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Evaluation of Transport Events with the use of Big Data, Artificial Intelligence and Augmented Reality techniques

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Abstract

The phenomenon of "smart cities" generalizes the use of Information and Communication Technologies. The generation and use of data to manage mobility is a challenge that many cities are betting on and investing in. Through the Internet of all things (IoT) and the use of sensors and mechanisms for capturing information, the number of data analysis tools such as Big Data, Artificial Intelligence (AI), and Augmented Reality (AR) has increased. With the constant use of assisted process learning (Machine Learning), it’s possible to improve event interpretation through the customization of learning protocols. Repetitively trained software can identify relevant events and report changes in critical scenarios that can trigger a series of protocols. The use of artificial intelligence techniques makes it possible to automate monotonous processes and improve transport management.
This article analyzes different technologies used to generate transport information and data validation. It is intended to experiment with the use of technologies in the detection of relevant facts, changes of state, and identification of events. It also measures the reliability level when detecting events, and studies the implementation of possible solutions into the transport management system, in order to assist in decision making processes.

Keywords: Smart cities; Big Data; Artificial Intelligence; Augmented Reality.

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1. Introduction

There is an increasing interest in the potential of Information and Communication Technologies to manage and police urban transport issues. Recent advances in urban monitoring and sensor applications have broadened the landscape of transport management operations. The challenges posed by "smart cities" and their concretion in "smart mobility" involve the implementation of new technologies (Vidal Tejedor, N. 2015; Vives, A. 2018).

This article aims to show a series of experiments in the field of transportation management in which Big Data, Artificial Intelligence and Augmented Reality techniques are used with different levels of interaction and integration. The experiments carried out are intended to show, in an empirical way, the potential uses of these technologies on their own and with different degrees of integration in order to try to manage specific situations like parking space management in urban sections. The experiments are based on the recognition of traffic-related events, specifically the identification of changes in traffic and parking status.

The study is forward-looking in approach. The initial objective was to produce a large number of images that will allow for the building of a database in which each image will be linked to certain attributes. Starting from the basic information, the learning process was conducted, following which the levels of accuracy were evaluated. Then different techniques were applied to improve the reliability of the results. Finally, the results are presented and a proposal is made for uses and future developments.

