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A Data-Driven Model for Pedestrian Behavior Classification and Trajectory Prediction

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ABSTRACT Pedestrian modeling remains a formidable challenge in transportation science due to the complicated nature of pedestrian behavior and the irregular movement patterns. To this extent, accurate and reliable positioning technologies and techniques play a significant role in the pedestrian simulation studies. The objective of this research is to predict pedestrian movement in various perspectives utilizing historical trajectory data. The study features considered in this research are pedestrian class, speed and position. The ensemble of these features provides a thorough description of pedestrian movement prediction, whilst contributes to the context of pedestrian modeling and Intelligent Transportation Systems. More specifically, pedestrian movement is grouped into different classes considering gender, walking pace and distraction by employing random forest algorithms. Then, position and speed prediction is computed employing suitable data-driven methods, in particular, the locally weighted regression (LOESS method), taking into account the individual pedestrian's profile. An LSTM-based (Long Short-Term Memory) model is also applied for comparison. The methodology is applied on pedestrian trajectory data that were collected in a controlled experiment undertaken at the Campus of the National Technical University of Athens (NTUA), Greece. Prediction of pedestrian's movement is achieved, yielding satisfactory results.

INDEX TERMS Behavior classification, distraction, pedestrian speed prediction, pedestrian trajectory prediction, random forests, GNSS, position fix.

I. INTRODUCTION

The economic growth and technological advancements of the last decades resulted in a significant increase in transportation needs while paving the way to the concept of future cities. This requires all transportation modes to be integrated in connected and cooperative intelligent transport systems (C-ITS), necessitating the representation of all system actors' interactions [1]. Although walking is the most commonly used form of transport, until recently the majority of research efforts were focused on vehicular transport, while analyses of pedestrian motion dynamics is limited. Pedestrian safety, though, comprises a key aspect of sustainable mobility and is essential for the implementation of C-ITS.

Pedestrian movement is quite complex, as it is sudden with random or occasional changes [2]. At the same time collision avoidance systems should accommodate for pedestrian movement predictions at a millisecond level [3]. Besides, it is important to develop online solutions that would enable redirecting suitable information and guidance back to pedestrians when moving in public spaces and large facilities (malls, airports, etc.), but also in cities within the context of pedestrian- vehicle interactions [4]. The development of C-ITS necessitates for accurate, real-time detection of pedestrian movement. The analysis of pedestrian behavior is also crucial for security, marketing and urban planning purposes as well as for infrastructure design [5]. Nowadays,

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the rapid advancements in localization technologies, coupled with the development of smart positioning algorithms, pave the way towards the provision of ubiquitous positioning data of increased accuracy, robustness and availability [6]–[7], enabling the improvement of pedestrian trajectory prediction tools.

In order to make the best of large volume of the pedestrian data generated in the big data era, it is imperative that efficient data management and analysis techniques are followed. A classical approach includes the classification of data into individual groups with common attributes. Classification of pedestrian behavior enables a finer perception of pedestrian motion, as it assists the differentiation and interpretation of the way pedestrians react to various distinct situations. Moreover, the acquisition of different pedestrian profiles facilitates the training of detailed pedestrian models. Furthermore, classification approaches provide further insight on the contribution of different factors in shaping up pedestrian behavior, thus proving to be a significant tool in movement prediction.

Pedestrian behavior refers to a multitude of motion attributes (speed, acceleration, direction, etc.) and it is affected by various factors [8]. Firstly, pedestrian behavior is highly correlated with the physical and anatomical characteristics of each individual (e.g., height, age, fitness level, state of mind). Secondly, it depends on spatial and temporal variations that pertain to environment type (mall, airport, metro, etc.), the time of day (rush hour or not), as well as the terrain type (flat area, multi-level area, etc.) that all together contribute significantly to movement dynamics and their variation. Furthermore, pedestrian-to-pedestrian, pedestrian-to-vehicle, as well as, pedestrian-to-infrastructure interactions affect pedestrian behavior. It is therefore apparent that pedestrian behavior is characterized by great heterogeneity resulting in the generation of various pedestrian behavior states. Distraction sources, including mobile phone use, affect also pedestrian behavior resulting, for example, to lower walking speeds [9]–[10]. The distraction effects incurred by mobile phone usage have received limited attention [11]–[13], though distracted walking entails high-risk, particularly in pedestrian-to-vehicle interactions [11], [14]. For instance, phone distraction and a fast-walking pace could raise serious safety issues as they lead in lack of attention. Also, they could lead to sudden change in route choice – for example, choose the shortest path while in a rush or the quieter route while talking on a mobile phone.

In this research, we develop a simple and integrated methodology to predict pedestrian movement. Initially, we group the available data into classes of different gender (male/female), walking pace (fast/normal) and phone use (if pedestrians make use of a phone or not while walking). Subsequently, we predict pedestrian position and speed considering individual heterogeneity. Several researchers have study pedestrian classification and trajectory prediction separately, whilst a limited number of studies treat them as part of the same system. The present research adopts a holistic approach treating both these processes.

The structure of the paper is as follows. In the next section, the scientific background in the field of pedestrian behavior classification and pedestrian movement prediction is described. Following this, the proposed methodological framework and its partial components, including emerging data-driven methods such as random forests, locally weighted regression (LOESS) method and Long Short-Term Memory (LSTM), are presented. The proposed methodology is demonstrated utilizing pedestrian trajectory data collected in a field survey at the NTUA Campus, Greece. Distributions of the collected data are explored and a classification of pedestrian behavior is performed. Pedestrian speed and position are then predicted using LOESS method and considering each pedestrian's heterogeneous profile. An LSTM based model is also used for comparison with the proposed method. The analysis of the data is presented followed by the discussion of the results. The conclusions, limitations and some future prospects are discussed in the last section.

