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ESTIMATION OF POLLUTANT EMISSIONS FROM ROAD TRAFFIC BY IMAGE PROCESSING TECHNIQUES: A CASE STUDY IN A SUBURBAN AREA

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ABSTRACT

This paper suggests a methodology based on the image processing technique able to automatically calculate the vehicle traffic and its components (light vehicles, heavy vehicles and motorcycles). The method also allows to evaluate instant vehicle speeds and, where necessary, to rebuild vehicle trajectories. Traffic data obtained through the procedure described below (capacities and speeds) can be also usefully applied to estimate pollutant emissions from vehicle traffic per year; therefore, the suggested method employs the algorithms defined with CORINAIR procedures, implemented in Copert 4 software. In order to evaluate how effective is the methodology, an experiment has been carried out in a suburban area, more precisely in a motorway section approaching the International airport "Falcone e Borsellino" of Palermo in Italy.

Keywords: air pollutant emissions, image processing techniques, traffic.

INTRODUCTION

In the latest years video recording digital technology has offered new opportunities to study and manage mobility with special regard to vehicle and infrastructure components of the transport system. The architecture of an image processing system generally consists of one or more video cameras, a video acquisition card and a computer. The image acquisition sensors can have different technologies, so video cameras can be divided into digital (CCD) and analog (VHS o Super VHS).

A video digital sequence, composed of a succession of images stored in the video camera hard-disk with prefixed discrete time intervals (more or less wide according to video recording system performances), has all the spatial and temporal information which, after a specific elaboration, can be usefully employed to rebuild infrastructure environment and/or vehicle motion. Such information can automatically be obtained by implementing in a processing information system various specialized algorithms which allow to detect and track objects and/or people of interest in the scene shot and to analyse any motion from a kinematic point of view. A video digital sequence can be schematized as a succession of two-dimensional matrices (cf. Figure-1), arranged by time t, in which each matrix element, denominated pel or pixel (picture element), has the value of function F(x, y, t), with $0 \leq x \leq m$ and with $0 \leq y \leq n$ integers. For a colour image which can be represented in a matrix form, the value of light intensity of each pixel is synthetically expressed as F [f_R (x, y, t), f_G(x, y, t), f_B (x, y, t)]. All that having been said, the following paragraphs concisely report the principles, considerations and algorithms, which can suggest the implementation of the image processing technique as suitable for monitoring the traffic flow and, along with specific methodologies, for estimating air pollutant emissions.

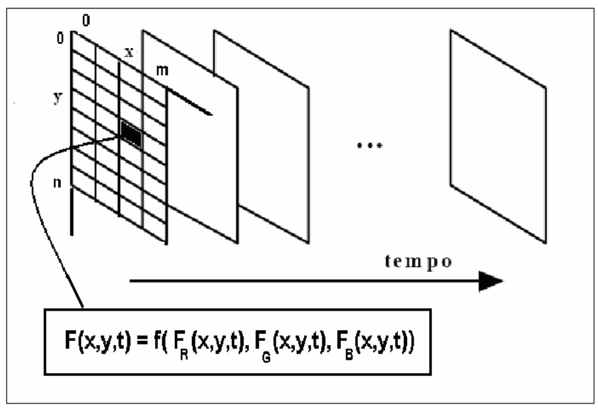

Figure-1. A schematic representation of video sequences.

SPEED AND TRAJECTORY MEASUREMENT AND VEHICLE COUNTING

Vehicle speed measurement is generally required to evaluate the operating conditions of road infrastructures already in place, the speed being a parameter characteristic of vehicle flow, like the volume and traffic capacity. Moreover, some road management authorities can be interested in finding out users' speeds in specific network sections, in order to verify any non-observance of speed limit. Based on this and other considerations, which are not dealt with now for the sake of synthesis, a procedure has been established to determine the speed and to rebuild the vehicle trajectories of any typology, just at a prefixed road section. Moreover, the system allows automatically counting vehicles and dividing them into prefixed typological categories (motorcycles, cars, commercial vehicles etc.). The elaborations necessary to determine instant vehicle speed by means of an imaging processing technique are divided into the following steps (cf. Figure-2):

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a) **Detection:** the pixels belonging to the objects in motion are found;
b) **Classification or recognition:** only the objects of interest (vehicles) are identified;
c) Labeling: a label is attached to each object of interest;
d) **Tracking:** occurring when the same object is present in different frames which follow one another in the time.

