A Hybrid Intelligent Agent for Notification of Users Distracted by Mobile Phones in an Urban Environment

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Abstract: Mobile devices are now ubiquitous in daily life and the number of activities that can be performed using them is continually growing. This implies increased attention being placed on the device and diverted away from events taking place in the surrounding environment. The impact of using a smartphone on pedestrians in the vicinity of urban traffic has been investigated in a multimodal, fully immersive, virtual reality environment. Based on experimental data collected, an agent to improve the attention of users in such situations has been developed. The proposed agent uses explicit, contextual data from experimental conditions to feed a statistical learning model. The agent's decision process is aimed at notifying users when they become unaware of critical events in their surroundings.

1 INTRODUCTION

Doing activities such as payment of bills, organization of the agenda and reading articles which used to be performed in indoor environments can now be done on smartphones outdoors as people move about. As a consequence, users are now likely to pay more attention to their devices than to the surrounding environment when navigating through busy urban areas.

This research aims to analyze the use of smartphones by pedestrians in urban environments. Our work presents contributions in two aspects: (i) using a CAVE environment, we analyze the impact of the use of mobile devices on pedestrian situational attention; (ii) from this analysis, we developed an agent with statistical reasoning to act in support of pedestrian decision making.

This paper is organized as follows: Section 2 presents relevant research context. Section 3 presents the base experiment of Situational Awareness. Section 4 presents the build of our decision support agent. Section 5 presents conclusions and further work.

2 RESEARCH CONTEXT

Studies concerning mobile devices in urban environments have considered both the pedestrian and drivers' perspectives. Considering the driver's perspective, (Choudhary and Velaga, 2017) presents the state-of-the-art on distraction effects considering reaction time, caused by conversation and/or texting, when using a mobile phone.

The work of Jiang et al. (Jiang et al., 2018), presents the use of mobile devices in a crossing environment by pedestrians who are college students. To achieve this, the experiment is performed in a real-life, outdoor environment, while subjects are distracted by texting, listening to music and talking on the phone. Data is collected from videos and an eye tracker.

Lin and Huang (Lin and Huang, 2017) also evaluate the use of smartphones in the roadside environment. The experiments are performed in a 'semi-virtual walking environment'. Distractions in the mobile phone are texting, news-reading, or a picture-dragging task. In the environment, the participants had to respond with a designed hand gesture to roadside events. The data was collected from eye tracker and video.

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Modeling situational awareness of pedestrians can also be viewed from the perspective of the car and pedestrians. Neogi et al. (Neogi et al., 2017) and Kooij et al.(Kooij et al., 2018) present an approach to predict the intention of pedestrians crossing the street based on contextual information.

It is clear, particularly from the works of Jiang et al. and Lin and Huang, that mobile devices are becoming an increasing problem in urban environments and solutions are needed. In the research presented here, we are interested in distraction from the point of view of a pedestrian, when engaged in the use of a mobile device near traffic and how this might affect their attention and situational awareness.

In our experiment, we have developed a scene in a fully immersive virtual reality environment, where the subject is required to perform a particular task, such as crossing the road or move away from a moving car. A virtual environment enables us to have more control over experimental variables and also acquire a larger amount of data. As a mobile phone distraction, we have used a game requiring constant attention. We propose a model of situational awareness of the pedestrian based on the data obtained from their interaction with the smartphone together with environmental, contextual data. The model aims output is then used to alert pedestrians and redirect their attention back to the roadside environment. To the best of our knowledge, this is the first time such approach is considered in this context.

3 SITUATIONAL AWARENESS

In this section, we present the study about the behaviour of pedestrians using smartphones in the urban environment. This study and the data collected are the foundation for the development of the agent presented in section 4.

There are many theoretical perspectives to approach situational awareness. The Three Level Model (Endsley, 1995) is composed of a chain of information processing: perception, comprehension, and projection. The Perceptual Cycle Model (Smith and Hancock, 1995) consists of the interaction between the agent and the environment. The Theory of Activity (Bedny and Meister, 1999) uses the activities to transform a current situation to the desired situation. In this work, we followed the Three Level Model by Endsley as the theoretical background for the design of our experiment.

3.1 Experimental Design

The experiment was designed using Octave[1], a fully immersive, multimodal (audio and visual) CAVE environment. It enabled us to create a safe testing environment allowing control of experimental variables and robust data collection.