II. SCIENTIFIC BACKGROUND

Several researchers have dealt with the identification and classification of pedestrian behavior under various conditions, while different types of parameters have been employed for different group definitions such as gender, walking style, and so on. In 2001, Lee and Mase [15] performed pedestrian behavior classification based on acceleration measurements for navigation purposes. They characterized each step as 'level', 'up' and 'down' of a stairway. Jan *et al.* [16] utilized Modified Probabilistic Neural Networks in order to classify pedestrian behavior into normal and abnormal and identify security threats. Chen *et al.* [17] classified pedestrian trajectory data in classes of different motion patterns to use them *a-* priori for vehicle-to-pedestrian collision avoidance. Okamoto *et al.* [5] classified pedestrian behavior in a shopping mall into three categories: 'going straight', 'finding the way,' and 'walking around,' based on each pedestrian's walking speed, trajectory variability, stopping rate and the movement of the pedestrian's head. Keller and Gavrila [18] and Völz *et al.* [3] estimated the next step of the pedestrian as 'crossing' or 'not crossing', also utilizing clustering techniques. Quintero *et al.* [19] classified pedestrian behavior into four distinct actions: walking, starting, stopping and standing. Raza *et al.* [20] recognized pedestrian gender based on body appearance using deep learning technique. More recently, Fayyaz *et al.* [21] employed both conventional and deep convolutional neural networks for pedestrian gender classification and achieved an accuracy of 89.3% and 82% respectively in their datasets. Gender recognition is a key issue in several applications such as visual surveillance, demographics, human–computer interaction [21].

Pedestrian speed prediction, utilizing machine learning techniques, comprises a topic that has attracted attention especially in recent years. Tordeux *et al.* [22] showed that

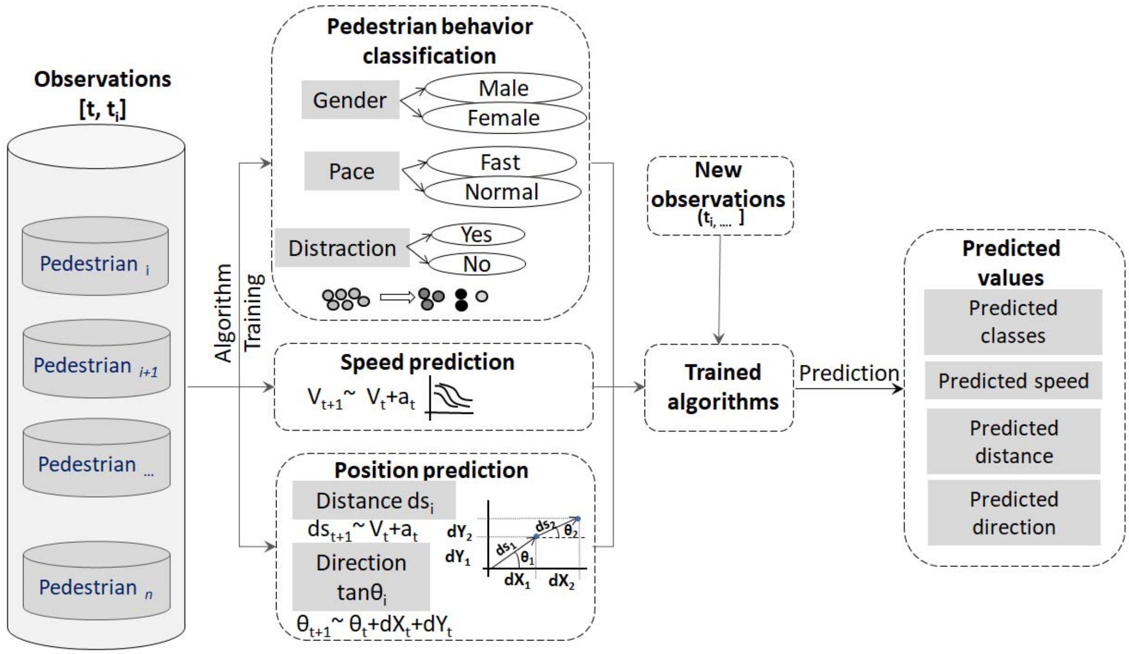

FIGURE 1. Methodology for pedestrian movement prediction.

neural networks are able to provide better estimation of pedestrian speed at corridor and bottleneck experiments, while outperforming the use of classical pedestrian models. Kouskoulis *et al.* [23] also suggested superior performance of a locally weighted regression algorithm compared to a social force model for speed modeling using real data.

Pedestrian position prediction comprises yet another significant element in future cities, as accurate predictions could prevent a considerable number of traffic injuries and improve pedestrian safety when employed in collision warning systems or embedded in autonomous vehicle path planning [24]. Pedestrian trajectory is usually characterized as series of generation actions [25]. Several researchers have used data-driven methods for pedestrian position prediction, including novel LSTM algorithms, Recurrent Neural Networks and Gaussian processes [24]–[31]. Pedestrian movement involves classes of behavioral status, speed and traveled distance values, as well as movement direction. Most existing pedestrian movement prediction models tend to deal with just one of these aspects. In this paper, we propose an integrated methodological framework to consider them all.

III. METHODOLOGY

A. METHODOLOGICAL FRAMEWORK

Capturing pedestrian behavior heterogeneity has the potential to offer accurate input in the development of Intelligent Transportation Systems. This research is based on [32] in order to expand the existing methodology considering also pedestrian trajectory prediction (i.e., position and speed features) further to pedestrian behavior classification. Thus, the present research develops an integrated methodology for pedestrian behavior classification and pedestrian movement prediction. The proposed methodology employs a classification and a regression algorithm in order to assign the obtained data into classes with similar characteristics, as well as to estimate pedestrian behavior state in real time and predict pedestrian speed and position in a short time span. In the proposed approach, the individual pedestrian profile is formed utilizing observations from previous time instants. New observations of the following time instants are then classified into the appropriate classes enabling trajectory prediction based on this personalized pedestrian profile. The proposed methodological framework is presented in Fig. 1.

B. PEDESTRIAN BEHAVIOR CLASSIFICATION

For the needs of this study, a database with pedestrian observations including position, speed, acceleration, etc. as well as individual characteristics such as age, gender and height, is utilized. The associations between these parameters are identified for every pedestrian. Initially, mean values for the attributes of each pedestrian are calculated. The classification step that follows divides the available observations into different pedestrian classes (i.e., gender, pace and distraction conditions). For the implementation of data classification, the random forests classification algorithm is applied to the relevant data. Speeds, accelerations and deviations from the mean pedestrian speed are considered in this process. The final result is a detailed historical database with classified data, while new data are assigned to the class with the highest resemblance.

