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Travel behavior characterization using raw accelerometer data collected from smartphones

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Abstract

In this paper, we compare different algorithms for the recognition of transportation modes based on features extracted from the accelerometer data. The performance and effectiveness of the transportation mode classifiers presented is evaluated and their accuracy is discussed. The data set used for training and testing algorithms was collected by a group of volunteers in the city of Valencia in 2013; an Android application designed for the recording of trips and transportation modes application was installed on their smartphones. This application collected GPS readings each 10-12 seconds and accelerometer data at 1Hz. While GPS data was only used for the validation of trips for the training of the algorithms, accelerometer readings were used entirely for their training. Results show the high performance of Recurrent Neural Networks in recognizing travel modes using accelerometer data.

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Keywords: Smartphones; accelerometer; transportation modes; mode detection; recurrent neural networks

1. Introduction

The use of smartphones for the collection of activity-travel information is gaining more and more prominence in the last five years. Current smartphones, embedded with sensors such as GPS and triaxial accelerometers, are able to capture raw data useful for recognizing human daily activity patterns and present advantages over other collection

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methodologies. For example, compared to traditional travel paper diaries, smartphones provide more accurate information about trips and address the problem of underreporting of short trips. Compared to GPS devices, one advantage of smartphones is that people tend to carry them almost everywhere they go and, in addition, their users are more likely to prevent battery from draining.

The identification of travel behavior characteristics by means of GPS data collected via GPS devices or mobile phones, has received much research effort in the last decade. Recently, some studies rely on the use of smartphone's accelerometer data for this purpose. While there has been some research in this direction, the use of classification algorithms has been limited to only a few types and a wide comparison between different algorithms in identifying transportation modes using only accelerometer data is required.

2. Background

2.1. The use of smartphones to collect travel behavior data

As GPS-enabled smartphones have been commercially-available, more travel surveys incorporating smartphone apps have replaced GPS devices and paper travel diaries. Smartphone-based surveys are generally administered using personally-owned devices and they offer a key benefit in reducing both the cost of data collection instruments and the cost of distributing and retrieving the hardware (Bricka & Murakami, 2012). One of the first examples of a smartphone application to collect travel behavior data is TRAC-IT (Barbeau, Labrador, Georggi, Winters & Perez, 2009), developed in 2007 by the University of South Florida, which was tested using 14 volunteers. Another example is the "Quantifiable Traveler" application, developed in UC Berkeley, recently piloted with about 80 people tracking their travel behavior for a period of more than two weeks (Jariyasunant et al., 2012).

Stenneth, Wolfson, Yu & Xu (2011) inferred user's mode of transportation based on the GPS data collected from mobile phones and transportation network information consisting of real time location of buses, rail lines, and bus stops spatial data. Later, Stenneth, Thompson, Stone & Alowibdi (2012) proposed a method to detect where in multinomial GPS traces the traveler changed transportation modes. Data was collected using GPS enabled mobile phones.

In spite of all the advantages of using GPS data in travel surveys, signal losses or degradation in high-density cities and cold/warm start issues are common problems of GPS-enabled devices. Accelerometers, measuring rotational and translatory movements, offer an opportunity to overcome some of the outstanding problems associated with GPS data as they are a very useful complementary tool for tracking people travel behaviour in places with a weak or even no satellite signal.

A few studies have attempted to detect transportation modes using GPS and accelerometer data from smartphone sensors (Reddy, Burke, Estrin, Hansen, & Srivastava, 2008; Manzoni, Maniloff, Kloeckl, & Ratti, 2011; Nitsche, Widhalm, Breuss & Maurer, 2012; Parlak, Jariyasunant & Sengupta, 2012; Fan, Chen, Liao, & Douma, 2013).

Some studies rely on the use of accelerometer data only for travel or activity identification (Nham, Siangliulue, & Yeung, 2008; Wang, Chen, & Ma, 2010; Siirtola & Röning, 2012; Lara, Perez, Labrador, & Posada, 2012), among others. Lara, Perez, Labrador, & Posada (2012) developed Centinela, a system that combines acceleration data with vital signs to recognize activities such as walking, running, sitting, ascending and descending.