The goal of the experiment is to analyze the behavior of smartphone users in a scenario representing urban traffic. The testing environment consists of two-way lanes in a residential area, where cars can travel in any direction along these lanes. Figure 1 shows the urban scenario from above and the six possible travel directions for the cars. Participants have been instructed to stay attentive to traffic whilst standing in one designated area and; to 'move to the safe lane' if they need to avoid being hit by traveling vehicles. Figure 2 shows a participant in the scenario. The green square on the ground represents the lane of the street in which the participant is considered safe, and the red square is the lane that the participant believes that the car will be passing. The square colors change according to the participant's position. During the distracted conditions, the participant is additionally asked to interact with a smartphone game that demands continuous attention.

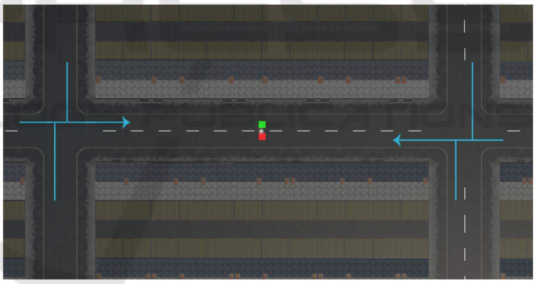

Figure 1: Superior view of the environment.

Figure 2: A participant in the environment.

Every simulation was composed of twelve cars, two cars for each of the six possible directions, one with sound and one without. This is so we can test car sound as a variable. Car instances are generated

[1]https://www.salford.ac.uk/octave

randomly from each possible direction with only one instance possible at any one time.

Twenty participants took part, each performing the ‘move to saftey task’ over three conditions with the following interaction on the smartphone:

- A “CAR” button to indicate awareness of an incoming car; no other distractions present (type 1).
- A “CAR” button to indicate awareness of an incoming car and; a game that required constant interaction (see Figure 3) (type 2).
- A button to indicate awareness of an incoming car; a game that required constant interaction and; wearing headphones with music playing (type 3).

Before the main experiment, participants could practice in an identical scenario where five car instances were generated. This allowed subjects to get familiar with the test environment. The data collected consists of videos, audios, object positions, actions, and event elapsed time. The smartphone game used as a distraction is a variation of a game called ‘Color Switch’ and is presented in figure 3. This game consists of a colored ball that has to be controlled to avoid hitting an obstacle that has a different color. It is a challenge that demands a high level of focus by the user.

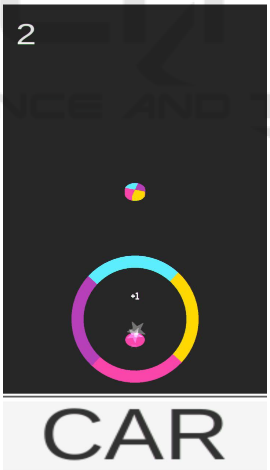

Figure 3: Game color switch, used for simulations 2 and 3.

3.1.1 Data Collection and Preprocessing

As only one car exists in the scenario at any one time, we can analyze the events occurring between the addition and removal of each vehicle. Taking the car information into consideration, the analyses use independent events, without continuity, and users distinctions. For each vehicle, the information obtained from the environment are:

- Added: Execution time in which the car was added;
- Removed: Experiment execution time in which the car was removed;
- Sound: A binary variable that indicates if the car produces sounds;
- Is Occluded: A binary variable that indicates if the car comes from an occluded position from the point of view of the participant (i.e.the side streets);
- Critical AVG Speed: Average speed computed by the car during the whole path, using the required time to reach the participant, and the traveled distance;
- Direction: One of the six possible vehicle paths;
- Critical Time: Absolute execution time in which the vehicle and user occupied the same position in the scenario;
- Critical Time from Added: Variable added with the main goal of obtaining the time of the interval between the vehicle appearing in the scenario and the moment that it occupies the same position of the user in the scenario;
- Safe Lane: Lane in the street where the user is safe;
- Simulation Type: Each of the three distraction conditions tested;
- SoundOff: using only the game as a distraction with no music on headphones;
- SoundOn: In addition to the distraction game, activates the music played in the headphones;
- Moved to Current Lane: Time in which the user crossed to the current position;
- Moved to Next Lane: Time in which the user crossed to other position;
- Time for Aware: Required time for the user to press the “CAR” button on the phone signaling awareness of a vehicle; measured from the insertion time of the car into the scenario. Figure 3 presents this feature;
- Run Over: Indicates if a user did not change lanes in time and was run over by the car;
- User Movement: Sum of the total absolute displacement of a user during an event;
- Head rotation: Sum of the total amount of rotation a user’s head during an event;
- Is Aware: Indicates if user pushed the “CAR” button in time. This state shows that the user was

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aware of the vehicle before it reached the critical time (see above).

