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DESIGN OF AN ALGORITHM FOR VEHICULAR TRAFFIC DETECTION USING COMPUTER VISION TECHNIQUES

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ABSTRACT

This work presents the design of an algorithm for vehicular traffic detection using computer vision techniques. The objective is to perform the counting of the vehicles that transit on a certain route and also know the average speed with which these vehicles travel. For the development of this project it was necessary to have devices whose technical characteristics allow the fulfillment of the proposed objectives. For this it was determined to use a camera with a resolution in high definition (1280x720p) and a capture rate of 30 frames per second. Another requirement for this project is based on the compiler, which must be compatible with the OpenCV library and the base programming language (C language). Thus, a compiler such as Qt Creator is required, with which all the programming of both the algorithm and the application are developed.

Keywords: artificial vision, images detection, openCV, traffic flow, video processing.

1. INTRODUCTION

The increase in vehicles on the roads around the world, and specifically in Colombia, makes engineering pose new challenges. The need for more structured and physically optimal and resilient routes is increasing. Due to this, it seeks to satisfy the needs of the inhabitants of the cities, without stopping to analyze that it is also the cause of one of the most conflicting aspects of the urban system in terms of its sustainability: Environmental pollution in its different forms, extensive land occupation and traffic safety.

For this reason, and taking as reference the municipality of Neiva, where vehicular flow has increased notably in recent years (Fenalco, *et al.*, 2015), it is proposed the development of a tool based on artificial vision techniques that automatically detect vehicular traffic. In this way, it is possible to establish the actual number of vehicles passing through a track, its speed and all the necessary indicators for the implementation of effective solutions to the mentioned problem (Cal, *et al.*, 2004).

Vehicle congestion can be defined as that condition of the vehicular flow when it is saturated by excess demand of the roads, due to the great influx of vehicles, especially in peak hours. According to Time magazine, the city of Sao Paulo suffers the worst traffic congestion in the world (Downie, 2008).

In traffic engineering three basic elements are identified on which this project is developed. These are the users (driver, pedestrian and passenger), the road (city roads) and vehicles (Cal, *et al.,* 2004).

Artificial vision is a technique that comes from artificial intelligence and that pretends to empower a computer to interpret an image, as close to the interpretation that a human being can make (Platero, 2009). However, the conception of artificial vision in monitoring and surveillance is not limited to replacing the human system, but also serves as an information processing tool that extends its perception and reasoning (Plataniotis, 2005).

One of the big problems in which the artificial vision can be a solution, is the monitoring and surveillance of the traffic. Part of this problem is to recognize and measure vehicular and pedestrian flow, to maximize the use of traffic lights in such a way that waiting time depends on traffic needs (Li, *et al*., 2004).

2. MATERIALS AND METHODS

In order to fulfill the main objective of this project, it is first necessary to determine the ideal place for sampling. This must comply not only with the environmental conditions of light free of shadows, roads in good condition without any gaps, or alterations in it, but also must also be a significant site as far as mobility is concerned. For this reason, the intersection between the Cr 7, Av 26 and Cll 27, in the north of the city of Neiva is chosen. This is a mandatory convergence point for the passage of the center to the north, from the north to the west, and from the west to the east as shown in Figure-1.

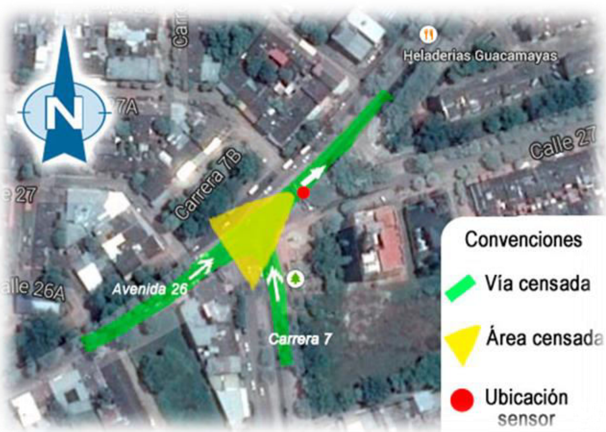

Figure-1. Geographic location of the sensor.