Each step involves the implementation of specific algorithms in the sequence as illustrated in the flow chart in Figure-2.

Step-1 and step-2

The recognition of an object in motion implies the preliminary detection of all the pixels which may belong to any object in motion. Such pixels are then grouped in such a way as to identify parts of homogeneous and connected images, whose peculiarities, or features, have to correspond to those of the object of interest (vehicles). The most commonly used algorithms can be classified into: a) algorithms based on the comparison with a reference image (background differences); b) algorithms based on the comparison between successive images (frame differences). The former are based on the assumption that any pixel differing, in terms of colour or brightness, from the corresponding background pixel is likely to belong to an object in motion. In other words, an object moving in the scene under observation overlaps the background and therefore belongs to a plane above it, i.e., the foreground. For such a class of algorithms (i.e., background differences), there is the problem to define and update a reference image, more precisely the background frame, so as to allow a correct detection of the pixels belonging to the objects in motion.

The latter, on the other hand, are based on the assumption that any object in motion has different positions and parts in the successive frames; therefore the value of some pixels of a generic image changes and differs from the value they have in the immediately previous image. In the procedure proposed here, both the techniques are adopted which, properly modified, allow to eliminate some of their typical inconveniences. The correct determination of the background (a scene artificially generated and devoid of moving objects) for the entire video-sequence is therefore the core of the elaboration for detecting objects of interest.

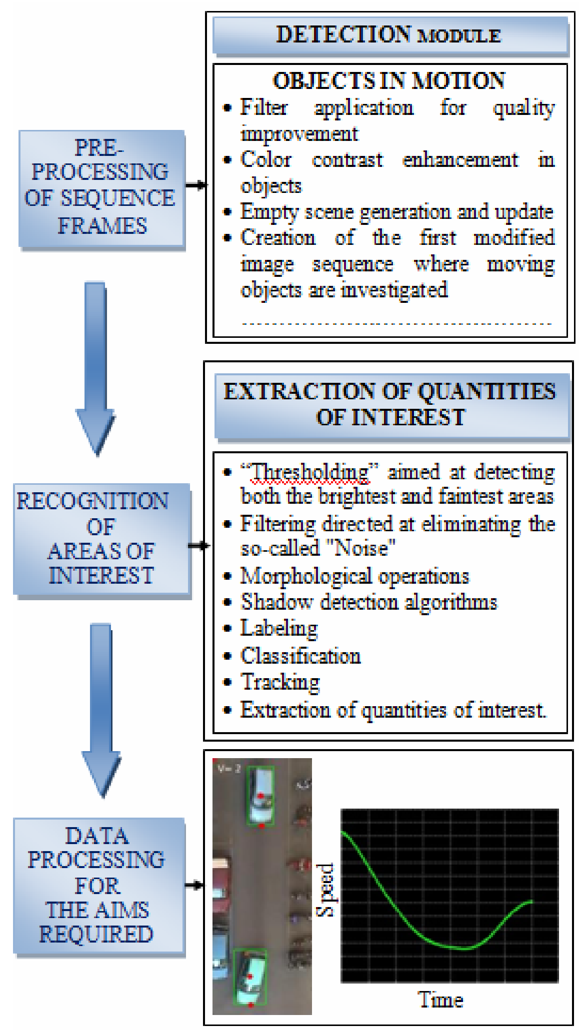

Figure-2. Flow chart on vehicle speed determination.

The entire procedure for determining the background can be schematized with two separate blocks as follows: the former aimed at extracting all the features of the objects moving in the image; the latter is directed at updating the data in the background image [1].