The information extracted from the app usage during type 2 or 3 conditions are:

- Points: The total amount of points earned by the user from playing the smartphone (distraction) game;
- Max Obstacle: Maximum level reached by the user during the period playing the smartphone (distraction) game.
- Deaths: The number of times the user lost the game;

4 DECISION SUPPORT AGENT

In this section, we present an agent for notification of users distracted by mobile phones in an urban environment. We use data collected from the experiment presented in section 3 to develop a predictive model using multiple statistical techniques. The decision of (not) notifying the user is made by a voting system from three approaches. The first approach uses a Tree Augmented Naive Bayes to model the relationship between the variables and their influence to the risk. The second approach uses categories to define user safety. And the third uses continuous values to measure the awareness level.

Gathering information about the pedestrian, such as their behavior and perceptions, and contextual knowledge about the environment, the danger is inferred using previously obtained data. Based on the output, the agent decides if the pedestrian should be notified or not. In figure 4 we present a general view of how our agent uses perceived information for pedestrian decision making. The model uses artificial and statistical intelligence using different methods to find enough patterns to suggest an alert to the user. The three models together work as a black box. Therefore, the agent receives the sensor parameters and indicates if it would be necessary to notify the user.

To perform the analysis of this study satisfactorily, it was necessary to create a scheme that would gather important information distributed in metrics of events that begin in the appearance of a vehicle in the scenario and finalize in its withdrawal. In this way, the purpose of the model uses independent events, without continuity and without distinction between users. By dividing the data set obtained through the experiment in this way, we were able to obtain enough information to find patterns and classify if a pedestrian is at risk.

Using the information extracted from the experimental data, the objective is to make the model able to obtain the configuration of factors that interfere in the perception of the vehicles by pedestrians, applying methods of statistical learning. The strategy used was to verify the correlation between the variables and define approaches that lead to a dependent variable that represents the level of situational awareness. Once this variable is defined, the remaining work consists of evaluating how information available in urban environments can aid in decision making, helping to reduce the number of pedestrian accidents on urban roads. Some variables were selected on the pedestrian, such as their level of immersion in the app (number of games played and obstacles), variation of head rotation and movement in the environment as independent variables (features) of the model. Vehicle data were also used, such as average speed, direction and presence of sound. As a dependent variable (response), variables of 'Is Aware' and 'Run Over' were combined to classify the decision to notify the pedestrian about a possible risk of a potential accident.

4.1 Bayesian Model

The Bayesian methods are used to reason about partial beliefs under the presence of uncertainty (Pearl, 1988)[pag.29]. The Bayes theorem, equation 1, states that the probability of a hypothesis h conditioned by some evidence e equals its probability $P(e|h)$ multiplied by a priory probability for any evidence $P(h)$ divided by the probability of evidence $P(e)$ (Korb and Nicholson, 2010).

$$P(h|e) = \frac{P(e|h)\,P(h)}{P(e)} \tag{1}$$

The first component of our statistical model is a Bayesian network. It is a graphical model with nodes and arcs. A node represents a variable, for example, the car direction. An arc represents a direct dependence between two nodes, for example, the causal connection between nodes 'car direction' and 'awareness'.

In this approach, we treat the user awareness of a car as a supervised classification problem, using the collected data from the experiment presented in section 3. The model is built upon Tree Augmented Naive Bayes (TAN) (Friedman et al., 1997), in which the nodes are aware, direction, sound, simulation type, is occluded, run over, and max obstacle. This algorithm is implemented on Netica and is used to classify the 'aware' node based on the other nodes. Figure 5 shows the correlation between the variable