Then it is decided to choose the tools and equipment necessary to capture the images (cameras), which will be recorded during a whole day and part of the night, taking into account the importance of two fundamental parameters, resolution and speed. A high resolution increases processing and storage capacity, as well as having more pictures or images in a second (speed), but capturing images at a lower resolution may lose vital information in the scene, such as detailing the captured objects. As for the speed of the camera, if in a scene, an object moves very fast with respect to the speed of the camera, its edges are very blurred or diffuse, making it difficult to automatically detect the object. Then the analysis of the images is done, in order to determine the techniques suitable for processing them. In this way, it is necessary to work with a processor with at least 2 cores, and 2.8GHz processing speed, parameters that meet the processors of the Core i7 family, with which this project is developed. The different system modules are shown in Figure-2.

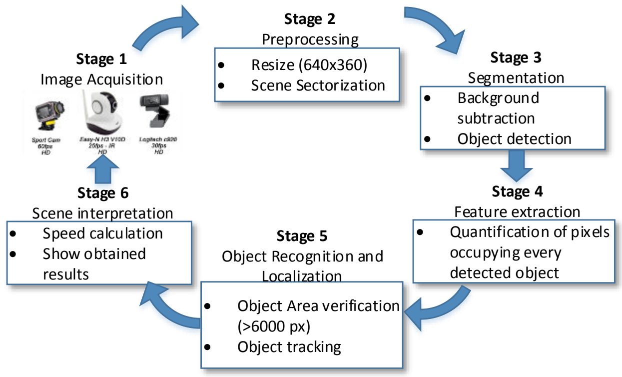

Figure-2. Stages of the project.

2.1. Hardware

In the project there are two key elements: first, the video camera (sensor); and secondly a computer for video recording, algorithm development and visualization.

2.1.1. Sensor

Although only one video camera is required, recordings are made in three different cameras in order to compare the quality of the images and responses against the angle and recording speed as well as changes in lighting. As a result of this comparison, the best images and sensor response can be seen in those captured by the Logitech WebCam c920 camera with a speed of 30fps (images per second), 1280x1080p (High Definition) resolution and automatic low light correction for night mode.

Figure-3. Sensors.

2.1.2. Computer

In order to capture the images, a laptop with a Pentium 4 processor and 4 GBs of RAM is used, however for the development of the algorithm, a more robust processor is necessary, taking into account that it is necessary to perform tests of image processing in high resolution. This is why the Pentium 7 is chosen, this time from a desktop computer, with RAM of 4 GB and a hard disk of 1 TB.

2.2 Software

For this requirement a library that works with images and that is also sufficiently robust to carry out extensive and specific processes of artificial vision is required. In addition, modification of the code to improve the results of this project should be allowed. For this reason, it is decided to work on the OpenCV library, which also handles open source, offering a very wide range of possibilities for image processing (Bradski, *et al.*, 2008).

The software consists of two elements of development. The first one consists of the image processing algorithm, in which one of the first procedures used is a focus mask that highlights the edges of the scene, complemented by the Canny algorithm, which thanks to its robustness, offers a definition of edges very effective (Maini, 2009). The second is an application that presents the algorithm within a graphical environment, where in this case the video to be studied is selected, with the possibility of parameterizing several regions of interest for the case where different distances are required as shown in Figure-4.

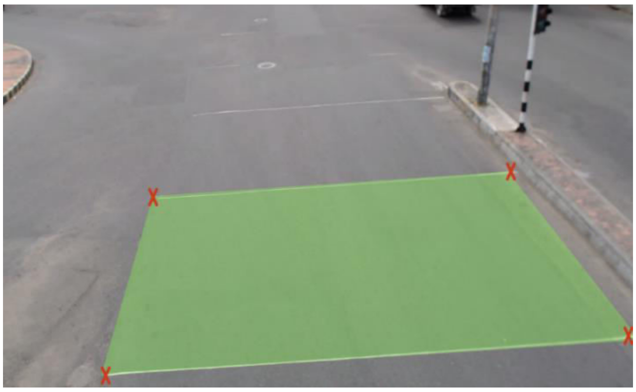

Figure-4. Reference area.