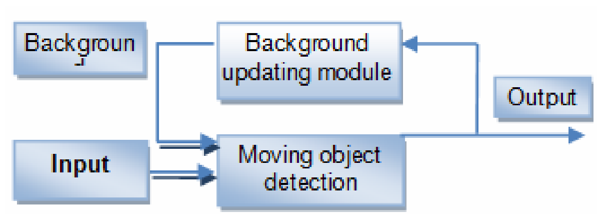

Figure-3. Explanatory algorithm diagram suggested for background image generation and update.

If the two modules operate after the scheme illustrated in Figure-3, moving objects are recognised by comparing their background which is updated by detection module outputs. It is clear that one module operates on the basis of the feedback information provided by the other.

Following the above suggested modes, it is possible to:

- detect objects in a detailed way and independently from their speeds;
- identify which elements are in motion and which are in temporary static conditions;
- update the background selectively on the basis of dynamic pixel characteristics.

In order to get the maximum precision in detecting the objects in motion, the segmentation technique has been adopted to identify objects with different features (objects in motion distinct from their shadows) or with different moving conditions. Such a choice was due to the fact that, if an object is temporarily static in the scene (e.g., in case of a queue in urban areas), it is not detected totally or partly by the difference process between the frames, while the subtraction background continues to identify the difference from the background model. With reference to the image shown below (see Figure-4) the previous algorithms for frame differences (see Figure-5), background subtraction (see Figure-6) and shadow detection (see Figure-7) allow to obtain selective and very precise object segmentation in the edge details (see Figure-8).

Figure-4. Original image.

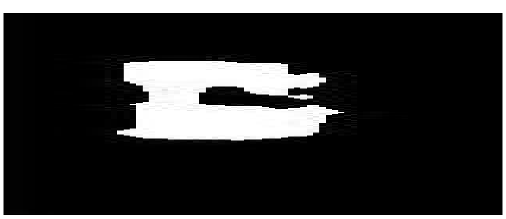

Figure-5. Double difference.

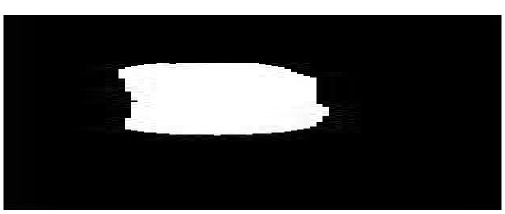

Figure-6. Background subtraction.

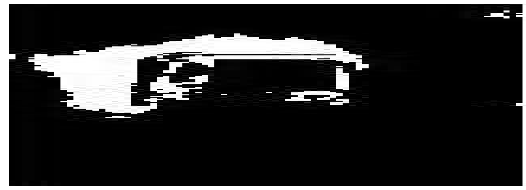

Figure-7. Shadows.

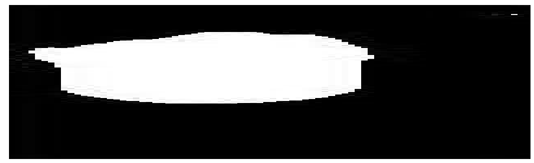

Figure-8. OR logic between the previous ones.

The logic sum (Boolean operation with OR logic) of the previous binary selections (see Figure-8), obtained downstream from the background difference, frame difference and shadow extraction algorithms, makes the moving object detection procedure extremely scrupulous. Compared to the methods reported in literature [1], the procedure in this paper allows limiting mistakes in selecting objects in motion as it enables to:

- create an updated background map through the double difference technique between the frames;
- detect objects in motion through the background subtraction method;
- segment the shadows in order to improve the selection area of an object of interest.