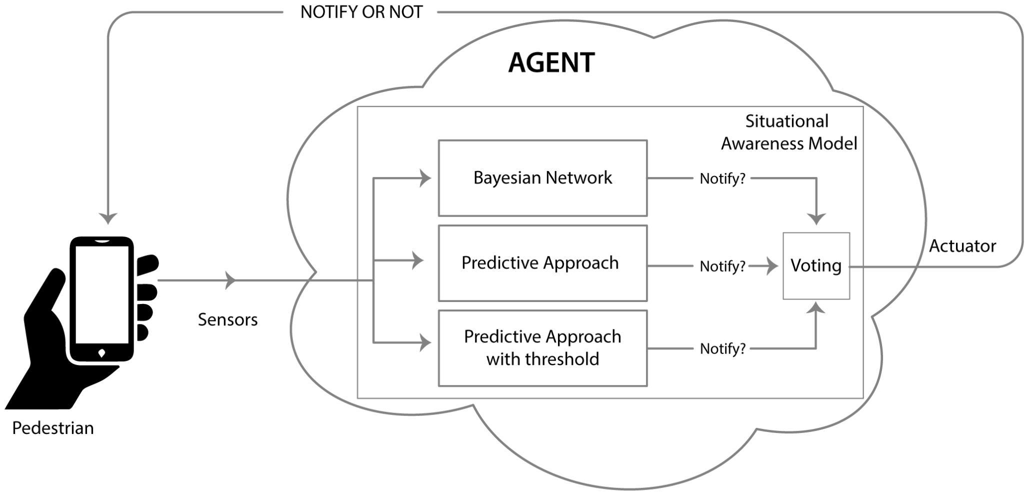

Figure 4: Decision Making on pedestrian notifications.

used during the developing of the Bayesian network and the network is presented in figure 6.

To estimate the probability of the user being aware of the car, this network uses the data collected by the agent's sensors. When the node variable 'true' in the node 'aware' is less than 60% the Bayesian component sends to the voting component that the user must be notified.

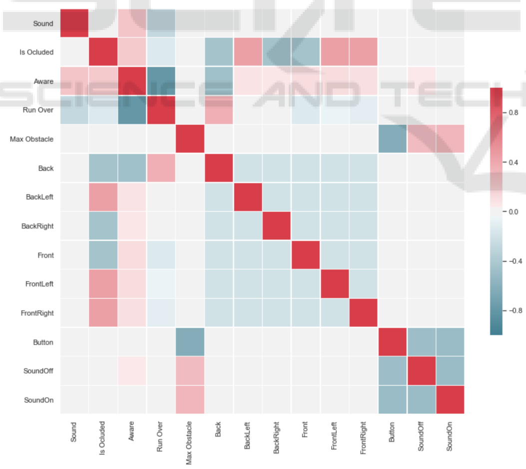

Figure 5: Correlation between variables - Bayesian network.

To exemplify the working of the Bayesian network, the following scenario consists of the following situation:

The agent perceives that the user is listening to music on the smartphone and thus the interaction level with a smartphone is 4 on a scale of 0 to 8. In the environment, there's a car approaching and, as the music is playing, it is unlikely the user will hear the car sound. Figure 7 states that there's a 48,4% chance of the user not being aware of the car. According to our proposal, this kind of situation requires an attention notification be sent to the user.

4.2 Predictive Model

As the intention is to obtain the representation of risky situations, some information from all extracted experimental data is selected to be used as parameter to create a new metric called *awareness*, which serves as a reference to evaluate the correlations and provide a computational model appropriate to the project objectives, to be used in the future. Based on the concept that an application derived from this model can use the information provided in real time to detect risk situations and alert the pedestrian, the level of situational awareness can be represented through pre-defined levels, where behavioral patterns suggest the possible warnings to the user. Another form of representation is to create a quantitative and continuous level of the situational awareness level, which assesses whether the user is fully aware of the risks of their surroundings, where 0 (zero) represents the minimum possible attention, and 1 (one) represents a completely watchful pedestrian.

As it was designed, the experiment provides enough information to evaluate the pedestrian's perception of the components from the scenario and to use the time it took to identify the presence of a vehicle coming towardS them, to avoid a possible accident. This information comes from the variables obtained in the pre-processing.