The image processing algorithm is developed taking into account the following structure (González, *et al.*, 2006):

- Acquisition of images
- Pre-processing
- Segmentation
- Feature extraction
- Recognition and localization of objects
- Interpretation of the scene

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3. RESULTS AND DISCUSSIONS

The analysis of the result obtained, after running the algorithm of detection and counting of vehicles, focuses on the evaluation of about 3 hours of recording both day and night, emphasizing the images where there is more activity (day). For this reason, 78 minutes of daytime recording can be observed in detail, making the manual counting of each vehicle (824), compared to the data obtained with the algorithm, and even reviewing the interpretation of the algorithm with each vehicle detected and with each situation. Finding that the effectiveness of the algorithm reaches 97.57% in the vehicle count. Within the 2.43% of mistaken interpretations that were found, three causes stand out: sudden changes in scene lighting (5%, 1 vehicle), counting of vehicles that circulate through enclosed lanes (15%, 3 vehicles), and presence of blind spots (80%, 16 vehicles).

These data, compared to other vehicle identification projects with very good results and using other methods (neural networks) whose effectiveness reaches 96%, indicate that the method chosen for the development of this algorithm is sufficiently robust for this work (González, 2006). The results of this project are constituted of 3 parts: vehicle count, speed and shadows.

3.1 Vehicle count

In order to perform not only counting but also vehicle detection as the main objective of this project, both daytime and nighttime images were analyzed.

3.1.1. Daytime images

Daytime images are the ones that present the best results when interpreted. However, after analyzing 78 minutes of recording in two videos, 824 vehicles were manually counted and, even though the automatic count was the same, 20 situations were presented where the interpretation of the algorithm was wrong. In this case, the situations that counted vehicles that did not really exist with those that omitted real vehicles coincided.

The 20 cases of misinterpretation of the algorithm were studied one by one in order to identify the actual cause of the error. It was found that 16 of these situations were generated by the presence of blind spots in the scene, another 3 by invasion of the space sensed by vehicles that move by other lanes and 1 case by abrupt changes in the illumination of the scene, particularly when very tall vehicles with very bright bodies pass beneath the sensor. The causes and percentages of errors in diurnal images, respectively, can be observed in Figure-5 and Table-1.

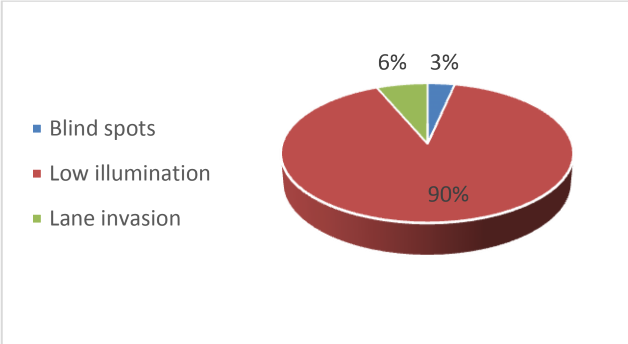

Figure-5. Causes of errors in daytime images.

Table-1. Percentage of errors in daytime images.

Error cause	Quantity	Percentage
Blind spots	16	80%
Invasion	3	15%
Illumination changes	1	5%

To minimize the negative effects of the algorithm, the causes of the problem were studied, which were related to the blind spots of the analyzed scene as seen in Figure-6.

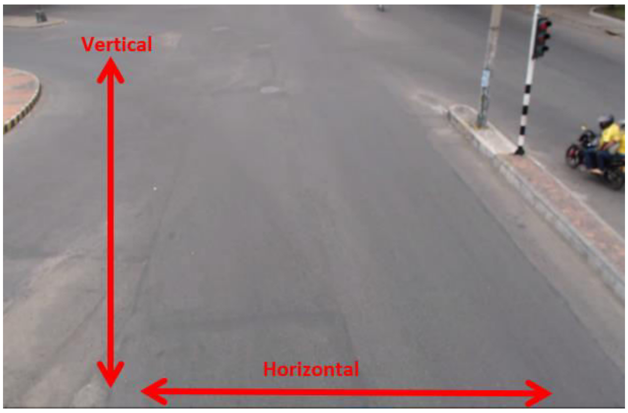

Figure-6. Forms of blind spots.