The efficiency of classification methods is usually assessed via the True Positive and False Negative rates [33]. Evaluation of the classification algorithm performance is achieved using a confusion matrix for the test data. Values on the diagonal correspond to true values (positives or negatives), whereas the rest correspond to false values.

C. PEDESTRIAN TRAJECTORY PREDICTION

Trajectory is defined as the time-profile of pedestrian motion states, such as his/ her position and velocity [34]. In order to develop a pedestrian data-driven model, the required explanatory variables should be determined first, and the appropriate trajectory data should be collected. Data driven modeling requires reliable data of high precision. Positioning accuracy, availability and integrity are often considered as the most critical parameters in the quality of a position fix followed by the update rate, position coverage, continuity and system latency [4]. For example, in the case of Global Navigation Satellite System (GNSS) positioning, the observation conditions of a receiver, such as signal blockage caused due to high buildings nearby or steep gradients, signal attenuation resulting from foliage and multipath / interference due to moving elements (vehicles and/or pedestrians), can result in poor positioning or even total inability to produce a navigation solution [34]–[35]. Therefore, appropriate tools should be utilized and appropriate measures need to be taken into account when collecting GNSS positioning data in order to minimize environmental effects.

In the adopted approach, model training is applied separately for each pedestrian in order to capture individual heterogeneity and develop more detailed and representative models. Since the algorithm is trained for each individual pedestrian/road user, it is trained in real-time conditions for the behavior of that individual pedestrian and in the prevailing environmental conditions. Thus, it becomes custom-made for the particular context of the training dataset that is fed to the model.

Such an approach is useful within the context of ITS applications, the operation of which requires a personalized profile of each user/pedestrian. The application will collect the required trajectory data of the user during a training period. The trained algorithm will in turn propose a more accurate prediction of the individual's path for the following time instants. Overfitting can be avoided by using data from an extensive training period and by setting the appropriate hyperparameters of the algorithm. As the training process requires a small amount of time, the training of the algorithm can be iterated utilizing the newly collected data when the pedestrian stops moving. Naturally, the exact amount of time depends on hardware constrains and on the size of the train data. Indicatively, for a dataset of a duration of about one minute processed on an average PC (RAM 16GB), the required training time is about 1 sec. The trained algorithm can give an immediate real-time response of the pedestrian's movement prediction. This response will be useful in pedestrian-to-vehicle (ex. danger alert for possible collision) and pedestrian-to-infrastructure communication (ex. synchronization of traffic lights).

In this research, three data-driven sub-models are developed, one for speed prediction, one for distance prediction and the last one for direction angle prediction. The latter two are utilized to estimate the position of the pedestrian. The model is trained using all the available observations up to the time instant t_i and it is then tested utilizing the following time instants.

In general, the training period can vary per case. Two approaches can be adopted to determine the training period. The first one is simpler and is usually applied in smaller datasets, while the second one is more customized and can be applied when large datasets are available. In the first approach, the training period is defined as a fixed percentage of the available dataset size, for example 50% of the observations are used for training and the rest for testing [35]. In the second approach, the optimal training period is determined by the desired prediction accuracy [36]. When the algorithm returns a low prediction error (lower than a set threshold values), the training process is accomplished at a satisfactory level. The training process can be repeated for better performance at suitable time periods, such as when the pedestrian stops moving. In our case study, the first approach is chosen due to limitations in the available data.

Model training can be achieved with the employment of machine learning techniques. In our research we apply the locally weighted regression algorithm (LOESS) and Long Short-Term Memory (LSTM). The first method was selected as it has been utilized for vehicle trajectory prediction and the results were promising [37]. Thus, in our research the validity of the method is assessed on pedestrian trajectory prediction. Furthermore, LOESS has been used for our analysis, as it combines the simplicity of linear least squares regression with the flexibility of nonlinear regression. LSTM is utilized, as a reference method, as it constitutes a fast-evolving field and is widely applied in trajectory prediction [38].

A number of different explanatory variables can be selected as input in the prediction algorithm. For instance, the social force model, a well-known classical pedestrian model, expresses the directed pedestrian's acceleration as a function of the deviation of the pedestrian's velocity from a desired velocity (which varies between individuals) and the distance from obstacles and other pedestrians [39]–[40]. In this study, we focus on the movement of each individual. In order to predict the speed $v_{i\_t+\tau}$ and distance $ds_{i\_t+\tau}$ of pedestrian i at the time instant $t+\tau$, where τ is the prediction time span, we utilize speed v_{it} and acceleration a_{it} of the previous time instant t as explanatory variables (Eq. (1) and (2)). In order to predict the angle $\theta_{i\_t+\tau}$ of pedestrian i at the time instant $t+\tau$, the angle θ_{it} and the transition on x and y axis of the previous time instant, dX_{it} and dY_{it} respectively, are used as explanatory variables (Eq. (3)). As function *f*, various data-driven methods can be used. In our research, LOESS method is proposed and LSTM is used for comparison.

$$v_{i\_t+\tau} \sim f(v_{it} + a_{it}) \tag{1}$$

$$ds_{i\_t+\tau} \sim f(v_{it} + a_{it}) \tag{2}$$

$$\theta_{i\_t+\tau} \sim f(\theta_{it} + dX_{it} + dY_{it}) \tag{3}$$

The performance and efficiency of the algorithms are evaluated using the Normalized Root Mean Square Error (RMSN) metric. RMSN assesses the overall error and performance of the proposed method on speed prediction estimating the normalized difference between the observed (Y_{obs}) and simulated values (Y_{sim}) (Eq. (4)) [41].

$$RMSN = \frac{\sqrt{N \cdot \sum_{n=1}^{N} \left(Y_n^{obs} - Y_n^{sim}\right)^2}}{\sum_{n=1}^{N} Y_n^{obs}} \tag{4}$$

The Final Displacement Error (FDE) metric is also used in order to estimate the difference between the predicted coordinates (X_{sim}, Y_{sim}) and true final points (X_{obs}, Y_{obs}) (pedestrian's positions).

$$FDE = \frac{\sum_{n=1}^{N} \sqrt{\left(X_n^{obs} - X_n^{sim}\right)^2 + \left(Y_n^{obs} - Y_n^{sim}\right)^2}}{N}. \tag{5}$$

D. METHODOLOGICAL COMPONENTS

For the classification step of the methodology, random forest algorithms [42] are used. They adhere to a machine learning method which allows data classification considering both numerical and categorical variables [43]. Also, they have been used for classification of pedestrian trajectory data [44]–[45]. Decision trees are built during the training process. Associations and interactions among the input data are identified. In each tree, the optimal prediction is selected among a subset of random predictions on each node [46]. This randomization reduces the correlation between the trees and contributes to overfitting avoidance.