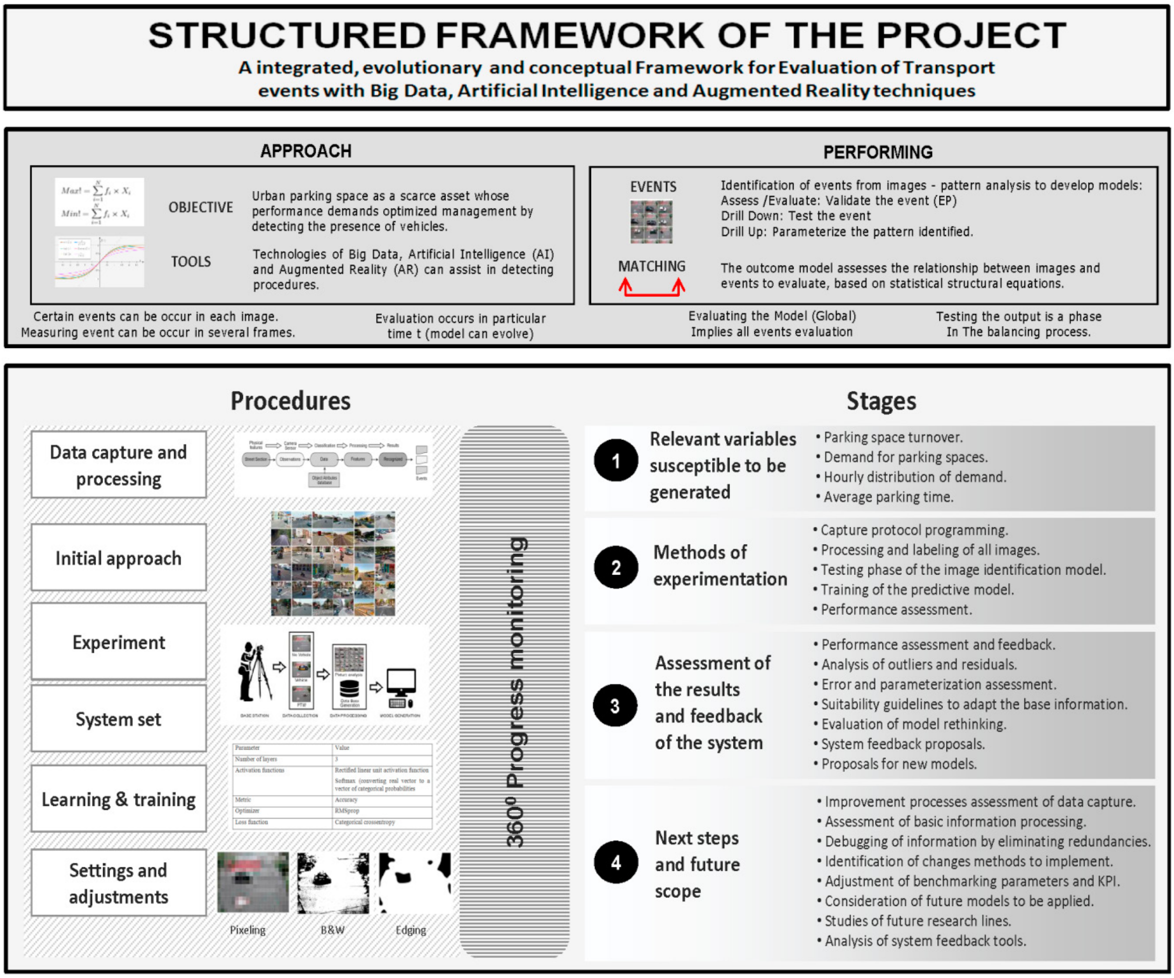


Fig. 1. Structured framework of the project.

2. Awareness of the problem

2.1. Urban parking as a scarce asset that should be optimized.

In urban environments, motorized vehicle trips require the reservation of space for circulation and parking, especially in areas with high demand and intense land use. The high demand for public space in dense urban environments puts pressure on specialized land use and its reservation for specific uses, both dedicated and by time slots. The management of such a scarce resource requires the application of different techniques and technologies that allow for optimization. The use of Big Data, AI, and AR applications in the field of urban mobility can bring advances in mobility control.

Table 1. Evolution of space distribution in the city of Barcelona (Sources: Ajuntament de Barcelona 2015; 2018).

Public Road	2011	2012	2013	2014	2015	2016	2017
Street KM	1361,8	1369	1369	1368	1368	1368	1368
Total Surface of Barcelona (km^2)	102,6	102,6	102,6	102,6	101	101,3	101,3
Surface intended for the vehicle (km^2)	10,9	11,4	11,4	11,4	11,4	11,4	11,4
Surface intended for the pedestrian (km^2)	15,32	15,81	15,81	16,18	16,83	17,52	17,52

3. Use of Big Data, Artificial Intelligence (AI) and Augmented Reality (AR) in urban transport management.

The use of Big Data, Artificial Intelligence (AI) and Augmented Reality (AR) tools will reshape urban transport management, leading to the fast adoption of more efficient transport integrated systems at an unprecedented rate. The exponential rise in crunch power lets ordinary-looking computers tackle tougher problems regarding Big Data and pattern recognition. Some authors have highlighted the potential that Augmented Reality has, so much so that they consider a breakthrough in not only machines that think, but machines that allow us to increase our perception and how the fact that officials will have improved cognition systems that can transform power relations (Anderson, R. 2020). (Bengtsson, P. 2018). Barlow, H.(1989) was one of the first to appreciate the importance of unsupervised learning as opposed to reinforced learning. The developments that Big Data has brought about in the processing efficiency of huge quantities of data are closely related to Artificial Intelligence and Augmented Reality applications, making better learning algorithms possible (Pastor, R. (2018). These technologies are used in vehicle identification, traffic management, tracking and locating vehicles in real time (Jin, J. &d Deng, Y. 2017), infraction detection (Chiverton, J. 2012); reckless actions and even driver workload (Manawadu, U. E. et al. 2018).

4. Relevant variables

The purpose of the experiments carried out in this study is to provide better tools for managing parking spaces in urban sections. Vehicle identification is considered as a challenging field in computer vision. Our research goal is to test a method to identify the presence of vehicles and types of vehicles in a street section. Once an object is detected, the next challenge is object localization in the section.

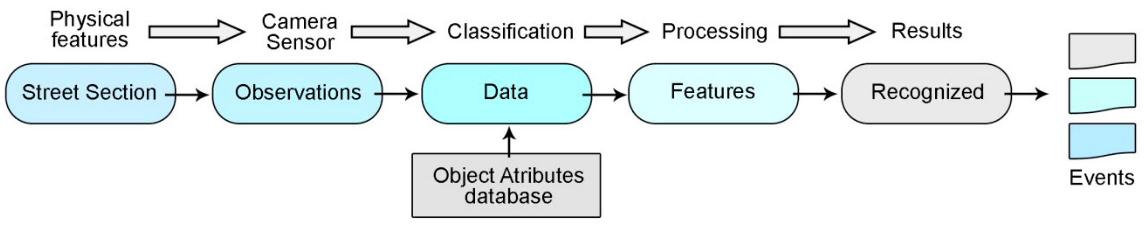


Fig. 2. Process scheme of the built-in procedure from the data collection system to the handling of the data and the identifying stages.

