# Real-time intelligent recognition of transportation modes via smartphones

Harada, Satoru; Wisetjindawat, Wisinee; Sresakoolchai, Jessada; Huang, Junhui; Kaewunruen, Sakdirat; Sakikawa, Shuichiro

# Real-time intelligent recognition of transportation modes via smartphones

Satoru Harada[1], Wisinee Wisetjindawat[1], Jessada Sresakoolchai[2], Junhui Huang[2], Sakdirat Kaewunruen[2], Shuichiro Sakikawa[3]

[1]Hitachi Europe Limited, ERD Office, 12th Floor, 125 London Wall, London EC2Y 5AL, UK
[2]School of Engineering, University of Birmingham, Birmingham B15 2TT, UK
[3]Hitachi Ltd. Tokyo, Japan.
Corresponding author(s): Satoru Harada (satoru.harada@hitachi-eu.com); Sakdirat Kaewunruen (s.kaewunruen@bham.ac.uk)

## Abstract

Travel mode recognition as well as activity recognition has gained some momentum in recent years. Travel mode recognition can be viewed similarly as activity recognition and can be solved as a classification problem where Machine Learning is widely used in this area. The University of Birmingham and Hitachi Europe have jointly developed new, innovative AI models, capable of recognising the complex and fuzzy patterns of mobility and transport modes. In recent years, mobile sensing has gained a strong momentum in various technological applications in the Industry 4.0 era. The real-time mobile sensing actually allows extensive applications including the use of mobile sensing data for transport mode classification, which forms the basis of this research. Its future implementation on blockchain can promote and decentralise public users' leaderships for sustainable mobility.

Keywords: human activity, smartphone, accelerometer, sustainable mobility

## 1. Introduction

Recognition of key transportation modes in real time will revolutionize future transport services and on-demand operational planning for all stakeholders. This real time recognition capability will allow transport operators, local and regional authorities, as well as governments, to plan for more personalized services and demand responsive infrastructures. Widely used smartphones and connected devices such as activity trackers and smart watches have been built and equipped with modern and precise integrated sensors with advanced capabilities and have become powerful tools for understanding people's activities. Beyond their application for traditional Activity Recognition (AR) such as gym activities, exercise and personal health, we can see potential for integration of this capability into several transportation applications and services.

Recently, smart mobile phones have been built and equipped with precise sensors with capabilities that incite various developments for daily life applications [1-4]. However, the emphasis of most applications is currently placed on human-based activities. The new sensing capabilities integrated within the recently built smartphones have unleashed a wide variety of creative ideas and innovations for solving pressing problems in the society. Modern mobile sensors usually include vibration (inertia sensors), gravity, location (GPS coordinates), gyroscope, and time. Vibration data is one of the most popular sets of data (after GPS location) used in various applications. The vibration signals enable real-time data records, which can be further analysed for new insights. This project thus adopts the vibration data since it enables specific data fusion for the classification of various types of mobility and transport modes.

Travel mode recognition as well as activity recognition has gained some momentum in recent years. Travel mode recognition can be viewed similarly as activity recognition and can be solved as a classification problem where Machine Learning is widely used in this area. We can see several applications regarding Activity Recognition (AR), such as gym activities, exercises, and personal health, such as works by [5] and [6]. An example of existing studies in this area is one by Ferrer and Ruiz [6] demonstrating the use of sensors in smartphones to capture persons' travel behaviours as an alternative method from the traditional paper-based/interview-based travel behaviour survey. The sensor was used to identify the transport mode used for making journeys.

Modern mobile sensors usually detect vibration, gravity, location (GPS coordinates), gyroscope, sound level, and time. Vibration data is one of the most popular datasets (after GPS location) used in various applications. The vibration signals enable real time data records, which can be further analysed for new and updated insights in near real time. The approach taken in this study was to adopt the use of vibration data since it can enable specific and customized data fusion for the advanced classification of various types of mobility and transport modes. Vibration signals can be easily obtained from mobile sensors during actions of users in relation to any mobility or transportation pattern. We used this vibration data in a tailored novel machine learning technique to enhance a rapid and real-time predictive application for recognizing and identifying key common transportation modes car, bus, train, bike, and walk. This innovative algoritm can be embedded in smart phones paired with any blockchain network, which enhance the promotion and decentralisation of public users' leaderships towards a greener mobility choice.