For speed, distance and direction angle prediction, data-driven models are developed using the LOESS method and LSTM. LOESS was firstly introduced by Cleveland [47] and the following analysis is based on [48]. Locally weighted regression $y_i = g(x_i) + \varepsilon_i$, where $i = 1, \ldots, n$ is the index of observations, g is the regression function and ε_i are residual errors, provides an estimate g(x) of each regression surface at any value x in the d-dimensional space of the independent variables. The LOESS method identifies correlations between the observed response variable y_i and the explanatory variables x_i. In particular, it estimates a function $g(x)$ at the point $x = x_0$ considering the parameter values in a parametric category. A regression surface is adapted to the data in the neighborhood of x_0. Hyperparameters of the LOESS method include the 'span' and the 'degree'. The span is a smoothing parameter of the surface which determines the percentage of the data that are taken into account for each local fit. Each local regression uses either a first or a second-degree polynomial that is specified by the value of the "degree" parameter of the method. The data are weighted according to their distance from the center of neighborhood x, therefore a distance and a weight function are required. In the application of the LOESS method, the Euclidean distance has been utilized as the distance function p to weight the data.

LSTM constitutes a Recurrent Neural Network (RNN) which is widely used in regression analysis, e.g., estimating values of future time-steps according to the observed values of past time-steps by minimizing a loss function. An LSTM network contains one or more LSTM layers that take as input a time series and produce as output another time series for future prediction. More specifically, LSTM architecture consists of three parts, known as gates: the input gate, the forget gate and the output gate [49]–[50]. Each LSTM has a cell state through which the information is carried to the gates. In the input gate, new information is stored in the cell. In the forget gate, the information is filtered and unnecessary information is dismissed. Finally, in the output gate, the final output, namely the prediction for the next time instant is produced. The whole process is run for a number of epochs (also known as iterations) in order to ensure more accurate prediction. The equations of the gates in LSTM are the following:

$$\mathrm{i}_{t+1} = \sigma\left(w_i \cdot \left[h_t, x_{t+1}\right] + b_i\right) \tag{6}$$

$$\mathrm{f}_{t+1} = \sigma\left(w_f \cdot \left[h_t, x_{t+1}\right] + b_f\right) \tag{7}$$

$$\mathrm{o}_{t+1} = \sigma\left(w_o \cdot \left[h_t, x_{t+1}\right] + b_o\right) \tag{8}$$

where, i_{t+1} is the input gate, f_{t+1} is the forget gate, o_{t+1} is the output gate, σ a sigmoid function, h_t the state of the current time step and x_{t+1} the input at the next timestamp, w_i, w_f and w_o the weights of the respective gates, b_i, b_f and b_o bias of the respective gates.

The equations for the final output are the following:

$$\tilde{c}_{t+1} = \tanh\left(w_c \cdot \left[h_t, x_{t+1}\right] + b_c\right) \tag{9}$$

$$c_{t+1} = f_{t+1} \cdot c_t + i_{t+1} \cdot \tilde{c}_{t+1} \tag{10}$$

$$h_{t+1} = o_{t+1} \cdot \tanh(c_{t+1}) \tag{11}$$

where, c denotes the cell state, $\tilde{c}_{t+1}$ is the candidate for the cell state at timestamp $t + 1$, c_{t+1} is the cell state memory at timestamp $t + 1$ and h_{t+1} represents the hidden state.

TABLE 1. **Scenarios of the conducted experiment.**

Pedestrian pace	Conditions		
	Base Scenario	***Talking on the phone***	***Texting***
Normal	Scenario 1	Scenario 3	Scenario 5
Fast	Scenario 2	Scenario 4	Scenario 6

IV. CASE STUDY

A. EXPERIMENTAL DATA

To develop and evaluate our approach, a field experiment took place at the NTUA Campus, Greece [12]. More specifically, during a controlled experiment participants were instructed to walk along a 220 m path under six scenarios (Table 1). These involved two pace conditions: normal and fast, and three distraction conditions: no distraction (base scenario), talking on the phone (distracted scenario) and texting (distracted scenario) while walking. This resulted in a total of six walks for each participant, the order of which differed between the participants to avoid order effects.

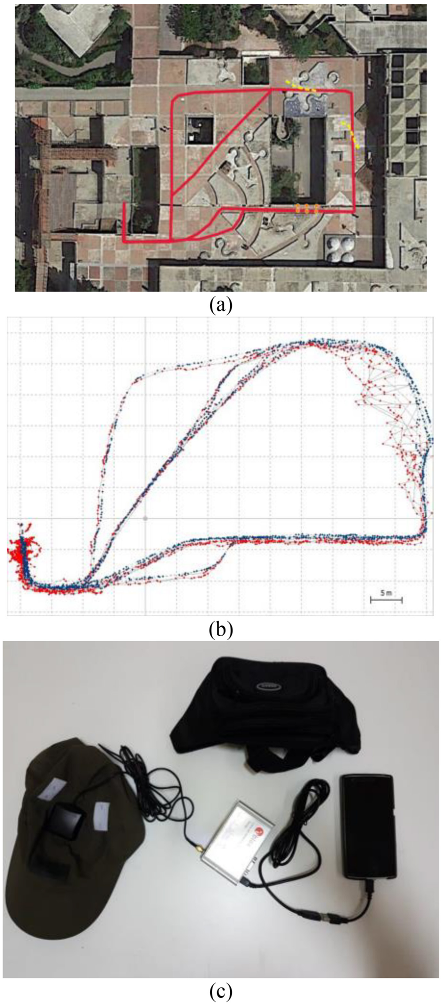

FIGURE 2. Experimental set-up. (a) Route followed by participants, (b) SPP (red) and PPK (blue) solutions trajectory comparison, (c) GNSS equipment employed for pedestrians.

