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DETECT THE ACCURACY OF THE DELAY FOR TRANSPORTATION MODE RECOGNITION BY USING DEEP LEARNING

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Abstract: Using sensor-rich smartphones to sense various contexts attracts much attention, such as transportation mode recognition. Local solutions make efforts to achieve trade-offs amongdetection accuracy, delay, and battery usage. We propose a real-time recognition model consistingof two long shottern memory classifiers with different sequence lengths. The shorter one is a binaryclassifier distinguishing elevator scene and the longer one implements a finer classification amongbus, subway, high-speed railway, and others. Light-weighted sensors are employed with a much smaller sampling rate (10Hz) compared with previous works.We present experiments on accuracyand resource usage and prove that our system realizes a latency-low and power-efficient scene recognition approach by trading off a reasonable performance loss (averaged recall of 92.22%)

Introduction:

In the big-data era, users' data are of much significance for content providers and software developers to unlock more smart and personalized services. Transportation mode detection (TMD) is a useful tool to guess users' travel modes [9]. Human activityrecognition (HAR) is meant for eldercare andhealthcare as an assistive technology [4]. Onthese bases, it inspires the telecommunicationcarrier or content providers to provide better service with pertinence. Commonly, TMD solutions can be categorized as being distributed (local) or centralized (remote). With the increasing capability of mobile computing, smart phones are gradually competent to deal with self-generated data rather than sending data to a remote cloud server. Local TMD solutions surveyed in [1]outperform the remote ones greatly in many ways, especially detection delay. Apart from travel modes, other complicate scenes arealso worthy of consideration, such as theelevator and gym. Therefore, we consider a generalized TMD problem where the elevatorscene and some transportation scenes are taken into account.

A. Relevant Work

Existing algorithms to solve TMD problems include supporting vector machines (SVM) [10], random forest [8] [6], decision tree [5] , hidden Markov model (HMM) and Bayesian Belief Network [11], convolutional neural network (CNN) [3], recurrent neural network (RNN)[2] [7]. The long short-term memory (LSTM) network is adopted in our method. Battery usage and system delay are not discussed in these remote based solutions. Among local-based solutions, previous works made efforts to 1) use as few sensors as possible, 2) avoid power-draining sensors, 3) design a tiny classifier to consume less power. As far as delay is concerned, [1] claimed all the local TMD approaches have implicitly met this requirement by performing classification locally (in comparison with remote based methods). we aim to design a more balanced scene recognition system that attains a better tradeoff among accuracy, delay, and power consumption. Data collection and analysisare simultaneously implemented on smartphones

B. Contributions

We propose an online scene recognition system that is composed of a datasampling/preprocessing module, a two-stageLSTM classifier, and an ensemble decision module. It's important to detect the scene in complicated environments as guidance to improve service quality, especially confined space or crowded space. Five common scenesare selected in this work A two-stage classifier is proposed to recognize scenes with different duration. The duration when people take the elevator is commonly short, around tens of seconds, whereas scenes like HSR and bus last tens of minutes or hours.Light-weighted sensors are employed excluding power draining GPS sensor. A lower data sampling rate (10Hz) is adopted. It in turn allows us to reduce the capacity of LSTM to 64 and represent the feature well atthe same time.

II. *Methodology*

A. System Architecture

In this paper, we proposed a novel real-time transport mode detection model that relies on the accelerometer, gyroscope, and magnetometer of a smart phone. Fig. 1 showsthe hardware and software configuration of our system.

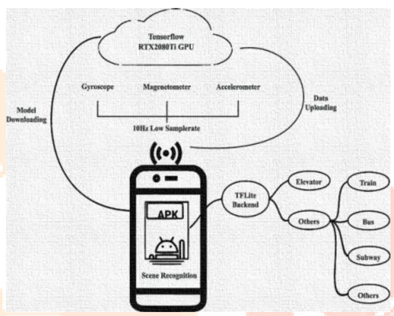


Fig 1

B. Data Preprocessing

Data preprocessing is composed of coordinate transformation, autoregressive moving average (ARMA) filtering, and data splitting. After data preprocessing, raw data are processed to uniform, smoothed, and structured frames

1) Coordinate Transformation

The data collected from the phone's sensorsare based on the phone's coordinate systemwhich changes with the orientation of the phone

Removing gravity

$$a_m = a_{sensor} - g \qquad (1)$$

$$p = (am; g)/(g; g)g \qquad (2)$$

$$h = am - p \qquad (3)$$

Equation (2) computes the projection of the motion acceleration **p** on the vertical axis. Equation (3) directly gets the horizontal acceleration by vector subtraction

2) ARMA Filtering

Data filtering is a necessary step since the movement of smart phones is not consistent with that of users.