2.2. Processing of the data and identification of transportation mode

The processing of the data collected involves two stages: the identification of trips and inference of the transportation mode. Previous studies have mainly applied two different approaches for the mode detection stage: rule-based algorithms (Bohte & Maat, 2009; Chen, Gong, Lawson, & Bialostozky, 2010) and machine learning approaches like fuzzy logic (Schuessler & Axhausen, 2009), Decision Trees (Manzoni, 2011; Reddy et al., 2010; Zheng et al., 2010; Siirtola & Röning, 2012), Bayesian Networks (Moiseeva, Jessurun, & Timmermans, 2010; Feng & Timmermans, 2012), Support Vector Machines (Bolbol, Cheng, Tsapakis, & Haworth, 2012), Neural Networks (Gonzalez et al., 2008; Stenneth, Wolfson, Yu, & Xu, 2011) and other methods based on decision trees (Random Subspace methods used by Nitsche, Widhalm, Breuss, & Maurer, 2012; Random Forest classifier used by Parlak, Jariyasunant, & Sengupta, 2012).

Bohte & Maat (2009) applied rule-based algorithms for the processing of the GPS and GIS data and for the detection of travel modes. Chen, Gong, Lawson, & Bialostozky (2010) developed GIS-based algorithms for the detection of travel modes and trip purposes from GPS traces. However, the range of methods used to infer the transportation mode has extended from logical procedures to Machine Learning approaches. Thus, Schuessler and Axhausen (2009) used a fuzzy logic approach based on the speed and acceleration characteristics extracted from GPS records. Moiseeva, Jessurun, & Timmermans (2010) developed a system called TraceAnnotator to process multiday GPS traces semiautomatically. The process of imputing transportation modes, activity episodes, and other facets of activity travel patterns was based on a learning Bayesian belief network. More recently, Feng & Timmermans (2012) examined the potential advantages of accelerometer data to identify transportation mode using a Bayesian Belief Network.

Several studies use decision trees to perform transportation mode classification, either alone or integrated with other techniques, such as Hidden Markov Models. Thus, Reddy et al. (2008) created a transportation mode classification system that classifies one second of data by using the GPS receiver speed value and energy, variance, and sum of FFT coefficients between 1-5Hz from the accelerometer. They used a decision tree followed by a first-order discrete Hidden Markov Model. Similarly, Manzoni, Maniloff, Kloeckl, & Ratti (2011) developed an algorithm that identifies transportation modes using decision trees as a supervised classification algorithm. Nitsche, Widhalm, Breuss, & Maurer (2012) used the Random Subspace Method to infer travel modes and the Viterbi algorithm to identify the most likely sequence of classifications. Additionally, Parlak, Jariyasunant, & Sengupta (2012) built a Random Forest with 10 decision trees to classify transportation modes and a Hidden Markov Model was applied on the classification output to remove short-term transitions. They also used a transit map matching algorithm to differentiate between motorized transportation modes: train, bus and car.

Stenneth, Wolfson, Yu, & Xu (2011), using data extracted from GPS and GIS data, compared five classification models including Bayesian Network, Decision Tree, Random Forest, Naïve Bayesian and Neural Network to identify travel modes. Bolbol, Cheng, Tsapakis, & Haworth (2012) performed the inference of travel modes from speed and acceleration values calculated from GPS data using Support Vector Machines. Other contributions identify travel modes using neural networks (Gonzalez et al. 2008) from GPS data.

The family of machine learning and pattern recognition approaches includes Recurrent Neural Networks, which are dynamic classification algorithms used for recognizing time-series patterns in several domains. However, the use of Recurrent Neural Networks has been restricted to human action recognition studies (Bailador, Roggen, Tröester & Triviño 2007; Baccouche, Mamalet, Wolf, Garcia, & Baskurt, 2011; Lee & Cho, 2012; Tan & De Silva, 2003, among others). Thus, the objective of this paper is to compare the performance of different classifiers to recognize transportation modes, incorporating Recurrent Neural Networks among them.

The rest of the paper is organized as follows. The methodology of the data collection is presented in the next section, followed by the presentation of the results. A summary of the main findings concludes this paper.

3. Data collection methodology

3.1. Development of the application PEATON

A data logging application called PEATON has been developed in Android and it is supported on smartphones running Android 2.2 or higher. The app PEATON acquires data from the accelerometer of the smartphone, and synchronizes this data with the available location and speed information provided by the GPS (Ferrer and Ruiz, 2014). When the GPS signal is lost, the phone calculates its position based on the available GSM Cell Ids and WLAN cells. The GPS records data at a sampling frequency of 10-12 seconds, as higher epoch rates lead to a greater battery consumption. The accelerometer samples at 1Hz. In addition to each GPS record, information about the accuracy of the signal is stored: the number of satellites in view and other parameters available. The GPS and accelerometer information is continuously stored in the smartphone, and it is periodically sent to a server using Internet connection and then deleted from the smartphone's memory. The user interface of the application to collect travel data was designed to be as simple as possible, with just a start button and stop button (Figure 1).