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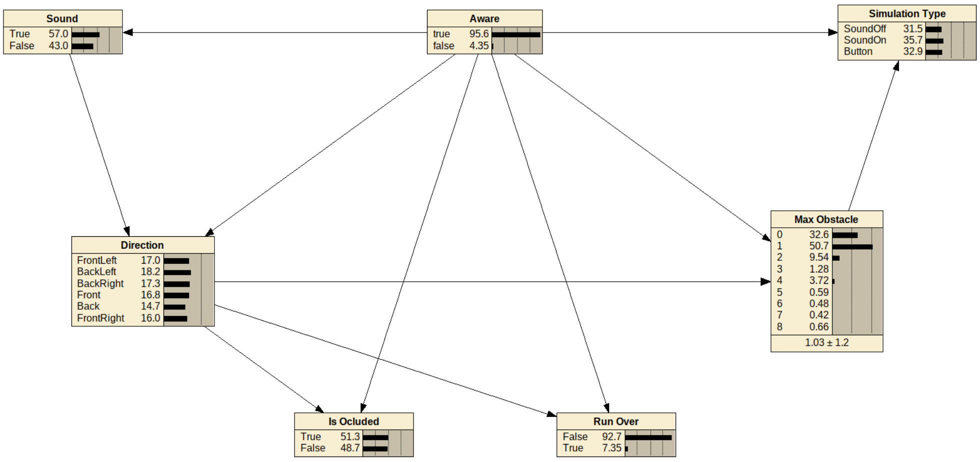

Figure 6: Bayesian network built with Netica.

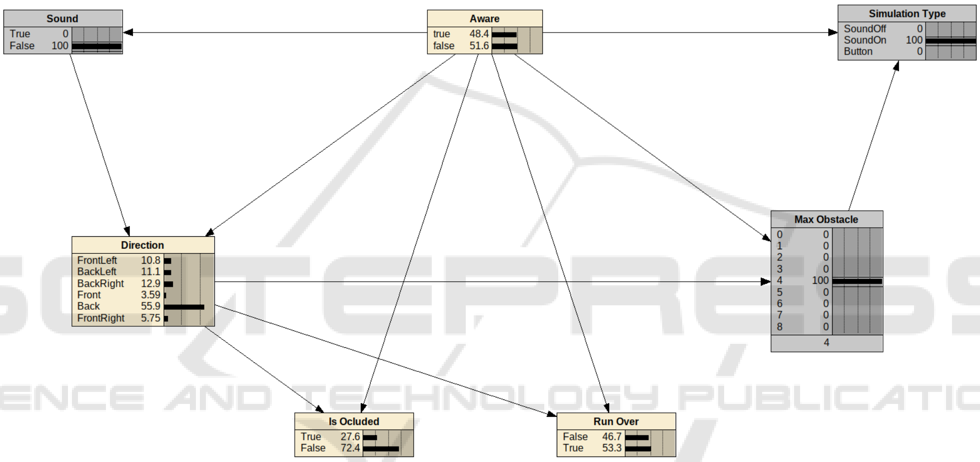

Figure 7: Bayesian network example. In gray agent's beliefs from the environment.

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4.2.1 Assignment of Situational Awareness Categories

Through the data chosen to define a dependent variable for constructing the situational awareness computational model, the first strategy is to create categories that demonstrate the level of pedestrian safety based on information about their perception. Because the 'Is Aware' and 'Run Over' variables can provide an answer to the pedestrian risks, they have been selected to compose the classes. Both variables are binary, culminating in four different combinations to classify each sample of the experiment, giving greater importance to the variable that represents the 'run over' occurrences, based on the premise that the user will prioritize avoiding an accident by moving lane, to pressing the "CAR" button to state that they are aware of the car. In this way the classes were defined as:

- danger: Category where the situation of the experiment tends to a circumstance where the user does not notice the car, nor does it avoid being run over;
- inattentive: Category where the user notices the car through the application but does not avoid being run over;
- at risk: Category where the user does not indicate the perception of the car but is not run over;
- safe: Category where the user notices the car and is not run over.

The quantitative distribution of events based on their classifications was given according to Figure 8, where the vast majority of users were in the safe state. Of the total of 732 data available, 53 were in danger, 12 were inattentive user situations, 88 were at risk and the other 579 were classified as safe situations. The data is unbalanced with 'safe' representing an overwhelmingly majority of the cases which affects our machine learning analysis.