Step-3 (labelling)

A very simple method for representing the form and position of an object in an image consists in coding the edge information of the same object. The most widespread method for memorizing a list of points (with position but no colour information) is commonly known as "chain code", which was proposed in 1961 by Freeman [2]. The basic idea is to go along the object contour and to code progressively the direction to be followed. Once identified the coordinates of a point in the object contour (generally the highest and the left-most), the successive point is identified only on the basis of the direction to be followed which links the barycentre of the pixels. It is worth remembering that, by convention, the coordinates are always referred to an orthogonal Cartesian system originating in the first top left-hand pixel of the image. The directions allowed are usually limited, so as to improve coding efficiency. Some of the most frequently observed conventions are shown in Figures 10 and 11:

a) in case of 4-connectivity it is possible to proceed only horizontally or vertically;
b) in case of 8-connectivity it is possible to proceed diagonally, horizontally and vertically;
c) in case of 6-connectivity the deviations are marked following the pixel edge (and not between the barycentres, as happens instead, in the two previous cases).

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Though more natural, the latter encoding requires the recourse to more complex algorithms than those applied in other approaches. The directions to follow are conventionally identified with integers (4 or 8 paths) (cf. Figures 9 and 10).

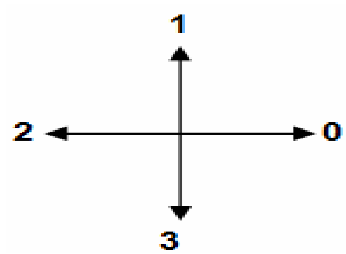

Figure-9. Connectivity neighbours

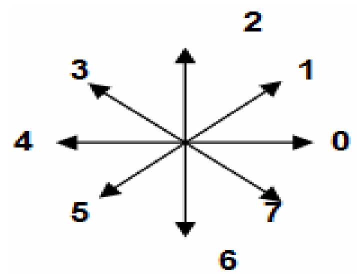

Figure-10. Connectivity neighbours.

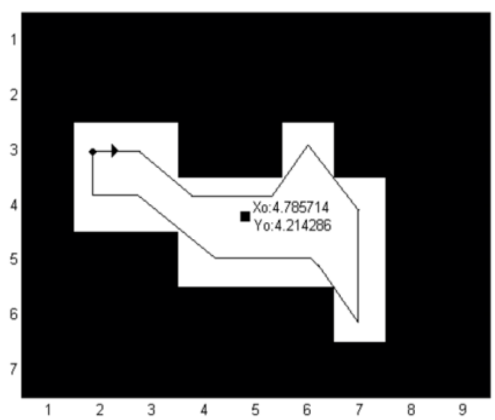

Figure-11. Binary object.

By applying an “edge descriptor”, derived from an 8-path algorithm, to the object schematically illustrated in Figure-11, the following encoding is obtained: [0701766344342].

Once detected the edge, the following geometric object data can be easily calculated [3, 4]:

- **Area** (A)**:** expressed in terms of pixel number representing the object;
- **Perimeter** (P)**:** pixel number forming the edge denoted with P;
- **Compactness** (C)**:** given from the following relation C=P2/A (the square of the perimeter makes the relation independent of the real dimensions of the object).

Often, the object detection in an image is performed on a small rectangle which comprises the area whose sides are tangential to the object edge. Such a rectangle, called bounding box, is easily identified by means of the four vertex coordinates. Generally the direction of two parallel sides of the rectangle is considered to coincide with the direction of the major axis of the object. In order to complete the necessary data useful for defining the object geometry and position, also the coordinates of the centroid (approximately the area barycentre) and of the central point of the front edge of the bounding box are determined. The extraction of some geometric quantities allows distinguishing vehicles from the other objects in motion. Any object is considered to be a vehicle only if the following conditions occur at the same time:

- the object centroid (see Figure-11) is to be inside the domain of the pixels along the strip destined to the movement;
- the length, width, area and compactness of the object are to be contained in pre-established domains.

The limits of such domains have been defined on the basis of the image resolution and the real dimensions of circulating vehicles.

Step-4 (tracking)

The tracking operations [5, 6, 7] of the objects in motion (blob or Binary Large Object) are calculated with "high-level" algorithms which can associate the same object to the positions it occupies in the different successive frames. A simplified schematization of the different operations employing the tracking algorithm is shown in Figure-12.