Fig. 1. Screenshot of the application

3.2. Collection of test data

To calibrate and validate the algorithms for detecting trips and transportation modes, a small sample of respondents collected ground truth data using the data logging application developed for this purpose (Figure 2). The application was designed to allow users to manually register in real time every single trip undertaken in outdoor public areas and the type of activity executed at the end of the trip.

Data was collected by 7 persons over a period of three months: 4 male and 3 female, between the ages of 25 and 38. The objective was to get sample data as varied as possible in terms of transportation modes used. This group of respondents installed the application in their smartphones; smartphones should be Android-based embedded with assisted-GPS and a triaxial accelerometer. The following smartphone models were used: Sony Xperia U, Sony Xperia ArcS, Samsung Galaxy S, Samsung Galaxy S II and Google Nexus S.

Participants were instructed to thoroughly select the travel mode chosen when starting a trip (walk, bicycle, motorcycle, car, bus, electric tramway, metro, train, or wait if participant is transferring between transport modes) and, once the trip was finished, respondents had to end it in the application and also choose the main type of activity to be performed at destination (to go home, work/study, have lunch/dinner, shopping, leisure time - sports, cinema, theatre, etc. -, services - hairdresser, doctor, etc. -, pick up someone or other type of activity).

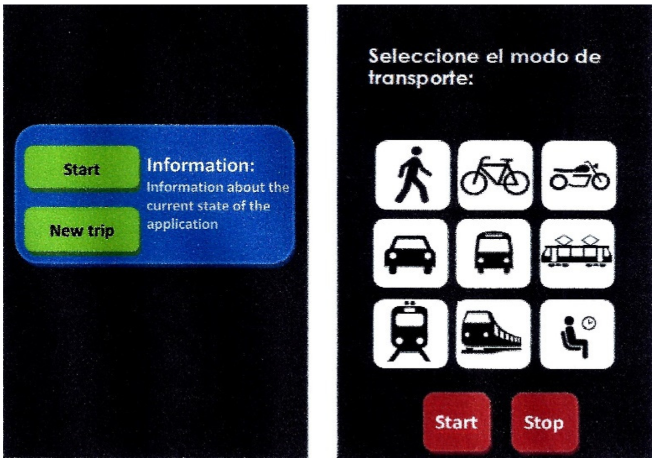

Fig. 2. Screenshot of the application for collection of test data

The total amount of ground truth data comprises 313.5 minutes of travel time with a variety of transportation mode shares (Table 1).

Table 1. Minutes of labelled data collected by transportation mode

Transportation mode	Minutes
Car	81.5
Metro	72
Walk	84.5
Bike	75.5

4. Data processing and classification

4.1. Data processing

A validation of the trips recorded is necessary to assure the quality of the data provided to train the algorithms. A feature extraction is performed only for those valid trips.

For the identification of trips, including the transportation mode, only features extracted from the accelerometer signal were used as the literature reveals that data from this sensor can be enough for recognizing travel modes (Nham, Siangliulue, & Yeung, 2008; Wang, Chen, & Ma, 2010; Siirtola & Röning, 2012; Lara, Perez, Labrador, & Posada, 2012). Thus, GPS data was only used for validation of the data used to calibrate the algorithms.

4.1.1. Validation of trips

For each of those trips collected and labelled by the users, a manual validation was performed. The validation process was necessary as the routes recorded by the users could contain different errors regarding the starting time, ending time or even transportation mode. Examples of these errors are: the trip was started before the real start time, the trip was ended after the real end of the trip or a short activity was executed at some point on the route. The validation of each trip consisted of four steps (Ferrer & Ruiz, 2014):

- Visualizing the route using the Google Maps-based website.
- Displaying the same itinerary in the route planner of Google Maps and calculating the travel time by the transportation mode indicated.
- Comparing the travel time annotated by the user and the travel time estimated by the route planner of Google Maps. Three possible cases arise from this comparison:
    - A:Travel time is not more or less than 20% of the travel time estimated using Google Maps
    - B: Travel time is more than 20 % of the travel time estimated using Google Maps
    - C: Travel time is less than 20 % of the travel time estimated using Google Maps

Whether we are in case A, B or C, influences the usefulness of the routes for calibration purposes: routes in case A can be used for calibration of the algorithms, and routes classified as B or C were not directly used for calibration as they may not be well labelled or recorded. Additionally, to ensure the quality of those routes that will serve as ground truth data for the algorithms, the first and last 30 seconds of a route A were not considered.