3) Data splitting

Twelve different raw data sources are used consisting of four three-dimensional vectors defined as Acc, Mag, Gra and Gyr, corresponding to accelerometer, gravity sensor, magnetometer and gyroscope.

Feature Extraction

Features	**Name**	**Description**
Time-Domain Features	Max Min Mean Rang eStd. RMS Cnt_zero Cnt_mean Cnt_slope	Maximum value of the dataframe. Minimum value of the dataframe. Mean of data frames. Range of data frames. Standard deviation of dataframes. Root mean square of dataframes. Number of times a data framepasses through zero. Number of times a data framepasses the mean. Number of time a data frame change direction
Frequency-Domain Features	Spectral Centroid Spectral Flatness RMS_f Max Index Max Rate	Center of the mass of thespectrum. numbers of peaks or stabilityof the spectrum Ratio of the maximum valueto the root mean square. Frequency corresponding tothe maximum modulus Ratio of the second-maximumfrequency component to the maximum frequency

C. Two-Stage LSTM Classifier

When using the sensor signal to recognize thestate of the scene, the dependency on timeseries data must be considered. Since LSTMis introduced to solve the vanishing gradientproblem and deal with long patterns [14]. Weexploit a novel two stage LSTM classifier toachieve a tradeoff among accuracy ,complexity and delay.

D. Post Processing

the prediction of the inference model is time independent, however, in practical use, the scene is consistent in a period and we don't expect the result to change frequently. the final decision will not be changed until the weighted confidence reaches over a threshold(70% in our system).

III. *Evaluation And Discussion*

Firstly, we briefly introduce the dataset collected for our problem and our phone application. Secondly, detailed performances of our system are presented including classification performances, latency and power consumption.

A. *Dataset*

To our knowledge, several datasets for TMD problems are built, e.g. the US-TMD dataset [4], HTC dataset [1]. However, the US-TMD dataset does not include a gravity sensor, magnetometer. TABLE 2 summarizes the dataset, including bus, subway, high-speed railway (HSR), elevator, and others. The class 'others' mainly consists of low-speed scenes.

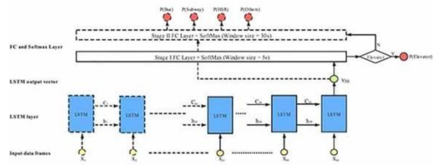


Figure:2 Architecture of 2-stage LSTM classifier

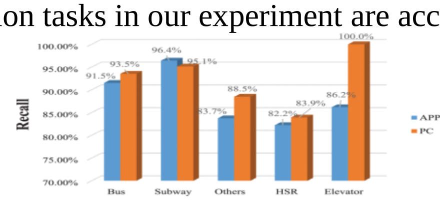
The raw dataset contains various data types, which can be divided into four categories: motion state, Radio Frequency (RF) signal, position information, and system information. The movement data is measuredby built-in sensors such as accelerometers, gravimeters, magnetometers andgyroscopes.

scene	#frames	#segment	#lines	Duration(hrs) our exp
Bus	14429	50	>20	4.00
Subway	34049	186	>13	9.45
Others	18847	51	-	5.13
HSR	20588	10	1	5.72
Elevator	3471	70	10	0.97

TABLE 2:Overview of dataset

Results

Models are trained with Tensorflow on RTX2080Ti GPUs using Adam [16] optimization algorithm. The initial learning rate is set to 0.001 and is reduced to its 1/10 three times until convergence. Evaluation metrics: The metrics evaluating the classification tasks in our experiment are accurate and recall.



Recall comparison between PC and APP

We calculate those metrics on each scene. The result is averaged in the samples of eachclass in the test dataset using the Kfold cross-validation strategy.

Conclusion

In this paper, we introduce a real-time and GPS-free method for recognizing five scenes including common public transportation and elevator scene. A two-stage LSTM classifier is proposed to adapt to scenes with different duration and reduce the latency in the short- term scenes like the elevator scene.

The system is proved prosperous as a tool to improve user experience. Follow up research includes 1) Dataset renewal. We plan to enrich our data set, including types of scenes, the number of lines for each scene. 2) Robustness enhancement. A robust model defends against noise arising from shaking interference. A more practical test needs to be done to evaluate the robustness of the model. We also begin to adjust the preprocess pipeline and network structure to achieve better performance for more scenes. 3) Power consumption improvement. Although our approach works with less power consumption than previous works, other strategies can be explored to slim the model further, such as feature reusing, model pruning, and otherpractical methods.

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