The walking path of the experiment is indicated with the red line in Fig. 2a. In total, trajectories of 36 pedestrians were recorded utilizing low cost GNSS technology. As this is ongoing research, about 15.000 observations (17 pedestrians) have been processed and studied for the six walking scenarios: base, talking on the phone and texting, all of them both at normal and fast pace.

The low cost GNSS receivers u-blox EVK-M8 /NEO-M8T, u-blox C94-M8P, the high-quality geodetic type Pinwheel 702-GG satellite antenna of NovAtel, as well as the RTKLIB software and the RTKGPS+ mobile application were used for the collection of the pedestrian data. The Base Station GNSS data were collected utilizing the u-blox C94-M8P receiver connected with the geodetic grade satellite antenna (NovAtel Pinwheel 702-GG) placed on a geodetic pilar of known coordinates. At the same time, it was ensured that the pedestrian localization sensor placement was as non-intrusive as possible to minimize potential effects on pedestrian motion. For this purpose, a u-blox EVK-M8/NEO-M8T GNSS receiver was placed in a small

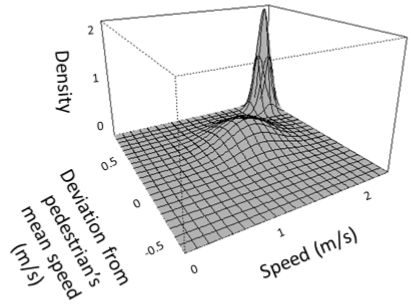

FIGURE 3. Density plot for fast and normal walking.

bag and the GNSS patch antenna was placed on the pedestrian's cap (Fig. 2(c)). The Rover Station raw GNSS data logging was handled by a smartphone device connected to the receiver via USB and running the RTKGPS+ application.

Notwithstanding the selected test site is generally free of obstacles, partial satellite obstruction and signal multipath effect due to nearby buildings - mainly due to the high-rise building located east of the area - pose a challenge to GNSS positioning. Preliminary evaluation highlighted the limitations of a single-point positioning (SPP) solution providing average accuracy at the order of ~3 m while the differential post-processing kinematic (PPK) solution provided accuracy levels of a few decimeters (Fig. 2(b)) leading to the selection of this data processing approach. The extraction of pedestrians' trajectories was implemented using the RTKLIB software resulting in an average position trueness of 0.2 m. The sampling rate of the data collection was set at 5 Hz. During analysis observations were down-sampled at 1 sec. Pedestrians' coordinates were computed during the experiment including computation of pedestrian speed and acceleration. From this point onwards the data analysis and classification, as well as the development of data-driven algorithms, have been performed in R programming language [51].

B. DATA PRESENTATION

This section presents the available data in order to draw a few preliminary conclusions. Regarding the walking pace two trends can be identified in Fig. 3. The curves that exhibit a sharp peak correspond to "fast" observations while those shown relatively flattened curves correspond to "normal" observations. The first set of curves associates with high speed values and deviations from pedestrian's mean speed, while the second one covers a wider area with lower speed values and deviations from pedestrian's mean speed.

Nowadays, the use of smartphones has been inherent part of our life, and thus, constitutes a new distraction on pedestrians' movement that takes various forms (e.g., talking or texting). As shown in Fig. 4, a consequence of phone related distraction while walking is slowing down the speed. From the same plot it is apparent that pedestrian speed decreases more rapidly when texting. Table 2 summarizes the average speed observed for different pace scenarios.

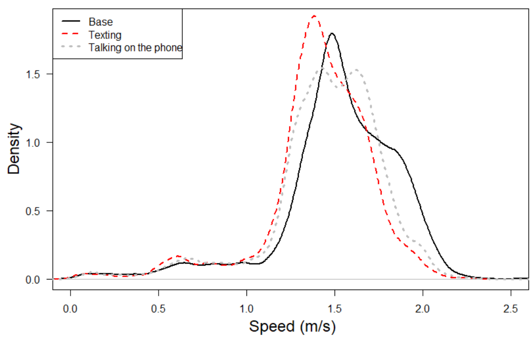

FIGURE 4. Speed density plot for different types of phone distraction.

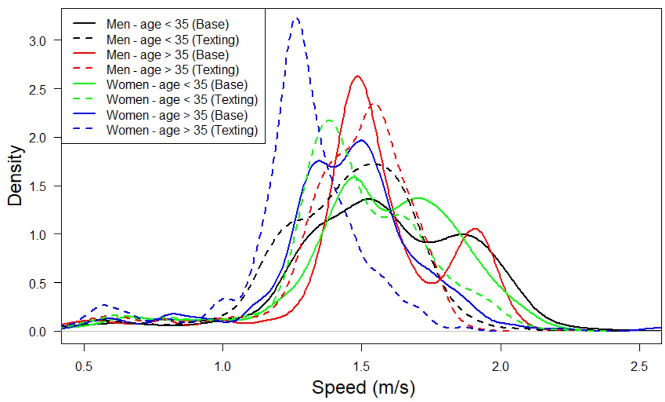

FIGURE 5. Speed density plot for pedestrian groups with different age and gender (base scenario and texting).

TABLE 2. Mean speed for all the experimental scenarios.