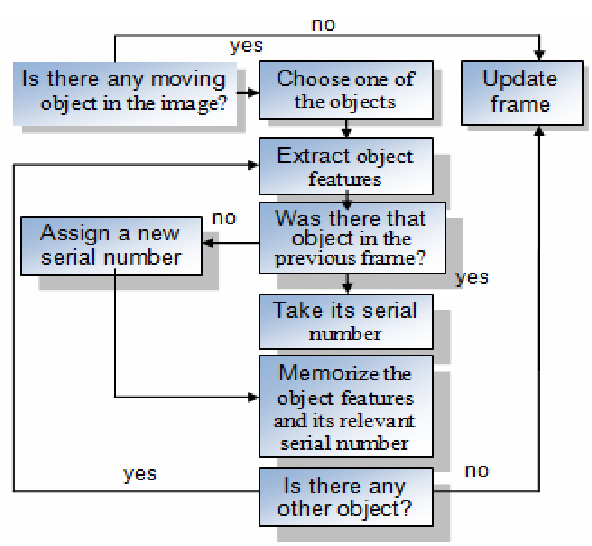

Figure-12. Tracking algorithm operations.

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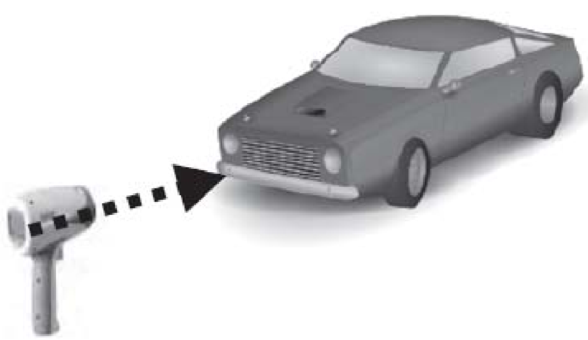

Figure-13. Scheme of a speed gauge.

The most important aspect of the tracking module concerns the recognition of the same object in successive video sequence frames (Matching operation). This operation is performed by maximizing a similarity measure which is rather complex if there are several blobs whose form, dimension and movement direction are not predictable.

In the application here developed, the blob number in an image is limited and the recurrence of the same blob can be established if the following conditions take place:

- similarity of colorimetric characteristics;
- similarity of geometry (regardless of any perspective distortion and slight noise);
- congruence of centroid positions in successive images.

In conclusion, the frame by frame centroid position is achieved for each vehicle detected near the entry and exit section of the image under examination. The blob movement direction is identified and, if it is consistent with that expected, the geometric features are shown to be compatible with vehicle features. Once such verification is made, the centres of the front side of the bounding box are calculated in two successive images to determine the vector distance between the positions of these points. The vector distance is then recon ducted to real measure. It is therefore necessary to proceed with a preliminary calibration in order to convert the distances measured in the image into real distances. The discrete performance of the vehicle speed with regard to a road section employed to calibrate the procedure, is shown in Figure-2. All that considered, image processing technique offers great potentialities to estimate kinematic parameters of the vehicle flow and therefore it can be utilized in urban or suburban area, as well as in studying conventional and innovative road intersections [8, 9, 10, 11].

Moreover, it can be implemented in other disciplinary engineering areas, for example in monitoring railway and road track wear [12, 13, 14, 15, 16, 19, 20].

Estimation of pollutant emissions

Pollutant emissions can be estimated by means of Copert software which has been developed as a European tool for determining road transport emissions [17, 18]. The model takes into account such traffic and vehicle parameters as vehicle types, categories and population, annual mileage (km/year), mean fleet mileage (km) etc. (see Figure-13). The methodology allows calculating the exhaust emissions of carbon monoxide (CO), nitrogen oxides (NO_X), non-methane volatile organic compounds (NMVOC), methane (CH_4), particulate matter (PM) and carbon dioxide (CO_2).

