GPS coordinate, state transition rule, comparing currently recognized, previously recognized and previously corrected activity, classification error is corrected to exactly conclude the final activity
  - The results shows that natural vibration features can achieve higher accuracy than existing methods

Future work

- Include more vehicles such as motorcycle or kickboard
- Make the window in variable length to precisely segment the activity

Publications

Journal : 17

SCI/E	First author 2 (SCIE)	Co-author 10 : 2(SCI) / 8(SCIE)
Non SCI/E	First author 2	Co-author 3

First author SCIE

- MDPI, Sensors (IF: 2.033, Published, 2017)
- MDPI, Sensors (IF: 2.475, Published, 2018)

Conference : 16

International	Co-author : 5
Domestic	First author : 11

Patent Registration: 1

Domestic	First author : 1

Total publications : 34

First author : 16

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Thank you

Question & Answer