Pedestrian pace	Mean speed (m/s)		
	Base Scenario	*Talking on the phone*	*Texting*
Normal	1.40	1.38	1.32
Fast	1.70	1.59	1.54

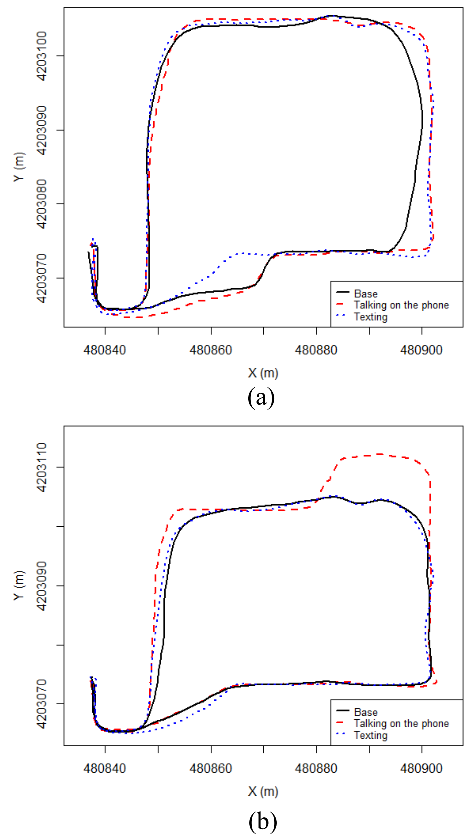

FIGURE 6. (a) Indicative routes (X and Y coordinates) under the three different scenarios: base, talking on the phone, texting. (b) Indicative routes (X and Y coordinates) under the three different scenarios: base, talking on the phone, texting.

TABLE 3. Gender recognition- confusion matrix.

Prediction	Real Data	
	Male	*Female*
Male	1779	94
Female	7	1870

Speed densities are plotted for different pedestrian groups for different conditions (base scenario and texting scenario) in Fig. 5. Results indicate that speed reduction is more intense for women.

Also, analysis proved that in addition to the walking speed, distraction can affect pedestrian route choice. Few pedestrians may not turn on time due to lack of attention resulting by phone distraction. Fig. 6 illustrates this effect for a number of indicative routes and different distraction states.

C. PEDESTRIAN BEHAVIOR CLASSIFICATION

Following the preliminary analysis we classify the available data according to gender, walking pace and distraction state. For all the classifications, the following variables have been considered for every pedestrian: walking speed and acceleration, deviation from the mean speed, traveled distance (Euclidean distance) as well as pedestrian age and height. The height variable has been omitted for gender classification as this variable was highly correlated. Half of the available data were used as train data and the remaining as test data. At first, we develop a random forest for gender classification using the train data and the explanatory variables per time instant. In this case the objective of the classification is to classify all observations of all datasets to gender classes, based on the movement characteristics. The number of decision trees is selected to be 500 as defined by the algorithm which ensures the optimal classification of the available data. Then, the trained algorithm is applied on the test data leading up to 97% gender recognition accuracy. The performance of the algorithm is evaluated considering the confusion matrix (Table 3).

At a second stage, a random forest is developed using the train data in order to identify relationships between the explanatory variables and the predictor variable "walking pace" at a time instant.

TABLE 4. Walking pace recognition- confusion matrix.

Prediction	Real Data	
	Fast	*Normal*
Fast	1196	202
Normal	499	1853

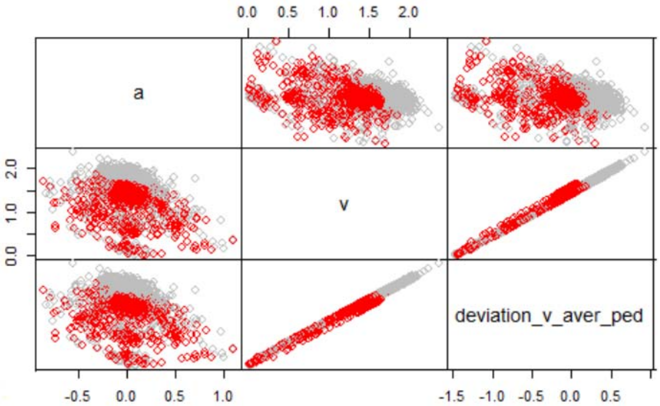

FIGURE 7. Variable relationships for "fast" and "normal" walking pace.

TABLE 5. Phone use recognition- confusion matrix.

Prediction	Real Data	
	Base (do nothing while walking)	*Using the phone (talking/ texting)while walking*
Base (do nothing while walking)	258	141
Using the phone (talking/ texting) while walking	896	2455

Then, the trained algorithm is applied on the test data leading to 81% (Table 4) accuracy for pedestrian's walking pace prediction, either normal or fast.

Fig. 7 plots two classes of pedestrians, those walking at fast pace and those at normal pace. Evidently, the higher the walking speed the higher the acceleration and the deviation from pedestrian's mean speed. In the same plot, the class with high values of these features is depicted with grey color and corresponds to the fast motion. When walking at a fast pace, pedestrians tend to move at higher speeds and perform more abrupt maneuvers than they usually do, resulting in higher values of accelerations and deviations from their mean speed.

Finally, the development of a random forest aiming at investigating the effects of phone use (texting or talking) was attempted. The trained random forest recognized the type of phone use with 73 % accuracy. The phone use recognition confusion matrix is presented in the Table 5. As this is an ongoing research, the last of the three random forests should be further improved, by exploring alternative explanatory variables through increasing the number of previous time instants and using a larger number of data series in general. Deep learning could also be tested in this context.

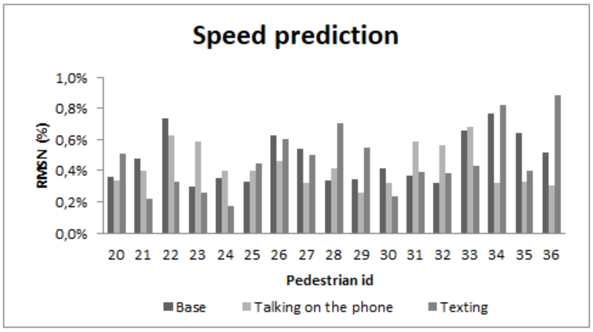

FIGURE 8. RMSN (%) of speed prediction for the pedestrians under three different scenarios using LOESS method.

For the aforementioned classifications, all the variables are significant, as p-values of less than 2.2e-16 were estimated.