The emission factor (EF) for each exhaust emission and for each transport modality m is calculated by means of the following equation:

$$EF^{m}_{\lambda jk} = a^{m}_{\lambda jk} + b^{m}_{\lambda jk}\, v^{c^{m}_{ijk}} + d^{m}_{\lambda jk}\, v^{2} \text{ (g/km)} \quad (1)$$

Where: λ index is the vehicle age; J index is the fuel type; K is the engine displacement; a, b, c are three parameters correlated to single pollutant emissions.

$$EF^{m}_{\lambda jk} = a^{m}_{\lambda jk} + b^{m}_{\lambda jk}\, v^{c^{m}_{ijk}} + d^{m}_{\lambda jk}\, v^{2} \text{ (g/km)} \quad (2)$$

The total emissions E_i for the pollution *i* can be calculated as:

$$E_i = EF_i \cdot N_i \cdot \overline{p}_i \text{ (g/year)} \quad (3)$$

Where: $\overline{p}_i$ is the mean length of the annual trip (km) and *Ni* is the number of annual vehicles belonging to the same emission group.

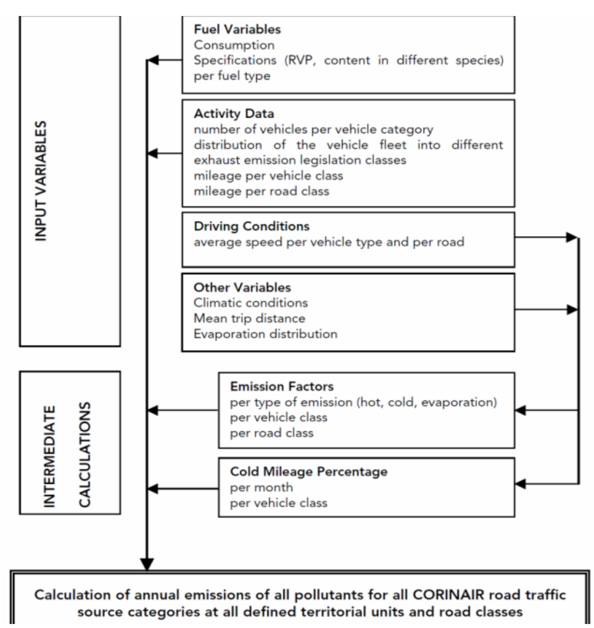

Figure-14. Flow chart of the application of Copert methodology.

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A case study in suburban areas

In order to better clarify the potentialities of the suggested method, the following is the estimation of pollutant emissions in a road section (km. 3.5 long) which links the city of Palermo to the international airport Falcone-Borsellino (see Figure-14). The traffic measurement has been performed with two infrared video cameras and a high-capacity recorder. Each video camera, installed just at the service road adjacent to the motorway link road (via della Tonnara), has shot the vehicles driving along both carriageways, day and night. The video recordings have been utilized to determine the hourly traffic volumes as well as the contribution given from light vehicles (motorcycles and cars) and heavy vehicles, respectively. By way of an example, the result from detection and tracking analysis is shown in Figure-15. The image processing technique has also allowed to evaluate average speeds. In order to verify whether the processing results were correct, the point speed measurement has been performed by means of a very speed camera, made up of speed radar with digital technology (precision equal to ± 2 km/h). The driving speed in the link road under study has shown to be, on average, around 10 km/h higher than the limit imposed, equal to 80 km/h, thus becoming 90 km/h or so. The speed mostly remains constant all along the road.

The analysis results and the average daily traffic projections until the year 2020 are reported in Table-1. ADT values have been obtained by taking also air passenger traffic projections into consideration.

Figure-15. Survey station location for vehicle counting.

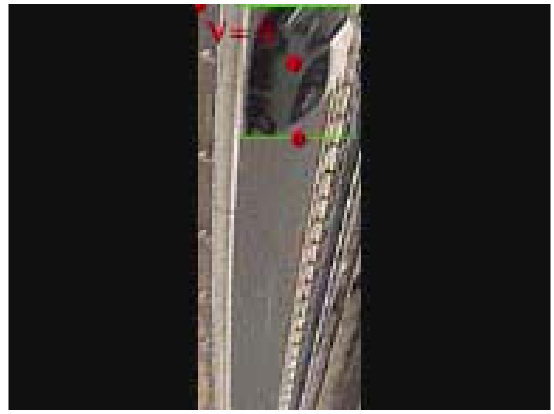

Figure-16 (a). Vehicle detection and tracking in the link road under study.