Horizontal blind spots

They are those areas that are hidden to the sides of the vehicles, usually the large ones, which overlap with other vehicles or part of them. When this situation occurs, and even though the vehicles are recorded in the video, the algorithm will interpret the whole as a single vehicle as shown in Figure-7.

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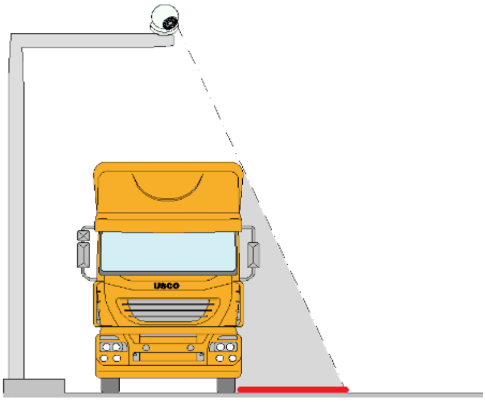

Figure-7. Horizontal blind spot.

The solution to this problem lies in the location of the sensor, which must be located on the midpoint of the roadway under study. In this case, which is made up of only two lanes, it must be located on the dividing line as shown in Figure-8.

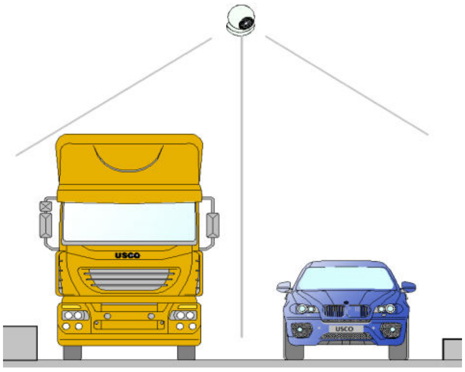

Figure-8. Removal of the horizontal blind spot.

Vertical blind spots

They are those spaces that are hidden behind each vehicle and that affect the interpretation that makes the algorithm when another vehicle is located in this space. The situation worsens as the first vehicle is located farther from the camera. Here, three determining factors come into play: sensor elevation, slope with which it operates, and distance of the region of interest with respect to the vertical component of the sensor. For this reason, it was necessary to revise the geometry of this situation in the scene. According to Figure-9 it is concluded that the line delimiting the region of interest at the top (farthest point of the sensor), should not exceed 10 meters, with the same 5 meters of region of interest. In case a larger region (10 meters, for example) is required, it is necessary to raise the sensor by at least 2 meters, in order to counteract the effects of this phenomenon.

After the previous analysis, it follows that at a higher height of the camera, the covering of the track will be better. However, the costs of raising this device increase, since the structure must withstand and resist the strong winds, requiring not only more material but also much more resistant materials.

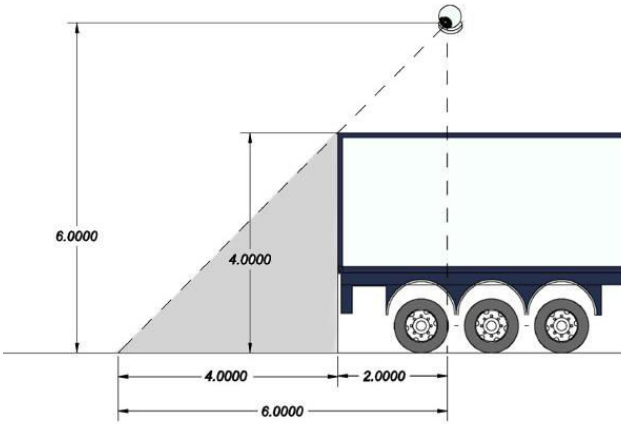

Figure-9. Geometry of the vertical blind spot.

