Phased Human Activity Recognition based on GPS

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ABSTRACT

This paper describes an activity recognition method for Sussex-Huawei Locomotion-Transportation (SHL) recognition challenge by team TDU_BSA_BCI. The classification accuracy has been improved by switching the estimation model, depending on whether the location is available. Data, including location were classified by Deep Neural Network including LSTM layer. Data that exclude location were classified by the Gradient Boosting Decision Tree. The 2 outputs have been combined. They were optimized by applying a median filter. In the submission phase, the best F-measure obtained for the SHL validation-set was 65%.

CCS CONCEPTS

• **Computing methodologies** → **Activity recognition and understanding.**

KEYWORDS

Classification Flow; LSTM; Gradient Boosting Decision Tree, Median Filter

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1 INTRODUCTION

Many studies are attempting to estimate the movement state using the smartphone's sensor. We participated in Sussex-Huawei Locomotion-Transportation (SHL) recognition challenge as the team TDU_BSA_BCI. Our target is developing the movement state classification algorithm using the SHL dataset 2021 [1]. We participated in the SHL recognition challenge with the team TDU_BSA in 2020 [2]. Accelerometers, geomagnetic sensors, gyro sensors, and barometric pressure sensors cannot be used in this challenge. It is necessary to consider a method appropriate for GPS, Wi-Fi, and Cell that can be used in this challenge. [5] shows activity recognition using GPS. [5] does not consider the case where the current position cannot be obtained from GPS. For improving classification accuracy, we changed the model which is used to determine whether it has the location information or not. It was changed to Deep Learning if location information is included, and eXtream Gradient Boosting (XGBoost) if it is not included. This method, shown in [4], was effective in improving the estimation accuracy.

2 SHL CHALLENGE DATA

The data are divided into 3 parts: train, validate and test. The data comprise 59 days of the training set, 4 days of the validation set and 39 days of the testing set. The training set is collected by User1. The validation set is a mixture of User2 and User3. The testing set is a mixture of User2 and User3. These three data are collected at Hips. The SHL Challenge data set in 2021 has Location, GPS, Wi-Fi, Cells, and Label. Location, GPS, Wi-Fi, and Cells are collected at 1Hz. In the validation set, there is a day that Wi-Fi is not collected.

The location has the accuracy of this location, Latitude, and Longitude. GPS has Satellite ID, Signal-to-noise ratio, Azimuth, and Elevation. Wi-Fi has Basic Service Set Identifier (BSSID), Service Set Identifier (SSID), Received Signal Strength Indicator (RSSI), Frequency, and Capabilities. Cells have a type of cell: LTE, WCDMA or GSM, status of the connection of the phone to this cell, Cell identity, Mobile Country Code, Mobile Network Code, Physical

Cell Id, Tracking Area Code, and Signal Strength. Furthermore, the label has activity labels: “Still,” “Walking,” “Run,” “Bike,” “Car,” “Bus,” “Train,” and “Subway,” corresponding to each epoch time.

This challenge recognizes labels in the testing set.

3 PREPROCESSING

The epoch time of each sensor data and labeled data in the dataset weren’t synchronized. We synchronized the epoch times of each sensor data and labeled data. We used the merge_asof function in Pandas for the synchronized of epoch times. We set the tolerance to 5 s. One sensor data corresponds to one label data with the closest epoch time within 5s before and after. We filled the sensor data of the label data whose sensor data was not synchronized with NaN.

To calculate the distance traveled in 1 s from the longitude and latitude we used the Hubeny formula first term as shown bellow. The geodetic system is the World Geodetic System (WGS84).

$$D = \sqrt{(M \times dP)^2 + (N \times \cos(P) \times dR)^2}$$

D: distance between 2 points (m)

P: mean latitude from 2 points

dP: latitude difference between 2 points

dR: longitude difference between 2 points

M: radius of curvature

N: radius of prime vertical circle

Velocity was calculated from the distance calculated using Hubeny formula first term. The unit of Velocity is [km / h]. Since D is the distance traveled in 1 second, Velocity can be obtained by multiplying D by 3.6.

$$V = D \times 3.6$$

V: velocity (km/h)

Angular acceleration was calculated from the azimuth angle. Angular Acceleration is the difference in azimuth angle.

$$AA = \arctan\left(\frac{\sin(dR)}{\cos(LP) \times \tan(TP) - \sin(LP) \times \cos(dR)}\right)$$

AA: azimuth angle

dR: longitude difference between 2 points

LP: latitude of the starting point

TP: latitude of the end point

4 METHODS

We classified these data into 8 activities using classification flow.

The data were first sorted to determine whether it contained any location information. If the latitude and longitude corresponding to the label data is NaN, that data does not contain location information. We call it “no location data”. No location data were classified by a model that estimates it into seven activities: “Still,” “Walking,” “Bike,” “Car,” “Bus,” “Train,” and “Subway.” This model didn’t estimate the activity “Run” because no location data in the Validation-set do not have “Run” data. Next, data including location information were classified into 8 activities with deep learning. NaN cannot be input to Deep Learning. Therefore, we classified no Location data by XGBoost using statistical features.