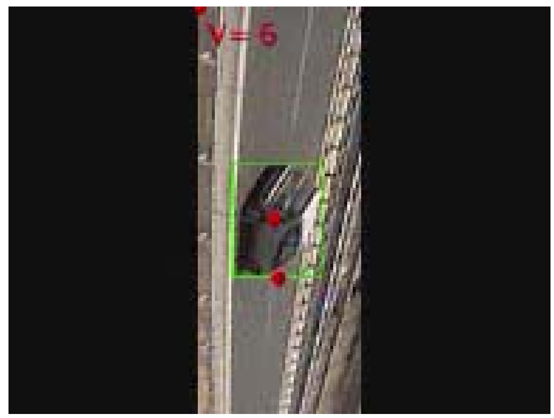

Figure-16 (b). Vehicle detection and tracking in the link road under study.

Figure-16 (c). Vehicle detection and tracking in the link road under study.

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Table-1. ADT values estimated for the period 2013-2020. Such vehicle traffic has then been associated to the distribution per emission class equal to that covering the circulating park in Italy.

Year	ADT_{7-19}	ADT_{6-22}	wt %	ADT_{19-7}	ADT_{22-6}	ADT_{20-22}	wt %	ADT
2013	10967	13987	2,4	5250	2231	1458	4,4	16217
2014	11466	14623	2,4	5489	2332	1524	4,4	16955
2015	11987	15287	2,4	5739	2438	1593	4,4	17725
2016	12532	15982	2,4	5999	2549	1666	4,4	18531
2017	13101	16709	2,4	6272	2665	1741	4,4	19373
2018	13697	17468	2,4	6557	2786	1821	4,4	20254
2019	14320	18264	2,4	6856	2913	1904	4,4	21176
2020	14973	19096	2,4	7168	3045	1990	4,4	22141

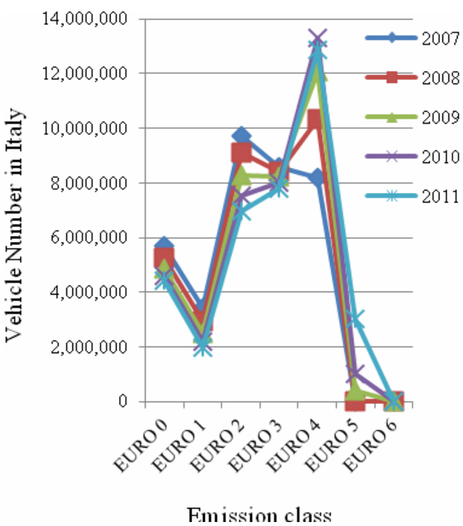

Figure-16. Vehicle park development per emission class and year.

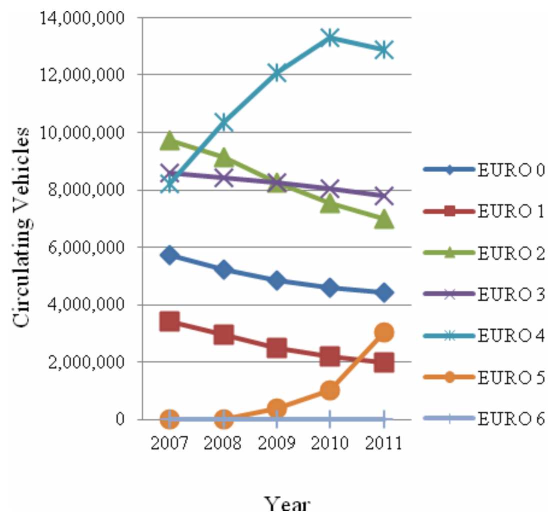

Figure-17. Vehicle park development per emission class and year.

Table-2. Vehicle park distribution per emission class in Italy.