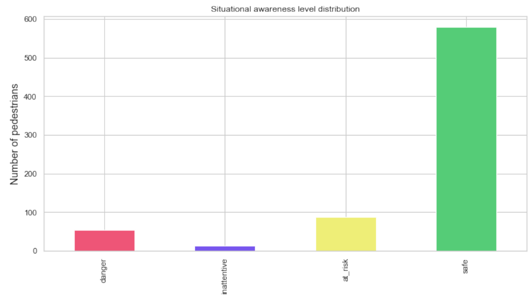

Figure 8: Distribution of pedestrian by situational awareness categories.

Using the data resulting from category creation, statistical learning techniques that work as classifiers can be used to create a model that represents each class according to the independent variables that are of the highest importance. This provides precision to enable possible notifications to aid in pedestrian decision making when the final model resulting from that work is implemented.

However, since the final objective of the project is to define whether the pedestrian and the driver should be warned about the risk of an accident, it is interesting that the classification is given in a binary way. Therefore, we can train the model based on whether a notification should be issued if the user's class is not safe, leading to a new boolean derived variable, named 'notify user'. The distribution of pedestrians in each notification class is contained in Figure 9. In this way, the mentioned method can be used to create the final model. This approach does not take into account the time required for 'car' perception by the user.

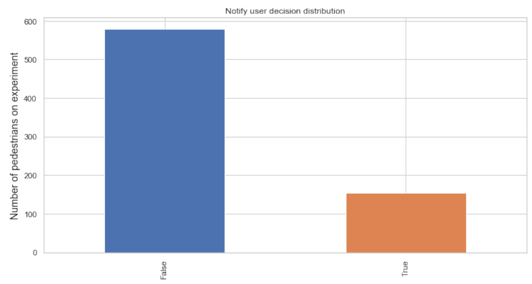

Figure 9: Distribution of pedestrians by notify user decision.

4.2.2 Assignment of Situational Awareness Continuous Level

The analysis performed through the first approach provides modeling of the problem using discrete dependent variables on the negative or positive result of each vehicle event in the experiment. As the four classes were used to understand the behavior and separation between a situation where a notification with danger alert would be necessary to the user or not, the model tends to be more restricted but this does not mean worse performance. The second approach uses the information regarding the user's safety time, i.e., did the user notice the car with enough time to avoid a dangerous situation?

Based on the variables generated in the data preprocessing step, the 'Time for Aware' variable (which indicates the time required for vehicle perception since its inception in the scenario) together with the 'Run Over' information (which indicates a crash situation) can be used together to demonstrate a quantitative level of situational awareness of pedestrians in each situation.

Since 'Time for Aware' is a variable with continuous values and 'Run Over' is a binary variable, a formula must be used taking into account a weight for each metric. Assuming that the time for a pedestrian to perceive the vehicle is inversely proportional to their level of attention, we can use this information to create a formula of the level of situational awareness of the user and using as a multiplicative factor of weight n as the data that the user was not run over in the experiment, as demonstrated in equation 2.

$$\begin{aligned} awareness = \\ & (maxTFA - userTFA)* \\ & (n - runOver*n + runOver) \end{aligned} \quad (2)$$

Where:

- awareness: final situational awareness level of each user;
- maxTFA: maximum time users took to perceive the car (constant);
- userTFA: time current user took to perceive the car;
- n: security multiplicative factor;
- runOver: a binary value, where 1 indicates that the user was run over in the experiment;

Then, for each event in the data set, the formula is applied and its values are normalized, as are all independent quantitative variables that can be used later in the statistical learning model. The value used for the multiplicative factor n was 2, which represents a doubling in the assignment of the level of situational awareness of the pedestrian case to avoid being run over. The distribution of the normalized level of the awareness variable occurred according to Figure 10.

4.2.3 Exploratory Data Analysis (EDA)

In this section, we provide some analysis based on variables extracted from the experiment in different

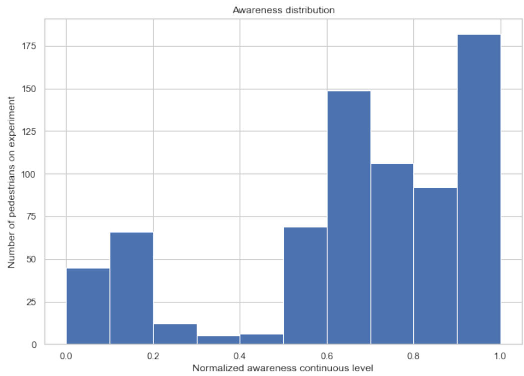

Figure 10: Pedestrian distribution by situational awareness continuous level.

approaches. For example, using continuous data for the dependent variable awareness obtained in the continuous approach, we can analyze how much it is influenced by the presence of sound in the car through a Box Plot type graph, as shown in Figure 11. The influence of sound on the level of situational awareness of a pedestrian is clear, the orange box indicates the vehicles that produce sounds, and the median is close to 90% of the maximum level measured, besides having the lower and upper quartiles near this value. Analyzing the blue box, we can observe that the number of pedestrians with a lower level of situational awareness for cars without sound is larger.