D. SPEED PREDICTION

In this case study, pedestrian speed is computed every time instant (time step of 1 sec) considering the speed and the acceleration values obtained at the previous time instant ($v_{t+1} \sim v_t + a_t$). A LOESS algorithm is trained separately for each pedestrian, so that personalized profiles are developed. For every pedestrian, the first half of the dataset is used for training purposes and the remaining set of data for testing. The optimal hyperparameters have been chosen using the 'train' function, which estimates algorithm performance through resampling [52]. The training step involves the selection of the optimal span (between 0.1 and 0.9) and degree (1 or 2). 'Span' at a value of 0.75 and 'degree' at a value of 1 were chosen as the optimal values of hyperparameters by this function.

Fig. 8 presents the results obtained using RMSN as a quality metric. The results are promising, as the algorithm provides an error less than 1% of the complete dataset. The less accurate speed prediction seems to correspond to walking while texting situations. This can be attributed to the fact that texting causes the highest reduction on pedestrian speed compared to the other scenarios, namely the base and the walking while talking on the phone scenario.

E. POSITION PREDICTION

The position prediction includes the computation of the distance (ds) between sequential position fixes and the direction angle (θ). The distance ds_{t+1} at the next time instant is estimated considering the speed v_t and the acceleration a_t of the previous time instant ($ds_{t+1} \sim v_t + a_t$). The direction angle θ_{t+1} at the next time instant is estimated considering the pedestrian's transitions dX_t and dY_t and the direction angle θ_t of the previous time instant ($\theta_{t+1} \sim \theta_t + dX_t + dY_t$).

In order to estimate the predicted pedestrian coordinates at the next time instant based on the predicted distance and direction angle (Fig. 9), the following formulas are used:

$$X_{t+1} = X_t + ds_{t+1} * \cos\theta_{t+1} \tag{12}$$

$$\Upsilon_{t+1} = \Upsilon_t + ds_{t+1} * \sin\theta_{t+1} \tag{13}$$

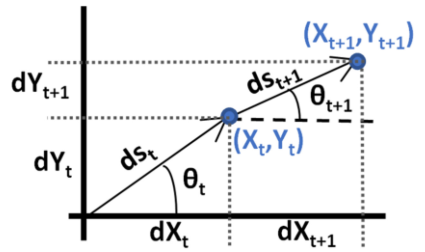

FIGURE 9. Estimation of predicted coordinates.

TABLE 6. Final displacement error per pedestrian, per scenario and method.

	Final Displacement Error (m)					
Scenarios	Base		Talking on the phone		Texting	
Pedestrian id	*LOESS*	*LSTM*	*LOESS*	*LSTM*	*LOESS*	*LSTM*
20	0.22	0.22	0.21	0.31	0.20	0.22
21	0.25	0.30	0.20	0.23	0.18	0.31
22	0.32	0.40	0.28	0.48	0.18	0.40
23	0.18	0.26	0.31	0.46	0.18	0.40
24	0.30	0.46	0.27	0.29	0.25	0.28
25	0.33	0.28	0.46	0.33	0.20	0.34
26	0.31	0.41	0.48	0.41	0.39	0.32
27	0.30	0.50	0.30	0.30	0.32	0.40
28	0.20	0.18	0.19	0.40	0.24	0.27
29	0.24	0.39	0.20	0.24	0.20	0.21
30	0.30	0.27	0.18	0.29	0.19	0.32
31	0.40	0.37	0.34	0.42	0.35	0.41
32	0.25	0.53	0.47	0.49	0.16	0.35
33	0.34	0.36	0.61	0.63	0.44	0.53
34	0.38	0.43	0.25	0.22	0.28	0.61
35	0.65	0.53	0.46	0.41	0.28	0.42
36	0.31	0.48	0.19	0.51	0.36	0.42
Average	**0.31**	**0.37**	**0.32**	**0.38**	**0.26**	**0.37**

As LSTM approach is widely used in trajectory prediction, it is also utilized in this study for prediction performance comparison (Table 6). We built an LSTM Model in R programming language using TensorFlow 2.7.0 [53] and Keras 2.7.0 [54]. The hyperparameters were tuned based on the validation error. An LSTM layer is followed by two dense layers whilst the Rectified Linear Units (ReLU) are used as an activation function.

The loss function to minimize is the Mean Squared Error. We train the model with a batch size of 60 for a time span of 20 epochs. The learning rate is 0.001 and the validation split is 0.5.

Table 6 contains the results of the aforementioned analyses. In our case study, both algorithms offer good results. However, the LOESS method seems to produce slightly better results. The results of less accurate prediction correspond to situations such as walking while talking on the phone. This is accounted to distractions resulting in bypasses on the pedestrian's route as opposed to other (base and texting) scenarios – see (Fig. 6a, b).

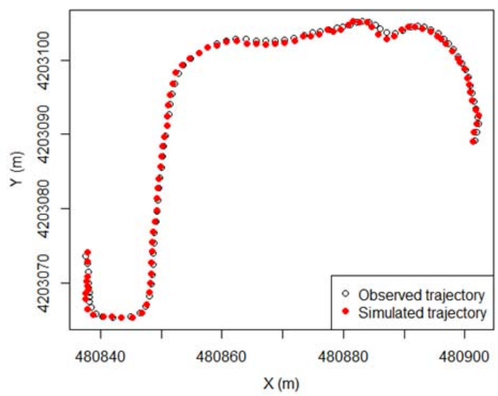

FIGURE 10. Position prediction with high accuracy for pedestrian No. 34 and the scenario walking while texting.

Alahi *et al.* [26] have managed to achieve a pedestrian trajectory forecasting for a fixed period of 4.8 sec with an average Final Displacement Error at the order of 0.60 m using the Social Force Model and 0.61 m using their proposed Social- LSTM model. Li *et al.* [55] obtained final point errors 0.12-0.28 m in normal crossing scenarios at 1 sec ahead using data-driven methods including Gaussian Process (GP), LSTM, GP-LSTM, Character-based LSTM, Sequence-to-Sequence (Seq2Seq) and attention-based Seq2Seq. In addition, Rasouli *et al.* [30] propose an algorithm based on an RNN encoder-decoder architecture for trajectory prediction. Their model outperforms state-of-the-art by 26% on their dataset. More specifically, they achieved a prediction error of 1.44 km/h (equals to 0.40 m/sec) for a time span of 1 sec. They also adopted an LSTM-based model that produced a prediction error of 1.91 km/h (equals to 0.53 m/sec) for a time span of 1 sec.