## 2. AI for Travel Model Recognition

The AI technology is part of Hitachi's new mobility solutions that detects in real-time the travel mode that a person is currently using, from the vibration data. As shown in Figure 1, this technology automatically recognises the start/end of the journey as well as the travel mode that person is using throughout the journey. This technology is beneficial to multiple applications such as travel behaviour study.

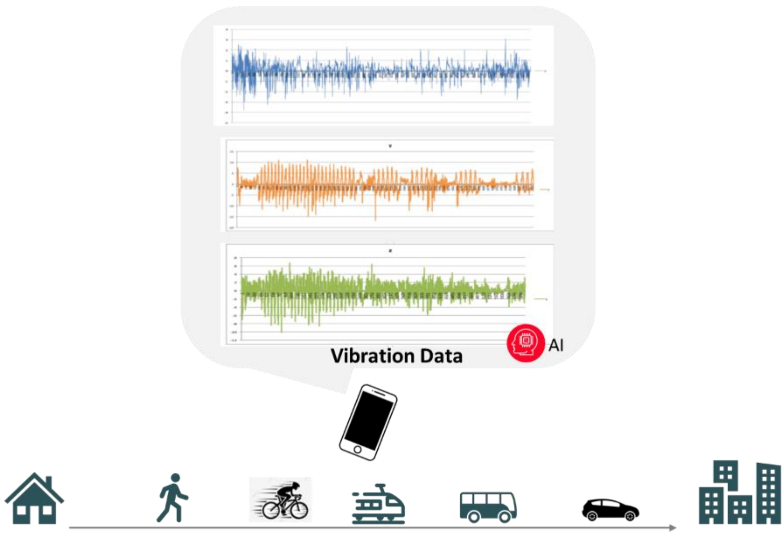



Figure 1 AI for Travel Mode Recognition

## 3. Methodology

This research develops a predictive model for transport activity recognition (AR) using smartphones' accelerometer as the main sensor for data collection. The datasets used for this investigation include (1) one collected by ourselves (with over 4,000 datasets) and (2) one obtained from secondary sources (which included over 20,000 datasets).

### 3.1 Data Collection

The sensor collects the vibration along three dimensional axes (i.e., x, y, and z) and time. The data was collected at 100Hz and 60s basis. An example of the application of the collected data can be shown in Figure 2.