3.1.2. Nighttime images

For the analysis of this part two minutes of night video were taken, taking into account the same algorithm developed for the study of diurnal images. It was then determined that in the 104 minutes of video, of the 1229 vehicles that crossed the region of interest, the algorithm registered 1254. However, and as in the case of daytime image processing, the erroneous interpretations are much larger than the difference of these two numbers, because a total of 265 errors were found, of which three causes stand out: deficiencies in the illumination of the scene where the light of vehicular headlights create regions with very sharp edges that end up deceiving the system doing it believe that they are vehicles (239 cases), which are equivalent to 90% of total errors; intrusion in the study region of vehicles traveling on other lanes (17 cases), 6.42%; and finally the presence of blind spots in the scene, as in case of daytime images (9 cases), 3.40%.The causes and percentages of errors in the nocturnal images can be observed in Figure-10 and in Table-2, respectively.

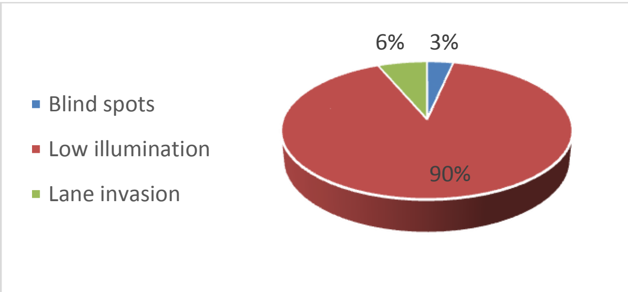

Figure-10. Causes of errors in nighttime images.

Table-2. Percentage of errors in nighttime images.

Error cause	Quantity	Percentage
Blind spots	9	3,4%
Low illumination	239	90,2%
Lane invasion	17	6,4%

Although initially it was intended to work on the solution through programming, it was determined that the

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scene does not meet the minimum requirements for such processing. Therefore, a solution was proposed that should be implemented in the scene, although for this situation the sensor that offers the best performance for the capture of these images is the WebCam Logitech C920, with its function of automatic correction lighting and gain.

It was found that the best solution is to improve the illumination of the scene, through light sources such as halogen or LED reflectors, or any other lighting device. In this way the background of the stage increases its intensity, approaching the intensity of the pixels illuminated by the vehicular headlights, fading the edges and minimizing the misinterpretations by this situation.

3.2. Speed

Two disadvantages were found in the calculation of this parameter. The first lies in the different paths that the vehicles follow within the scene and the second one to the speed factor of the sensor.

3.2.1. Trajectory accuracy

During the evaluation of the results in the calculation of the speed, it was found that some vehicles that enter the lane under study from the Cr 7 move with a path different from the path followed by those coming by the Av 26, increasing for the first case the trajectory of displacement in the same section of 5 meters, since an inclination angle appears as shown in Figure-11.

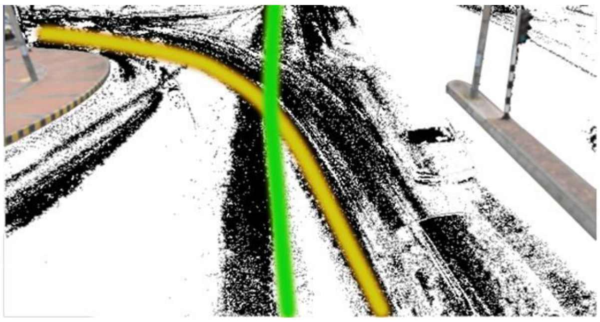

Figure-11. Trajectories of displacement.

Giving a review of the geometry of this situation, it was determined the variation of the parameters in scene and the result that this variation throws in the interpretation that makes the algorithm.

It was found that the inclination for a vehicle that comes with deviation has a variation of 30 ° with respect to the trajectory of the studied scene. With the determined angle it was found that the vehicles that take this inclination have to advance about 78 centimeters more of distance to the distance referenced in the algorithm (5 meters), which entailed alterations in speed detection. According to the above it was found that the absolute velocity error is 5.2% and the relative error of 0.13%.

After analyzing these calculations, it was tried to add to the algorithm a segment of code that calculates the trajectory that follows each vehicle, determining the angle and the real distance traveled, and thus a calculation of speed more reliable. When the basic cause of this situation is analyzed, the scene arises again, because at the moment of choosing the structure to install the sensors of this project there was no alternative, although it can be easily seen that the region of interest is practically in the turning radius of the vehicles coming from the Cr 7, so the solution is to ensure that the region of interest is within a single track, and not at an intersection point. In other words, it would need the camera to be located about 20 meters behind the place where it was initially located. In this way, the error in the calculation of the speed is automatically corrected.