Year 2012									
Supply	Euro 0	Euro 1	Euro 2	Euro 3	Euro 4	Euro 5	Euro 6	Others	Tot.
Other types	1.252	13	6	57	20	281	-	287	1.916
Petrol	3.501.542	1.532.101	4.941.095	3.404.866	5.594.974	1.180.596	5	7.978	20.163.157
Petrol or liquefied gas	254.854	108.140	269.883	128.131	938.604	76.398	-	245	1.776.255
Petrol or methane	48.292	26.709	97.293	71.518	344.691	92.455	-	36	680.994
Diesel fuel	630.361	300.722	1.667.401	4.189.465	5.999.079	1.694.993	2.460	420	14.484.901
Non identified	3.096	121	77	206	115	4	-	2.458	6.077
Total	4.439.397	1.967.806	6.975.755	7.794.243	12.877.483	3.044.727	2.465	11.424	37.113.300

Table-3. Vehicle park distribution in the motorway link road examined, per emission class.

Year	Euro 0	Euro 1	Euro 2	Euro 3	Euro 4	Euro 5	Euro 6	Others	Total
2013	2112	936	3319	3709	6128	1330	1	5	16217

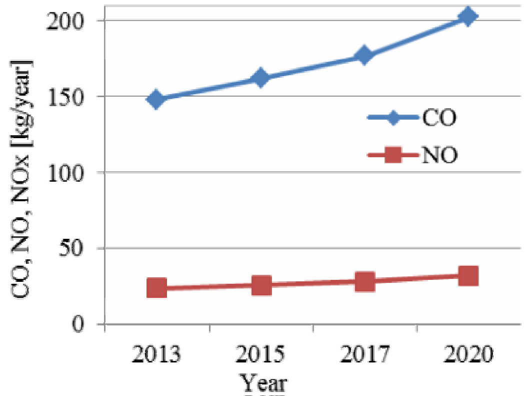

Figure-19. Pollutant emissions estimated.

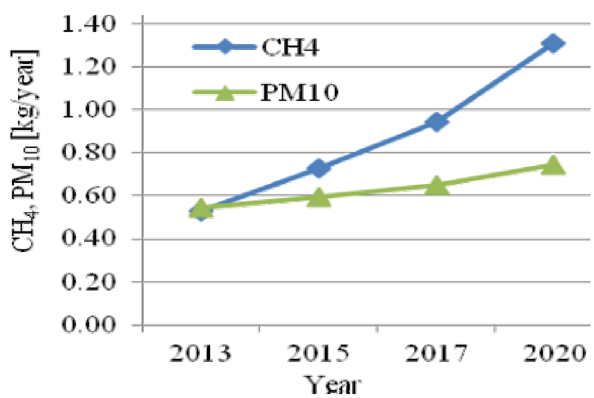

Figure-20. Pollutant emissions estimated.

By way of an example, Figures 19 and 20 show CO, NO, CH_4 and PM_{10} emission values estimated by means of calculations (1), (2) and (3) from 2013 to 2020, obtained by considering ADT developments from 2013 to 2020 and the traffic composition per emission class.

CONCLUSIONS

Among the high-efficiency automated survey methods, used for monitoring the characteristic parameters of a transport infrastructure, image analysis techniques are of paramount importance for their great operating potentialities and the limited purchasing and management costs.

This paper proposes a procedure for monitoring the vehicle traffic which allows to count vehicles (and distinguish them by size into light and heavy vehicles and motorcycles) and to determine the driving speed. Traffic and kinematic data can be used as input data for implementing models to estimate pollutant emissions. To this end CORINAIR procedure implemented in Copert software is suitable to be applied.

The methodology has been carried out in an experiment on an Italian major arterial route which links the city of Palermo to the international airport Falcone-Borsellino. As expected, the proposed method has allowed estimating the average daily traffic (ADT), the driving road speeds and the air pollutant emissions. Moreover, by utilizing the air passenger traffic and vehicle ADT projections, the future pollutant emissions have been estimated covering a seven-year period, from 2013 to 2020.

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