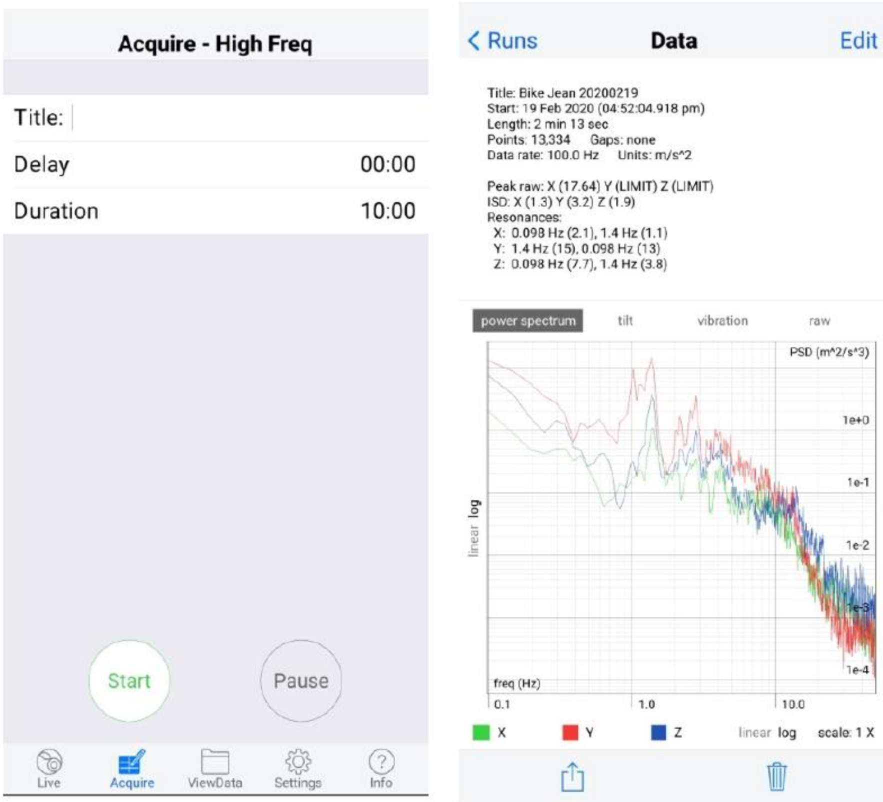



Figure 2 Example of collected data

Data collection was conducted by volunteers within the research group while they make their journeys. The travel modes considered here include: walking, cycling, taking a bus, taking a train, and taking a taxi. The volunteers were asked to install our own developed mobile application which automatically collects the vibration data throughout their journeys. During each journey, volunteers would need to label each set of the data correctly according to their actual travel model for model training and validation purposes. Table 1 shows the number of samples collected in each class.

**Table 1. The number of samples in each class**

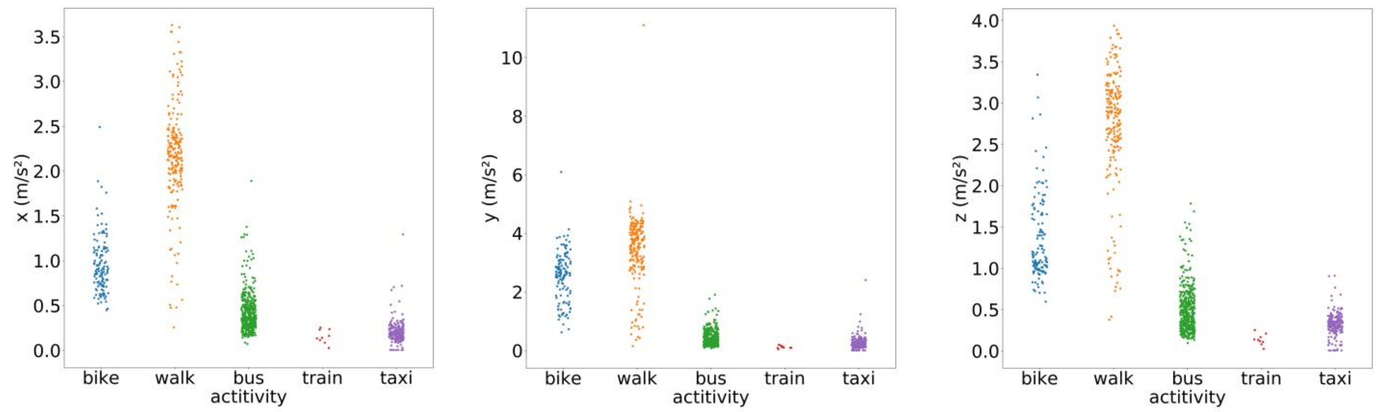
| Class | Number of Samples |
|---|---|
| Walk | 378 |
| Bike | 275 |
| Bus | 485 |
| Train | 290 |
| Taxi | 1069 |
| Total | 2497 |

### 3.2 Pre-processing Data

Collected data is labelled for specific categories, which include walking, cycling, taking a bus, taking a train, and taking a taxi. Then, the collected data is pre-processed to make it in a form that can be used for developing predictive models (data fusion). Each set of data in this project is called as a sample. Each sample is prepared by gathering together to feed in the system as a database. Then, the data is split into 2 groups, training data and testing data. Training data is used to train models and develop predictive models while testing data is used to evaluate the performance of developed models. These 2 groups of data are used independently to make sure that there is no over-fitting issue from using all data to develop models. The proportion of the splitting can be varied depending on many factors such as the sample size, model design, etc. The proportion might be 0.7, which means that 70% of data is used to train models while another 30% of data is used to test models. A technique, which used to split data, is called sampling. Sampling can be done in multiple ways such as linear sampling, shuffled sampling, or stratified sampling.

## 4. Results

Figures 3(a) and 3(b) show the relationships of the 5 activities with x-axis and y-axis vibration, respectively. Visually, we can observe that the vibration in x-axis and y-axis of bus and train are very similar. Due to this similarity, the prediction accuracy of machine learning techniques that might not be suitable for non-linear or complex data such as K-means clustering algorithm can turn out be unsatisfactory because features do not have significantly different characteristics. From Figure 3, it can be seen that x-axis and y-axis vibrations of each activity are not much different especially y-axis vibration that values of every activity are in the same range.