3.2.2. Sensor accuracy

The velocity error was determined by the frame analysis as shown in Table-3 and Figure-12.

Table-3. Percent error of speed according to the frames.

# Frames	**Speed**(Km/h)	**Error**(%)
2	270,0	
3	180,0	
4	135,0	
5	108,0	16,7
6	90,0	14,3
7	77,1	12,5
8	67,5	11,1
9	60,0	10,0
10	54,0	9,1
11	49,1	8,3
12	45,0	7,7
13	41,5	7,1
14	38,6	6,7
15	36,0	6,3
16	33,8	5,9
17	31,8	5,6
18	30,0	5,3
19	28,4	5,0
20	27,0	4,8
21	25,7	4,5
22	24,5	4,3
23	23,5	4,2
24	22,5	4,0
25	21,6	3,8
26	20,8	3,7
27	20,0	3,6
28	19,3	3,4
29	18,6	3,3

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30	18,0	3,2

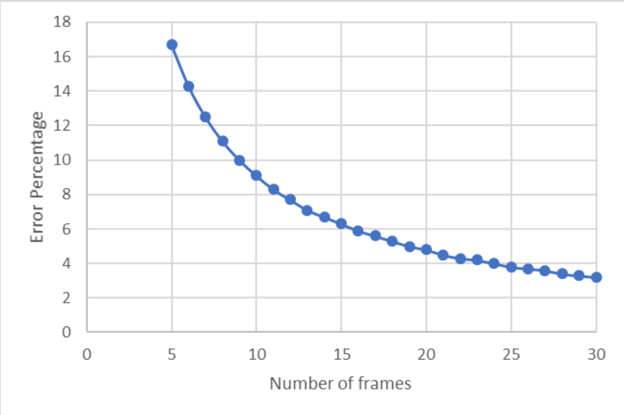


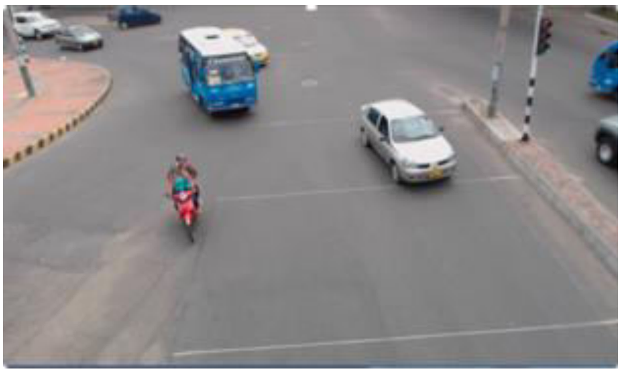
Figure-12. Speed error vs. frame rate.

It is evident that at a lower number of frames per path, the speed error calculated by the algorithm is greater. This situation is reflected in the moment the vehicle leaves the region of interest, but the sensor does not detect it instantaneously, but a moment later as shown in Figure-13. Thus, the time it actually takes the vehicle to complete the sensing shift increases.

Figure-13. End of displacement.

3.3. Shades

Among the determining factors in the success of this code are the identification and elimination of shadows. Especially when clouds are present, making the illumination very diffuse, making it difficult to detect the edges of the shadow.



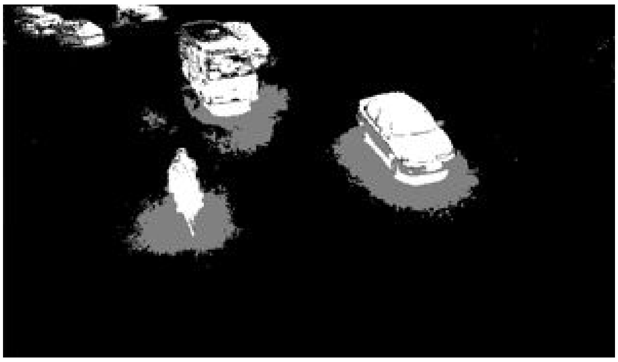


Figure-14. Shades.