5. Methods of experimentation and procedures to detect the presence of vehicles in a street section

5.1. Experiment

The experiment consisted of selecting a stretch of urban space to initially analyze the phenomenon of vehicular presence. Figure 4 shows the elements of the set process. Image capture was conducted with a Canon camera (model EOS 50D DS126211; zoom lens EF-S 17-85mm F 4-5.6 IS USM). OpenCV, and a computer-vision library.

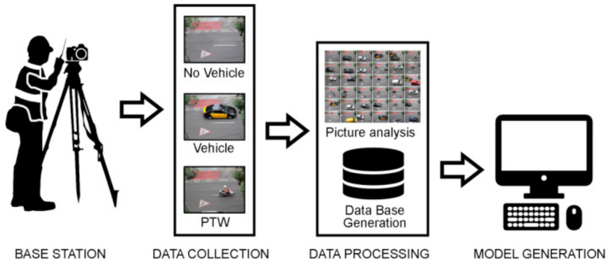
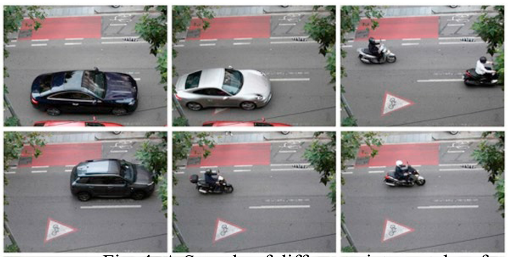


Fig. 3. System Setup. Design of the image capture system from a base station and data processing.

The phases of the project were: 1) Capture protocol programming. In order to obtain images from the installed cameras, it was necessary to develop a computer program to capture the images; 2) Processing and labeling of all images: Generation of image database; 3) Testing phase of the image identification model; 4) Training of the predictive model. 5) Test run and 6) Performance assessment. Each photo was analyzed by a specialist and a database was created in which the following fields were filled in with binary data (0: negative; 1: positive): presence of vehicle, the vehicle is a: car, a PTW, a heavy goods vehicle, a cab. (Lim, G.H. et al.).



Picture #	Vehicle presence	Car	PTW	heavy	Cab
#00001	0	0	0	0	0
#00002	0	0	0	0	0
#00003	1	1	0	0	0
#00004	1	0	1	0	0
#00005	0	1	0	0	0

Fig. 4. A Sample of different pictures taken for the performance and the table with the fields of the dataset

The use of deep learning allows for the detection of an object with certain accuracy. Open source AI libraries and data flow graphs were used to develop the neural network. To create neural networks with different layers, TensorFlow and Keras (an end-to-end open-source platform for machine learning by Google) as R modules were used, which permits the building of a neural network based on the requirements of the model with the Keras deep learning API. Once pre-processing data was completed, before training the sequential model, values for hyper parameters were chosen. Batch size (number of training examples present in a single batch), epoch's number (number of iterations passing the full dataset by the network) and learning rate (amount that the weights are updated during training) have to be fixed.

Table 2. List of the selected values for the hyper parameters selected for sequential training.

Hyper parameter	Value
BATCH - SIZE	128
NUM EPOCHS	100
LEARNING RATE	0.01

The API requires other general parameters to compile the Keras model that were fixed, as the table 4 summarizes:

Table 3. Summary table of additional general parameters applied in the compilation procedure of Keras model.

Parameter	Value
Number of layers	3
Activation functions	Rectified linear unit activation function Softmax (converting real vector to a vector of categorical probabilities
Metric	Accuracy
Optimizer	RMSprop
Loss function	Categorical crossentropy

About 2100 images were prepared to training. In our research, the primary target output is whether or not there was a vehicle on the section of road. Two experiments were performed: The first experiment consisted of identifying (or not identifying) the presence of a vehicle on the section. Then the second phase commenced, where testing was performed on the previously carried out training. Once the algorithm is selected, we proceed to split the pre-processed data. A percentage of the data, typically 80% of the total, was used as training data and the rest 20% to evaluate the model performance.