4.1.2. Acceleration feature extraction

A feature extraction process is realized for each validated trip. This step involves extracting suitable features from the accelerometer signal that can provide meaningful information to the classifier to identify travel modes (driving, taking the metro, walking and biking). As the orientation of the smartphone affects the values of three acceleration channels, an orientation independent variable needs to be calculated to eliminate this effect. Thus, the three acceleration directions are combined to obtain the magnitude of acceleration, calculating the square root of the sum of the squares of the three components of the acceleration.

The transportation mode recognition is done using a sliding window technique. With this technique, a certain size of the time window is chosen as the period of classification. The length of the sliding window is set as 30 seconds without overlapping between consecutive windows. As the ratio of frequency of the accelerometer is 1Hz, 30 sample points (magnitudes of acceleration) are used to calculate acceleration features. From each window, a total number of 6 independent features are extracted of the magnitude of acceleration, including: mean, standard deviation, maximum acceleration, minimum acceleration, first and third quartile. Other studies have shown that these statistics are helpful in the identification process of travel modes (Wang, Chen, & Ma, 2010; Siirtola & Röning, 2012).

Figure 3 is a representation of the features extracted from the accelerometer signal for each transportation mode. This representation is also helpful in the validation of the data as each travel mode presents different characteristic patterns. Thus, the visualization of the extracted features for each recorded route represents an additional tool to validate the trip annotated by the user.

4.2. Classification

This step involves the use of a classifier to infer transportation modes based on the feature vectors. To determine the most accurate transportation mode detection algorithm, we compared the precision accuracy of five classification models implemented in Matlab. The five models are: (1) k-Nearest Neighbors **(KNN)**, (2) Decision Trees **(DT)**, (3) Discriminant Analysis **(DA)**, (4) Multilayer Perceptron Neural Network **(NN)**, (5) Recurrent Neural Network **(RNN)**.

The technique of cross-validation was used to estimate how accurately a predictive model will perform in practice and to be able to compare the performances of the different classification models. 10-fold cross-validation was used for KNN, DT and DA. In 10-fold cross-validation, the original sample is randomly divided into ten subsamples. Of the ten subsamples, a single subsample is used as validation data for testing the model, and the remaining nine subsamples are used for training. The cross-validation process is then repeated 10 times, with each of the ten subsamples used once as validation data. The ten results are then averaged to produce a single estimator. In our case, the estimator is the fraction of correctly classified data of the model. 10-fold cross-validation is repeated ten times and results are averaged.

In the particular case of the NN and RNN, a simpler form of cross-validation is used, called repeated random sub-sampling validation, were the available data is randomly separated into a single training set and a single test set. The estimator used is the average of the percentage of correctly predicted instances after ten runs of the model.

5. Modelling and classification

5.1. Configuration of the classifiers

5.1.1. K-Nearest Neighbors

The K-NN classifier (Cover and Hart, 1967) assigns a new feature vector to the most common class amongst the most similar k feature vectors in the dataset. The 3 nearest neighbors were chosen based on comparing the accuracy of various number of neighbors using 10-fold cross validation. Thus, the best performance is obtained when k is set to three, which has a recognition rate of 88.7%.

5.1.2. Decision Tree

The application of decision trees to classification was popularized in machine learning by Quinlan (1986). The final configuration of the tree is obtained after pruning to simplify it, achieving a recognition rate of 88.4%.

5.1.3. Linear Discriminant Analysis

In linear discriminant analysis (Fisher, 1936), the model assumes that input variables have a Gaussian mixture distribution. It also considers that the model has the same covariance matrix for each class and only means vary among classes. The accuracy of the model is 84.4%.