Figure 1: Classification Flow

The Testing-set was classified in this flow, and we got an estimation. Figure 1 is the classification flow.

4.1 No Location

No location data were classified by a model that estimates it into 7 classes: “Still,” “Walking,” “Bike,” “Car,” “Bus,” “Train,” and “Subway.” In this method, we used XGBoost. The following feature values were calculated every one second, then used classification. Figure 2 shows the confusion matrix in the validation-set data that exclude location information.

- The number of each cell (LTE, WCDMA, and GSM)
- Mean and valiance of each signal strength from the cell (LTE, WCDMA, and GSM)
- The number of received Wi-Fi access points
- Mean and standard deviation of Wi-Fi access point’s RSSI. Calculated from each frequency
 - Each 5MHz from 2412MHz to 2472MHz
 - Each 5MHz from 5180MHz to 5320MHz
 - Each 5MHz from 5500MHz to 5700MHz
- The number of SSID from 29 Wi-Fi access points that is received high frequency in the Training-set
- The number of Wi-Fi access point includes the text “free” in its SSID
- The number of Wi-Fi access point includes the text “hotel” in its SSID
- The number of Wi-Fi access point includes the text “restaurant” in its SSID

4.2 Deep Learning

To classify data with location information into eight activity labels we employed a Deep Neural Network (DNN) model with a Long-Term Short Memory (LSTM) layer. Feature values were velocity, acceleration, and angular acceleration for 100 s before including estimated epoch time calculated from longitude and latitude. If feature values were not acquired for 100 s, and we centralized it

True label	Still	45.45 (7195)	6.16 (975)	0.00 (0)	0.25 (40)	0.08 (12)	47.01 (7441)	1.05 (167)
	Walking	17.05 (639)	26.53 (994)	0.00 (0)	0.93 (35)	0.00 (0)	44.60 (1671)	10.89 (408)
	Bike	100.00 (1251)	0.00 (0)	0.00 (0)	0.00 (0)	0.00 (0)	0.00 (0)	0.00 (0)
	Car	0.62 (11)	0.00 (0)	0.00 (0)	45.35 (800)	0.00 (0)	24.60 (434)	29.42 (519)
	Bus	53.65 (1072)	1.10 (22)	0.00 (0)	0.00 (0)	41.74 (834)	2.25 (45)	1.25 (25)
	Train	10.13 (1433)	1.73 (245)	0.00 (0)	2.57 (364)	0.00 (0)	75.17 (10637)	10.40 (1471)
	Subway	0.09 (18)	0.00 (0)	0.00 (0)	1.20 (228)	0.01 (1)	4.93 (940)	93.78 (17002)
	Predicted label							
		Still	Walking	Bike	Car	Bus	Train	Subway

Figure 2: Confusion matrix of No Location (Data that does not include Location information of Validation-set)

with padding by zero. Figures 3, 4 and 5 show examples of velocity, acceleration and angular acceleration inputs.

The DNN is as follows. First, velocity, acceleration and angular acceleration are input to the 2 D convolutional layer. The kernel size of the convolutional layer is (1, 3). This layer weights the three features and outputs the values to be input to the LSTM layer. Then, they were input to the LSTM layer. After that, they are input to 5 fully connected layers and get the output probabilities of 8 activities as output. Rectified Linear Unit (ReLU) was applied to the output of each layer other than the output layer. Softmax function was applied to the output. Figure 6 shows the DNN architecture.

Figure 7 shows the confusion matrix in the validation-set data that include location information.

4.3 Post-processing

We applied a median filter to estimate from the combined output of two model outputs. The filter length is 101 s. If epoch time has a time gap of more than one second, we split that data and applied it to each data. By applying a median filter to the output, erroneous outputs that appear fragmentarily during the same continuous output can be corrected. The output is corrected more accurately by slicing at the part with the time gap. By using this process, the F1-score of the Validation-set was improved from 63% to 65%. Figure 8 shows the confusion matrix before applying the median filter, and Figure 9 shows the confusion matrix after applying the median filter.

5 RESULTS

The F1-score of the Validation-set data, including the location information classified by the deep learning model, was 58% (8 classes). The F1-score of the Validation-set data exclude location information classified by the No Location model was 27% (7 classes). The F1-score of "Bike" of the data not including the location information was 0%. However, the ratio of "Bike" data that exclude location information is about 10% of the total number of "Bike" data, so it did not significantly affect the F1-score of the entire Validation-set. The two outputs have been combined. By applying the median filter to

Figure 3: Example of Velocity

Table 1: The detail of the models created in this challenge

Model names	Model size	Learning time
No Location	1.5 MB	5 minutes
Deep Learning	14.1 MB	5 minutes

them, we got the final estimation result. The final F1-score of The Validation-set was 65%. These methods estimated the Test-set.

6 CONCLUSION

In this paper, we performed classification flow for activity recognition. The classification flow switched the estimation model used for classification depending on the availability of location. DNN including LSTM layer classified data, including location. XGBoost classifies data that exclude location. The outputs of the two models were combined, and we obtained the final estimation result by applying the median filter. In the final verification, the F1-score of the Validation-set was 65%. The recognition result for the testing dataset will be presented in the summary paper of the challenge [3].