In this study, considering the findings of previous research, we exercise the LOESS method leading to an average Final Displacement Error at the order of 0.26 m at a time span 1 sec, and an LSTM model resulting to an average Final Displacement Error at the order of 0.37 m for the texting scenario. Generally, our proposed model offers good performance in comparison to the existing baselines.

Indicatively, Fig. 10 and Fig. 11 show an accurate and a less accurate prediction of a pedestrian's route. Even for the less accurate prediction, the route is very similar to the observed one. This is confirmed in Fig. 12 and Fig. 13 where the observed versus predicted coordinates are plotted for all pedestrians and scenarios.

V. CONCLUSION

In this research, a methodology for pedestrians' speed and trajectory prediction, adopting pedestrian classification as an intermediate step, has been proposed. The proposed

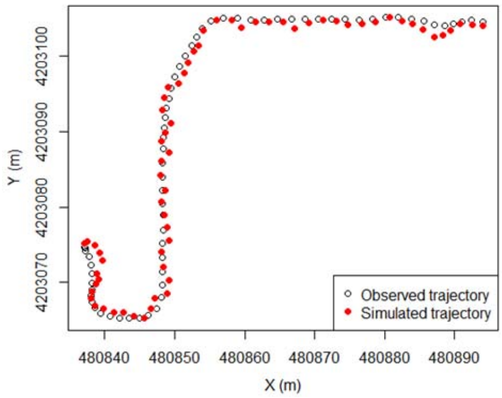

FIGURE 11. Position prediction with lower accuracy for pedestrian No. 33 and the scenario walking while talking on the phone.

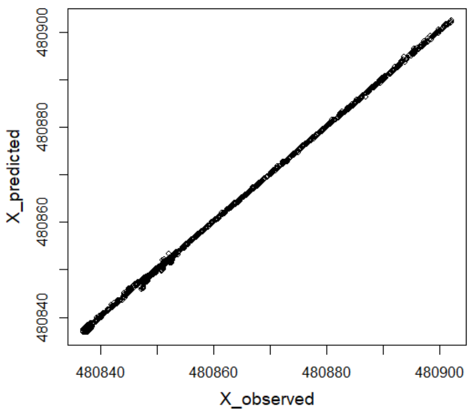

FIGURE 12. X observed coordinates versus X predicted coordinates of the pedestrians.

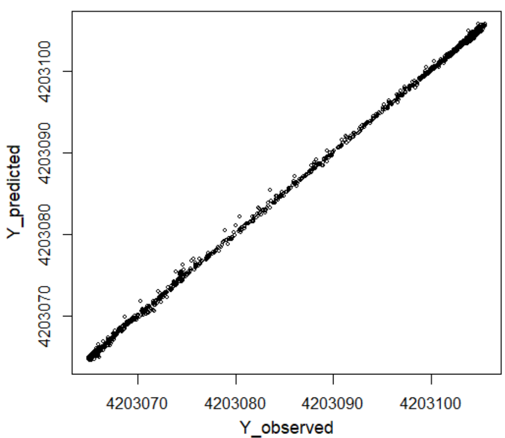

FIGURE 13. Y observed coordinates versus Y predicted coordinates of the pedestrians.

methodology utilizes random forests and the LOESS method, while an LSTM algorithm is used to provide further evidence.

The results indicate the potential of the proposed methodology and a slightly better performance of LOESS technique in comparison to LSTM for trajectory prediction on the available data. Gender recognition, walking pace and mobile phone usage recognition have also been predicted satisfactorily, though further investigation is necessary. Speed and position prediction has been achieved successfully for the majority of the data. The identification of personalized profiles can contribute to more robust pedestrian models for various regimes. The proposed methodology can predict pedestrian characteristics (gender) and characteristics of pedestrian movement (walking pace, distraction) as well as pedestrian trajectory. This type of information may be extremely useful in the context of Intelligent Transportation Systems and can be used as input for smart applications which are now being developed for pedestrian and vehicle movement prediction such as smart traffic lights, application for danger proximity, interactions with autonomous vehicles, etc.

This research contributes to pedestrian modeling as it offers an integrated methodology for classification and trajectory prediction, utilizing data driven methods. However, there are some limitations. At first, the proposed methodology is validated on experimental data considering a limited number of participants, and therefore, limited variability. In addition, the data were produced through an experiment undertaken under controlled conditions leading to discrepancies in pedestrian behavior between real life and experimental conditions. Nevertheless, despite the inherent limitations in data collection, the experimental data set offers a great opportunity to apply and test the proposed methodology, as well as a firm basis for further development. As far as the limitations in the application of the methodology are concerned, the methodology was applied for the prediction of pedestrian movement in a constrained time span. Any future efforts should extend the time span. Finally, the study does not deal with interactions between pedestrians, but focuses on the movement of one individual.

In order to cope with these limitations, further testing is necessary to study the discrepancies between realistic and controlled conditions either through incorporating pedestrian interactions at high density scenarios or scenarios that would adopt vehicle-pedestrian interactions. In this study we estimated the speed and the trajectory at the subsequent time instances using the values of the previous time instant. A multi-step ahead prediction can also be applied utilizing the estimated values for the prediction of additional time instant(s), aiming at a longer prediction time horizon, a methodology that has already been applied in other studies (e.g., for vehicles in [56]). Furthermore, in order to demonstrate the effectiveness of the proposed methodology, it should be tested on multiple datasets.

As data-driven approaches are becoming increasingly popular within the ITS domain, the utilization of novel and more efficient positioning systems is making it possible to adopt more detailed models for such applications [1]. Finally, provided that microscopic modeling reliability depends on the positioning quality and by extension on the effectiveness of the underlying pedestrian detection technologies, the collection of high-quality datasets in a minimally-intrusive manner still remains a widely open issue.

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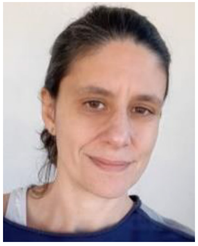

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