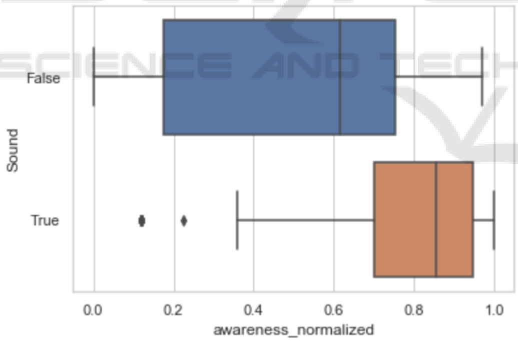

Figure 11: Box Plot of info that car has sound and measured awareness.

A larger view of the correlation between all variables is shown in Figure 12 (SA categories approach) and Figure 13 (SA continuous level approach), where the gradient in red color indicates a positive correlation and the gradient in blue indicates a negative correaltion. The data such as 'direction', 'safe lane', and 'simulation type' were transformed into multiple columns as these are categorical variables. One can not simply enumerate the values from these categories because they do not have an order of magnitude that sorts them.

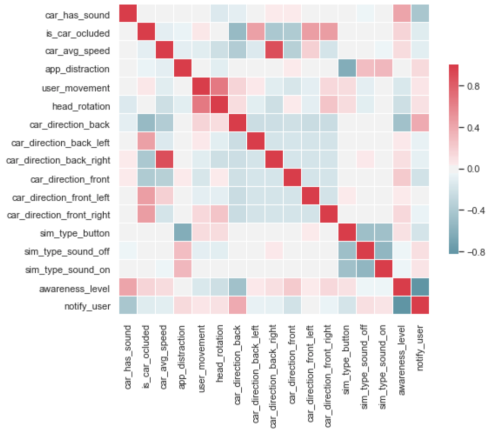

Figure 12: Correlation between variables (categories approach).

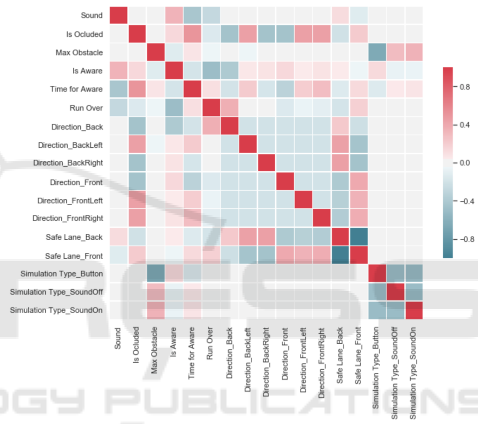

Figure 13: Correlation between variables (continous level approach).

4.2.4 Applying Statistical Learning Techniques

Following the guidelines found in the theoretical basis, some learning methods were chosen according to the characteristics found in the data extracted from the experiment, covering techniques such as linear and neighborhood, as well as ensemble learning methods, which can improve prediction efficiency. The methods chosen for classification were:

- Logistic Regression;
- K Nearest Neighbors (KNN);
- Support Vector Machines (SVM);
- Decision Trees;
- Adaptive Boosting (AdaBoost);
- Bagging;
- Gradient Boosting;
- Random Forest.

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For each method used, the cross-validation method was used (using Stratified K Folds, where each fold contains the same number of samples representing the classes), together with a selection of variables for more accurate classification. Then, accuracy metrics, confusion matrix for false negative and positive numbers were extracted, besides the ROC and precision-recall curves for verification of the integrity and reliability of the algorithms.

The best-performing techniques were those of ensemble learning, especially Bagging and Random Forest, which was more accurate and returned lower false negative rate than others, which is a very important metric since the absence of a notification can be disastrous to the pedestrian.