5.1.4. Multi-layer feed-forward Neural Network

In the configuration of the NN, the number of neurons chosen in the hidden layer is an important parameter as it

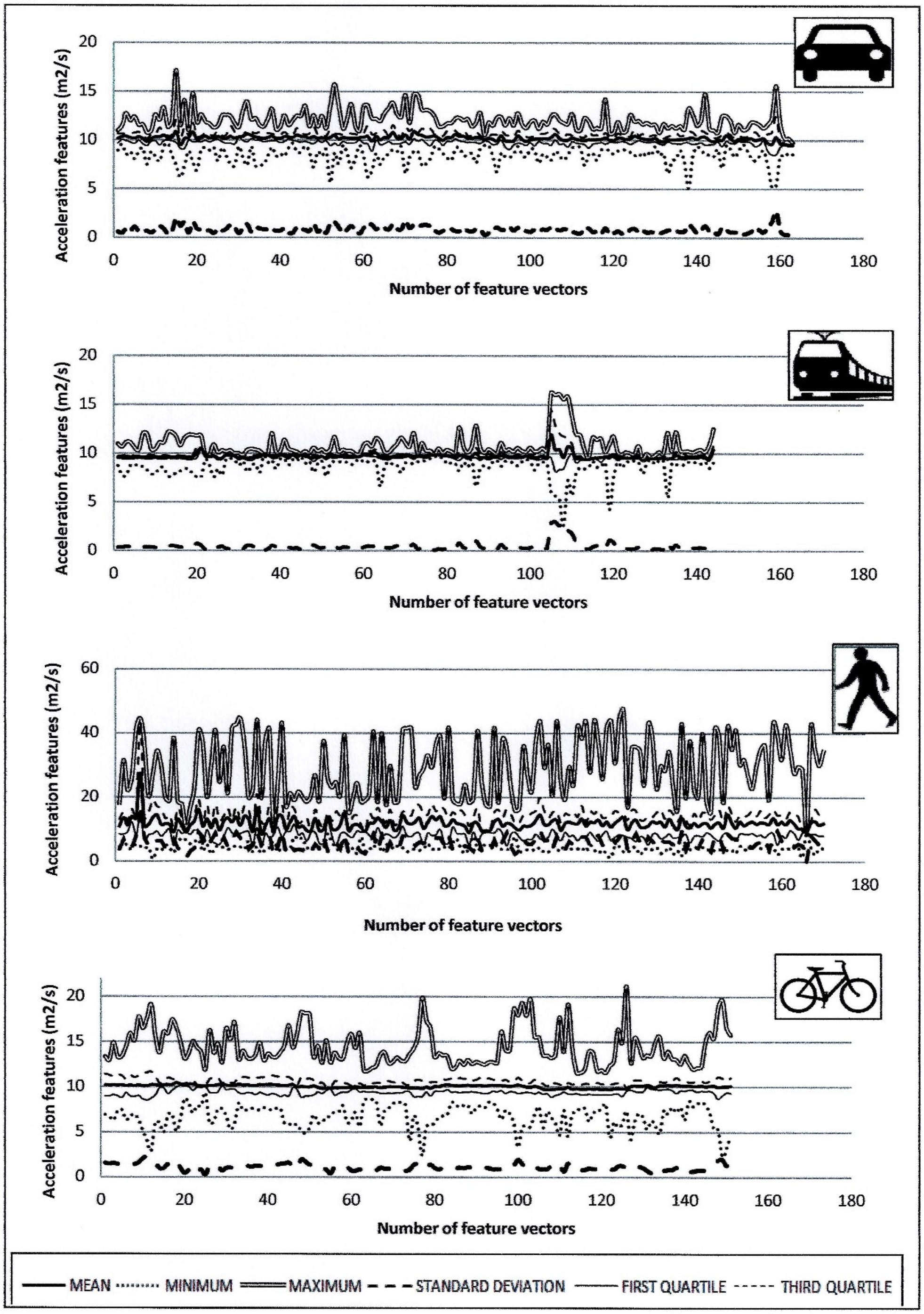

Fig. 3. Representation of accelerometer features by transportation modes

affects the accuracy of the network in recognizing patterns. The less number of neurons in the hidden layer, the network may not be able to deal with a complicated problem. However, too many neurons may lead to model noisy fluctuations in the data set which is unfavourable for the accuracy of the network. The optimum number of hidden neurons is determined by finding the lowest validation error as a function of the number of hidden neurons. In our case, 7 hidden neurons is the optimum.

In the present study a feed-forward network with three layers (input layer, hidden layer and output layer) is considered (Figure 4a). The training method used in the learning process of the NN is the standard error back-propagation rule (Rumelhart & McClelland, 1986), commonly used for the calibration of this type of NN. The output function is a tan-sigmoid transfer function that constraints the outputs of a network between 0 and 1, this function is commonly used for pattern recognition problems. In our case, the output vector has four elements, one for each class, and for an input corresponding to a certain class, that element is 1 and the others are 0.