This factor was the one that required the most time, since the minimum value of each shade, which was part of the vehicle, had to be found. In addition, to raise Gaussian surfaces, both for extraction of the bottom, and for the identification of objects. Considering that a shadow with low levels of intensity considerably increases the area of the vehicles, joining them and creating spaces that disappear quickly affecting the result of the program. On the other hand, a shadow with high minimum values, alters the resulting shape of the object, confusing the car body with the scene background removing parts of the cars, making it difficult to recognize.

4. CONCLUSIONS

This project developed a tool for the counting of vehicles and the measurement of the speed of the same, in an automated way. This allowed to know for the first time, and in real time, the behavior of mobility at least one point in the city of Neiva. The real data were taken automatically by an algorithm combining various techniques of artificial vision and processing each image in a sufficiently short time. This allows this algorithm to be used in real-time applications. Another important feature of this system is the use of the least amount of possible functions, reaching at the end a program with few lines of programming, but with very satisfactory results 24 hours a day. Following the suggested recommendations can ensure a minimum of 95% average effectiveness. Although in the tests carried out on previously captured videos, a 97.57% effectiveness was achieved for daytime images, at night it dropped to 78.4%. However, the average of 88% is a good indicator of reliability of the system, taking into account the difficulties with which the sensor was installed.

From experience and the results obtained in this project there is no doubt that taking into account the following recommendations, it can reach, and even exceed, 95% effectiveness. These recommendations are made following 3 items (sensor, structure and environmental conditions).

There are three key recommendations from the sensor. The first is due to the sensor reference, since the WebCam Logitech C920 was the best images captured, it is recommended to use this sensor, as it also has the best system to counteract the poor lighting in the scene. The second is the speed, being 30 fps, the recommended speed.

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Ending with the ideal resolution for applications of this type, containing enough information of the ideal scene and a low computational cost in the process, is therefore the suggested resolution 640x480.

The structure is recommended to be robust and stable enough, especially at the top, with a height of not less than 6 meters above the level of the road, and with the support for the sensor just at the middle of the road which will be studied. In addition, the structure should be at least 20 meters away from the nearest corner, and if possible away from parking lots or commercial establishments, noting that it must have an electrical connection and if possible a backup system, for the cases in which the electrical system fails.

Regarding environmental factors, it is recommended to choose the study site whose surface of the road is as homogeneous as possible, free of gaps and shadows. For the night hours, it is necessary to use two 150W LED spotlights, with an automatic ignition system, once the natural light goes down.

REFERENCES

[1] Bradski, Gary, Kaehler. A. 2008, Learning OpenCV. 1ª Edición. O'Reilly Media Inc. EE. UU.

[2] Cal., Rafael, Reyes M., Cárdenas J. 2004. Ingeniería de tránsito, Fundamentos y aplicaciones. 7ª Ed. Alfaomega. México.

[3] Downie A. 2008. The World's Worst Traffic Jams. Times Magazine.

[4] Fenalco, Andi, Comité Automotor Colombiano. 2015. Informe del Sector Automotor a diciembre de 2014. Bogotá D.C.

[5] González A., Martínez F., Pernía V., Alba F., Castejón M., Ordieres J., Vergara E. 2006. Técnicas y algoritmos básicos de visión artificial. Universidad de la Rioja. España.

[6] González Z. 2006. Medición de Flujo vehicular basado en visión artificial. Quindío Colombia, Universidad del Quindío.

[7] Li X., Yao X., Murphey Y., Karlsen R., Gerhart. G. 2004. A real time vehicle detection and tracking system in outdoor traffic scenes. International Conference on Pattern Recognition. 2: 761-764.

[8] Maini R., Aggarwal H. 2009. Study and Comparison of Various Image Edge Detection Techniques. Penn State University.

[9] Platero C. 2009. Apuntes de visión artificial. Cap. 1. Dpto. Electrónica, Automática e Informática Industrial.

[10] Plataniotis K. 2005. Visual Centric Surveillance Networks and Services. IEEE Signal Processing Magazine. Vol. 22.