Once the model is fitted, the next step is the model evaluation phase. This was done with the remaining data, which was not used for the training phase, and will be referred to as model evaluation data. It will be the data that will be applied to the fitted model, and will be used to achieve the initial objective and evaluate it. The metric for assessing the results of the experiments is accuracy (simply a ratio of correctly predicted observation to the total observations) and precision (ratio of correctly predicted positive observations to the total predicted positive observations), which are calculated as shown below:

Table 4. Relation of the parameters applied in the classification of the classes and results of the events.

	Predicted class		
Actual Class		Class = Yes	Class = No
	Class = Yes	True Positive	False Negative
	Class = No	False Positive	True Negative

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

Where TP= correctly predicted positive values, TN= correctly predicted negative values, FP= incorrectly predicted positive values and FN= incorrectly predicted negative values.

The experiment identifying vehicles on the road section was performed and a match level of 64% was achieved. The results had a level of significance that allowed us to progress to performing calculations that count the number of vehicles in a street section. The second experiment was to try to identify the type of vehicle. It must be taken into account that this was already part of a high determining factor, that of the system having an accuracy level of 64% to detect or not detect vehicles in the section, so there is already a degree imprecision.

After the training phase (machine learning) and testing of the second experiment it was found that the results were not representative and therefore the type of vehicle that circulated on the section could not be reliably identified. Once the two initial experiments were carried out, the conclusion was reached that for the time being we should discontinue advancing the identification model of vehicle topology on a section of road and we should focus on a model identifying the presence/absence of vehicles in a section of urban road. The next steps carried out in the following sections were the implementation of image processing and the use of augmented reality techniques, in order to improve the reliability and reduce the volume of information.

5.2. Reduction of image size by pixel processing.

One of the problems of working with photographs is that the more information they contain, the more accurate they are, but there is a significant increase in file size, which makes them difficult to manipulate and process during the analysis and elaboration of results. (Dey, V., et al. 2010). Image pixilation allows the clustering of spectral information and enables the matrix comparison of a smaller quantity of data, which increases the processing rate of the information. In this stage, we proceeded to apply techniques to reduce the size of the photographs by increasing the pixel size. The size of the photos was reduced by enlarging the pixels.

By means of image pixilation techniques it was possible to significantly reduce the size of the images. The training phases (machine learning) and testing of the results were carried out and a reliability of 51% was achieved.

5.3. Transformation of black and white images.

Working with black and white images also helps to mitigate problems such as errors associated with shade and mitigates problems with bright light. The processing of the images goes through a phase of change to grayscale and then to black and white. It should be noted that the focus cannot cope with gradual illumination changes in the scene. Vehicle detection is hampered by bright sunny conditions combined with shaded areas. Using black and white images can diminish the influence of excessive brightness and shadows "noise" in the frame. If the shadow contour is not clearly detached from the objects, the possibility of detecting moving targets is enhanced. Different algorithms for moving object detection work on detaching vehicles from their shadows to achieve better results (Kilger, M. 1992). It is stated that the processing of the images to black and white allows for frame size reduction in the order of 7 times lighter in weight and thus simplifies data processing and transmission. Once the images were processed and rendered to black and white, the training process (machine learning) and testing of the results was carried out and a reliability of 48% was found. A significant reduction in the accuracy of the results was noticed.

5.4. Use of augmented reality techniques.

One technique that can be employed is to focus the analysis on the areas of the photograph where changes can occur. When working with a vehicle detection algorithm, one of the problems faced is that of redundant features not associated with the object to be detected. That is why in order to reduce the risk of presence of redundant elements it is useful to narrow down the plane of possible relevant events. The subtraction or reduction of study areas involves analyzing a reference image, shrinking the analysis area in each frame and scaring the result threshold. This is achieved by reducing the information and adjusting the binary segmentation of what is to be examined in the image, especially the detection of non-stationary objects. A reduction in the size of the images of more than 9 times the size was verified. After the training process (machine learning) and testing of the results, a reliability of 42% was checked. Therefore, a remarkable reduction in the accuracy of the results was recorded.

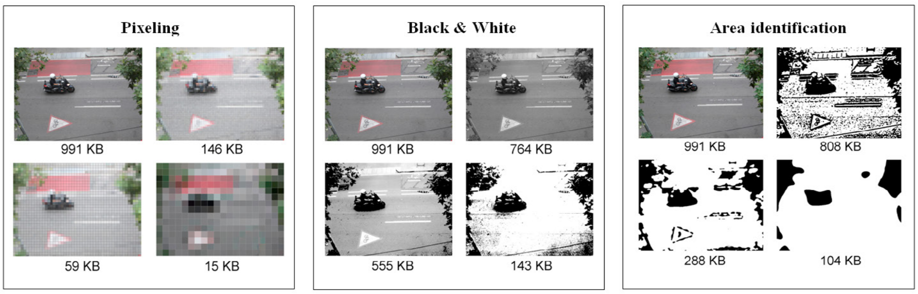


Fig. 5. Pixel processing; Black & White treatment and area identification.