COMPUTER RESOURCES

CPU Ryzen9 3900XT, 3.8GHz, 12 core 24 threads, RAM 128GB, Geforce RTX 3080. Table 1 shows the learning time of the models created in this challenge.

Figure 5: Example of Angular acceleration

Figure 6: DNN model

Still	75.87 (10628)	1.94 (272)	0.00 (0)	0.04 (6)	17.75 (2486)	2.60 (364)	0.65 (91)	1.15 (161)
Walking	1.23 (275)	68.43 (15359)	8.41 (1884)	2.16 (483)	16.57 (3711)	2.13 (478)	0.86 (192)	0.22 (50)
Run	0.00 (0)	19.97 (554)	49.06 (1361)	23.76 (659)	7.21 (200)	0.00 (0)	0.00 (0)	0.00 (0)
Bike	0.47 (51)	3.31 (357)	12.25 (1321)	78.59 (9472)	3.73 (402)	1.61 (174)	0.03 (3)	0.00 (0)
Car	1.46 (273)	0.74 (138)	0.07 (14)	2.19 (410)	80.55 (15070)	10.98 (2055)	3.39 (635)	0.61 (114)
Bus	2.20 (158)	0.99 (171)	0.00 (0)	7.20 (517)	31.91 (2293)	52.72 (7165)	2.31 (106)	2.67 (192)
Train	2.76 (211)	1.45 (111)	0.00 (0)	0.57 (44)	68.79 (15068)	6.29 (482)	18.03 (1381)	2.10 (161)
Subway	3.48 (192)	0.23 (6)	0.00 (0)	2.46 (65)	35.00 (924)	13.37 (353)	9.81 (359)	35.64 (942)
	Still	Walking	Run	Bike	Car	Bus	Train	Subway

Figure 7: Confusion matrix of Deep Learning (Data including Location information of Validation-set)

Still	59.73 (17821)	4.18 (1247)	0.00 (0)	0.02 (6)	8.47 (2526)	1.26 (376)	25.24 (7532)	1.10 (328)
Walking	3.50 (914)	62.42 (16323)	7.20 (1884)	1.85 (483)	14.33 (3746)	1.83 (478)	7.12 (1863)	1.75 (458)
Run	0.00 (0)	19.97 (554)	49.06 (1361)	23.76 (659)	7.21 (200)	0.00 (0)	0.00 (0)	0.00 (0)
Bike	10.82 (1302)	2.97 (357)	10.98 (1321)	70.42 (9472)	3.34 (402)	1.45 (174)	0.02 (3)	0.00 (0)
Car	1.39 (284)	0.67 (138)	0.07 (14)	2.00 (410)	77.52 (15670)	10.04 (2055)	5.22 (1069)	3.09 (633)
Bus	13.40 (1230)	1.01 (93)	0.00 (0)	5.63 (517)	24.96 (2291)	50.33 (4619)	2.30 (211)	2.36 (217)
Train	7.54 (1644)	1.63 (356)	0.00 (0)	0.20 (44)	25.83 (5632)	2.21 (482)	55.11 (12010)	7.48 (1399)
Subway	0.51 (110)	0.03 (6)	0.00 (0)	0.30 (65)	5.31 (1152)	1.63 (354)	5.52 (1199)	86.71 (18623)
	Still	Walking	Run	Bike	Car	Bus	Train	Subway

Figure 8: Confusion matrix of the classification flow (Validation-set)

Figure 4: Example of Acceleration

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True label	Still	60.21 (17964)	4.15 (1238)	0.00 (0)	0.00 (0)	10.04 (2995)	0.08 (23)	25.17 (7510)	0.36 (106)
	Walking	3.22 (843)	63.74 (16667)	6.21 (1624)	1.27 (332)	16.36 (4277)	1.00 (262)	6.80 (1777)	1.40 (367)
	Run	0.00 (0)	29.99 (832)	36.88 (1023)	25.92 (719)	7.21 (200)	0.00 (0)	0.00 (0)	0.00 (0)
	Bike	10.61 (1276)	2.81 (338)	10.59 (1274)	72.07 (8671)	3.32 (400)	0.60 (72)	0.00 (0)	0.00 (0)
	Car	1.06 (218)	0.01 (2)	0.00 (0)	1.29 (265)	81.24 (18632)	8.90 (1823)	5.11 (1047)	2.37 (486)
	Bus	13.34 (1224)	0.07 (6)	0.00 (0)	4.42 (406)	23.32 (2140)	55.93 (5133)	1.70 (156)	1.23 (113)
	Train	8.23 (1794)	1.65 (359)	0.00 (0)	0.00 (0)	23.77 (5183)	1.38 (302)	63.94 (13943)	1.04 (227)
	Subway	0.41 (90)	0.02 (4)	0.00 (0)	0.00 (0)	2.51 (545)	1.99 (433)	7.16 (1555)	87.90 (19082)
		Still	Walking	Run	Bike	Car	Bus	Train	Subway
		Predicted label							

Figure 9: Confusion matrix of the median filter (Validation-set)

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