5.1.5. Recurrent Neural Network

A Recurrent Neural Network (RNN) is a class of neural network that exhibit dynamic temporal behavior. The proposed transportation mode classifier is based on the Elman architecture of the partial RNN (Elman, 1990). In this type of neural network, there is a feedback loop, with a single delay, around each layer except for the last layer. In our case, we focus on a simple RNN containing a single, self connected hidden layer. This recurrent connection allows the network to have a memory of previous inputs to persist in the network's internal state, and thereby influence the network output (Graves, 2012).

The number of hidden neurons is the same as in the configuration of the multi-layer feed-forward neural network, as this number is enough for achieving high performance of the network (Figure 4b). The configuration of an Elman network is the following: it has a tan-sigmoid function in its hidden (recurrent) layer, and a linear transfer function (purelin) in its output layer.

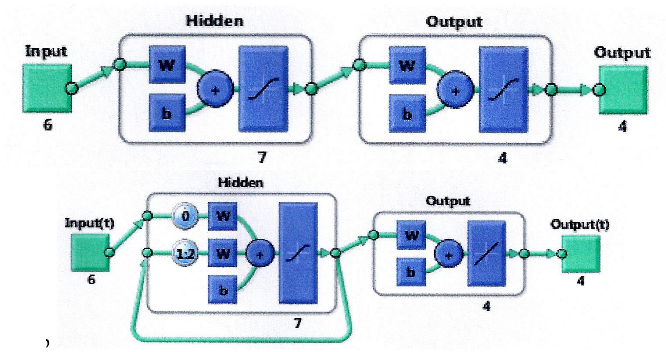

Fig. 4- (a) Multi-layer feed-forward Neural Network configuration for mode detection with 6 input neurons, 7 hidden neurons and 4 output neurons. (b) Recurrent Neural Network configuration with 6 input neurons, 7 hidden neurons, 4 output neurons and a feedback loop.

5.2. Comparison of classifiers

The performance of five types of classifiers in identifying transportation modes is evaluated in terms of classification accuracy (Table 2). Results show that RNN outperforms classification accuracy of the other techniques, significantly increasing the performance of conventional multi-layer neural networks (NN).

Table 2 - Precision accuracy of the five classifiers

	KNN	DT	DA	NN	RNN
Precision Accuracy	88.7%	88.4%	84.4%	75.25%	93.1%

For the RNN classifier, the confusion matrix is calculated for the complete test set to identify the percentage of predicted class labels with respect to the actual class (Table 3). As Table 3 shows, the overall accuracy of the RNN is 93.1%. "Walk" and "bike" are the transportation modes more correctly predicted with accuracies of respectively 98.2% and 93.4%. For the motorized modes, the accuracy is lower than for non-motorized travel modes but still around 90%: 90.8% of accuracy for the class "car" and 89.6% for "metro". The network has some problems in differentiating between trips by car and metro. Thus, the majority of the misclassified metro trips are confused as car and a high percentage of the misclassified car trips are confused as metro.

Table 3 – Confusion matrix of the RNN

Confusion matrix		Actual class				
		Car	Walk	Metro	Bike	TOTAL
Predicted class	Car	148	0	8	9	89.7%
	Walk	1	166	5	0	96.5%
	Metro	4	3	129	1	94.2%
	Bike	10	0	2	141	92.2%
	TOTAL	90.8%	98.2%	89.6%	93.4%	93.1%

6. Conclusions

The use of accelerometer features to recognize transportation modes is a recent approach in this field. Past research has used several machine learning approaches for inferring travel mode, however, not much attention has been paid to recurrent neural networks to classify travel patterns. This paper shows the usefulness of using Recurrent Neural Networks in classifying accelerometer data to identify transportation mode. The performance of this type of classifier is higher than K-Nearest Neighbors, Decision Trees and is much better than conventional neural networks like Multi-layer Feed-forward Network with backpropagation algorithm. The configuration of Recurrent Neural Networks allows them to exhibit a dynamic behavior that is convenient in transportation mode recognition.

In spite of these promising results, the performance of recurrent neural networks has to be compared to Hidden Markov models, as nowadays they are the predominant approach to classify transportation mode data.

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