6. Future scope

6.1. Debugging of information by eliminating redundancies through the identification of changes.

Shannon, C.E. (1951) emphasized how "redundancy" can be something like an opposite of information. Barlow, H. (1961) developed an idea about redundancy reduction and pattern recognition, whose ramifications have influenced the debugging of Artificial Intelligence models, vindicating the need for interpreting the goals of the system to avoid heaps of irrelevant data that may result in crucial observations being overlooked. According to information theory, this can be achieved by eliminating redundancy through inhibition and adaptation. Barlow, H. (1961) and Attneave, F. (1954) proposed the reduction of redundancies as a response through systems of transmission inhibition of non-relevant information. The movement of background objects would be regarded as permanent foreground objects. (Changalasetty, S. B. et al. 2014).

An intuitive method is to apply a Kalman filter to track changes in the background of each pixel in the image (Kalman, R.E.1960). That tool attempts to assist in predicting future states of the system by taking the series of previous records. An adaptive filter-based Kalman model could be implemented in future steps, to analyze the changing background conditions. The foreground is refreshed at each frame using the following update equation:

$$B_{t+1} = B_t + (\alpha_1(1 - M_t) + \alpha_2 M_t)D_t \tag{3}$$

6.2. Assessment of use of logistic regression to improve machine learning and binomial event classification.

In order to work with a dichotomous outcome predictor variable, Logistic Regression algorithms allows assigning the probability between 0 and 1. In this way a binary classification is obtained, with only two possible outcomes. The regression algorithm is one of the most prevalent and common classification algorithms found valuable in machine learning. The binary options plot the coordinates of the set of features with their values and then attempts the most accurate function possible that can predict the output values of the input features.

$$P(x) = \frac{e^{(\beta_0+\beta_1 x_1 \cdots\cdots \beta_n x_n)}}{e^{(\beta_0+\beta_1 x_1 \cdots\cdots \beta_n x_n)}+1} = \frac{1}{e^{-(\beta_0+\beta_1 x_1 \cdots\cdots \beta_n x_n)}+1} \in [0,1] \tag{4}$$

6.3. Use of other software or analysis procedures.

In the field of study there is a large and continuous amount of innovations and applications that can be implemented on the basis of images already available. In this case study it is relevant to have generated the images themselves, so that we can have our own base material. This material has been applied to carry out the present study, but as there are continuous innovations in the procedures, it is feasible to continue advancing in the improvement of the results already obtained from the use of other protocols and programs such as Wolfram, MatLab...

7. Conclusions

Several experiments were carried out in order to develop tools to identify vehicles in urban areas using different technologies such as Big Data, Artificial Intelligence (AI) and Augmented Reality (AR).

An initial attempt was made to identify vehicles in a stretch of road using images from different sources and it was found that it was not an adequate approach. Subsequently an experiment was performed based on the shooting of our own images by locating an observation station and collecting pictures pointing to a specific segment of road.

After applying image training techniques, it was found that the most reliable results were obtained with the least treated frames, which retain the greatest amount of raw information. By applying artificial intelligence techniques on the unprocessed images, a result of 64% identification of the presence of vehicles on the section was achieved.

The subsequent experimentation carried out consisted of image processing refinements, the application of augmented reality techniques, in order to improve the reliability of the model and the reduction of the volume of data to be handled. To this end, the black and white photos were processed, the images were pixelated to reduce, and an attempt was made to identify the volumetry of moving objects. The summary of the results obtained is as follows:

Table 5. Comparison table recognition accuracy (%).

Picture treatment	Recognition Accuracy
Raw	64
Pixel processing	51
Black & White	48
Edging	42

There has been significant advances in the use of individually self-collected in a controlled environment, because it permits working with data that is easier to treat and adjust the parameters in order to improve the result. Tests of different image treatments were carried out, obtaining mixed results. There were satisfactory results for the detection of the vehicle's presence, but in the application for the determination of vehicle type, the results were not reliable.

In global terms we must adequately validate the concept of the experiment, the location and the methodology adopted. We can consider the results as satisfactory and encouraging as a starting point for further progress.

The next challenges of using these technologies in the transportation sector will be to expand the fields of analysis to different areas such as pollution reduction, road safety, improved accessibility and seamless mobility.

Future lines of progress in the research could be considered such as the application of techniques for filtering the information by eliminating redundancies; exploring the implementation of mathematical models to increase machine learning and binomial events, as well as examining the application of other software or analysis protocols.

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