4.3 How These Models Influence Pedestrian Decision Making

Let the sensors inputs be: A = {car_has_sound = true, is_car_ocluded = true, car_avg_speed = 0.227491, app_distraction = 0, user_movement = 0.397433, head_rotation = 0.225124, car_direction = back_left, sim_type = button}. B = {car_has_sound = false, is_car_ocluded = false, car_avg_speed = 0.0564026, app_distraction = 0.272997, user_movement = 0.2551, head_rotation = 0.2004, car_direction = front, sim_type = sound_on}. C = {car_has_sound = false, is_car_ocluded = false, car_avg_speed = 0.0564026, app_distraction = 0.3038, user_movement = 0.4137, head_rotation = 0.5741, car_direction = back, sim_type = sound_on}. D = {car_has_sound = false, is_car_ocluded = false, car_avg_speed = 0.825519, app_distraction = 0.35905, user_movement = 0.177664, head_rotation = 0.107857, car_direction = back_right, sim_type = sound_on}. In table 1 we present a set of behavior of our agent according to these inputs.

The Bayesian network will send a message to notify only in case C, because the variable 'true' in the aware node is smaller than our Bayesian threshold of 60%. The categorical predictive model uses the Bagging Classifier technique, which provides an aggregation of decision trees with random samples from the training dataset in a setting that notifies the pedestrian only in case C and D. The predictive model with a threshold of 50% uses the Random Forests Classifier technique, in a way that fewer predictors are applied to each split in the aggregation of decision trees, providing reduced variance. Predicted the notification requirement on B and C inputs.

5 CONCLUSION

The use of mobile devices by pedestrians and drivers can increase the incidence of traffic accidents. In this research, we investigate the use of mobile devices by pedestrians and propose an agent to act as a notification system for critical distraction levels. The aims of this research were twofold: 1) to develop an understanding of the impact of mobile device usage on pedestrians' situational awareness and; 2) to develop an agent that can predict the level of awareness of a pedestrian who is using a mobile device in critical zones such as near roads.

Using a Cave Automatic Virtual Environment (CAVE), an urban environment has been designed and calibrated to simulate the interaction between a pedestrian user of smartphone and moving traffic. Based on the data collected three models were developed and with its outputs, a voting system defines if the user must be notified. We have demonstrated that an agent can effectively be built to warn a pedestrian user of potential threats in the environment. At this stage, our model requires explicit information from the environment that can be obtained through the vehicle to device communication systems or other means.

In the Bayesian model, it is easier to add a new behavior through nodes and CPT. On both predictive models, the use of statistical learning methods gives a whole set of different tools to enable finding data patterns that indicate threatening situations. Despite the satisfactory results, a larger and more balanced quantity of samples is likely to have a positive influence on the knowledge discovery for pedestrian situational awareness.

5.1 Future work

Our results with the Bayesian network must be improved. An approach we may try is to extend it as a Dynamic Bayesian Network (DBN). This approach already exists for the driver's view of pedestrians (Kooij et al., 2018). We also are planning to add online learning to fit the participant profile. Another interesting project is to develop a smartphone application with this agent. At this time we only define that the user should be notified, not specifying such notification. Depending on the level of attention, or lack thereof, the agent may have a set of actions. For example, if the user's attention is very low, and the user is listening to music, a beep may be applied. Other possible actions may be to interrupt texting, showing a warning message or blocking the display altogether.

In a future iteration, the system can further deploy on-device sensors such as camera and microphone to

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Table 1: Awareness model output.

Input	Bayesian Network	Predictive Model	Predictive Model with Threshold	Output
A	Not Notity (100%)	Not Notify (level 3)	Not Notify (0.7876)	Not Notify
B	Not Notify (99%)	Not Notify (level 3)	Notify (0.4887)	Not Notify
C	Notify (37.7%)	Notify (level 0)	Notify (0.0707)	Notify
D	Not Notify (96.2%)	Notify (level 2)	Not Notify (0.708979)	Not Notify

detect the threats. Also, with the evolution of technology, involving concepts such as Big Data and Smart Cities, cities tend to provide more and more information urban environment, making it possible to advance the potential of the model in representing the events of the context that relate to the level of situational awareness of pedestrians. In addition, if obtaining more distraction data through smartphones is possible, the model can become progressively more accurate to the decision-making process, as it will more satisfactorily the concentration level of the user.

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