(a) (b) (c)

Figure 3 Relationship between X-axis vibration and the five activities (a) and between Y-axis vibration and the five activities (b)

We used AI models, such as deep neural network (DNN) and convolutional neural network (CNN), to learn the patterns of the activities from the vibration data. From Figure 3, it can be seen that samples have non-linearity characteristics. Using these deep models is sensible to detect patterns in data. Each dataset lasts for 1 minute (60 seconds) and the data is only collected from the accelerometer equipped in a smartphone. Of the neural networks that we developed, one type of the model achieved over 90% accuracy using the full raw dataset.

Figure 4 shows the screenshot of the our own developed App that real-time demonstrates the predicted type of travel mode.

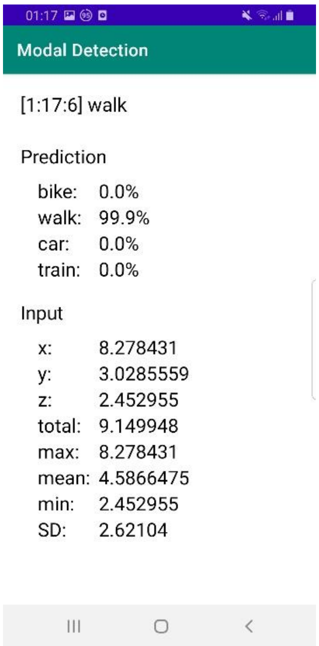



Figure 4 Screenshot of Travel Mode Detection Application, probability and data characteristic

## 5. Conclusion

The University of Birmingham and Hitachi Europe have collaboratively developed new, innovative AI models, capable of recognising complex and fuzzy patterns of mobility and transport modes. The development of AI pattern recognitions is focussed on five modes of mobility and transportation, including:

- Walking
- Bicycling
- Travelling by cars/taxis
- Travelling by trains
- Travelling by buses.

This paper presents the development for an innovative artificial intelligent (AI) model using mobile sensors that is capable of recognising travel activities including walking, bicycling, traveling by cars, buses and trains. The development of the AI model adopts Deep Neural Network and Convolutional Neural Network as the main architectures. A critical literature search has confirmed that there is no other AI model that is capable of classifying the data features for mobility recognition. This novel AI model has been confirmed as one of the forefront developments in this field. An alternative advanced AI model using Convolutional Neural Network for full data diagnostics has been additionally built in. The accuracy of the new AI model has been shown to be above 90%, which is highly satisfactory. This innovative algorim can be embedded in any smartphones for various real-time applications such as the promotion and decentralisation of sustainable mobility choices for public users. This can be linked with the global sustainability cryptocurrency tokens (such as ECO coin, etc.) that can influences and incentivise public users for more sustainable actions. This concept is directly aligned with the United Nation's Sustainable Development Goals.

## References


[1] Lee, S.M., S.M. Yoon, and H. Cho., 2017. “Human activity recognition from accelerometer data using Convolutional Neural Network”. in 2017 IEEE International conference on big data and smart computing (BigComp). IEEE.

[2] Inoue, M., S. Inoue, and T. Nishida, *Deep recurrent neural network for mobile human activity recognition with high throughput.* Artificial Life and Robotics, 2018. **23**(2): p. 173-185.

[3] Ronao, C.A. and S.-B. Cho, *Human activity recognition with smartphone sensors using deep learning neural networks.* Expert systems with applications, 2016. **59**: p. 235-244.

[4] Zeng, M., et al. *Convolutional neural networks for human activity recognition using mobile sensors*. in *6th International Conference on Mobile Computing, Applications and Services*. 2014. IEEE.

[5] Fridriksdottir, E. and Bonomi A.G., 2020 “Accelerometer-Based Human Activity Recognition for Patient Monitoring Using a Deep Neural Network”. Sensors (Basel). 2020 Nov; 20(22): 6424.

[6] Ferrer S. and Ruiz T., 2015. “Using Smartphones to Capture Personal Travel Behaviour”, in Rasouli S. and Timmermans H. (ed.) Mobile Technologies for Activity-Travel Data Collection and Analysis, A Volume in the Advances in Data Mining and Database Management Book Series. Information Science Reference, pp.171-186.

[7] Nighania, K. Various ways to evaluate a machine learning model’s performance. 2018 [cited 2020 21 March]; Available from: https://towardsdatascience.com/various-ways-to-evaluate-a-machine-learning-models-performance-230449055f15.