Ambulance detection for smart traffic light applications with fuzzy controller

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Article Info

Article history:

Received Dec 26, 2021
Revised Apr 20, 2022
Accepted May 15, 2022

Keywords:

Convolutional network
Fuzzy system
ResNet 50
Smart traffic light

ABSTRACT

In the development of intelligent cities, the automation of vehicular mobility is one of the strong points of research, where intelligent traffic lights stand out. It is essential in this field to prioritize emergency vehicles that can help save lives, where every second counts in favor of the transfer of a patient or injured person. This paper presents an artificial intelligence algorithm based on two stages, one is the recognition of emergency vehicles through a ResNet-50 and the other is a fuzzy inference system for timing control of a traffic light, both lead to an intelligent traffic light. An application of traffic light vehicular flow control for automatic preemption when detecting emergency vehicles, specifically ambulances, is oriented. The training parameters of the network, which achieves 100% accuracy with confidence levels between 65% with vehicle occlusion and 99% in direct view, are presented. The traffic light cycles are able to extend the green time of the traffic light with almost 50% in favor of the road that must yield the priority, in relation to not using the fuzzy inference system.

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1. INTRODUCTION

The means of transport are a fundamental part of the daily activity of man. Mainly in urban areas it is wanted to regulate the displacement by means of vehicles through traffic lights, which in spite of their apparent easy operation by time present a focus of investigative interest. From several fronts it is possible to improve the way they operate, for example, in [1] a strategy of traffic light control according to the vehicular flow is sought. In [2] a development towards wireless connectivity for traffic light control is presented. However, the development of intelligent systems for traffic light control presents a wide field of development, for example, based on the number of vehicles on the road [3], the action that may require image processing algorithms for this identification [4], [5], among other similar [6]–[9]. One of them is a study [10], which presents an intelligent traffic light system for emergency vehicles, using strategies for route identification and traffic light status change, mainly using the message queuing telemetry transport (MQTT) protocol.

Fuzzy systems have been used as a lighting control strategy [11], so they fit very well in traffic light control schemes, for example, for a large number of intersections [12], seeking to maximize the duration time of the green light [13], among others [14]–[18]. Some of these cases have been strengthened with the integration of fuzzy systems to neural networks [19], where nowadays one of the main neural architectures in pattern recognition are convolutional networks [20]. Among the applications of convolutional neural networks (CNN), vehicle detection [21] stands out, mainly by means of faster region-based convolutional neural network (R-CNN) architectures [22], [23], based on regions (R), which allow locating the location of the vehicle in the image, facilitating, among others, the counting of vehicles. In [24], the detection of emergency vehicles by means of faster R-CNN networks and residual architectures based on regions (ResNet) is presented, showing the best performance in the latter case.

Based on the presented in the state of the art, an algorithm is built for the detection of ambulances through ResNet and integrated to a fuzzy inference system. The algorithm allows the development of an intelligent traffic light model for priority of emergency vehicles, based on ambulance detection. The target is achieving a compensation of the priority of the road against the mobility of the emergency vehicle in order to evaluate when the other road really must yield the priority of vehicular passage.

The article is structured in four sections, the present introduction that refers to the state of the art. The second section that exposes the methods and materials in two subsections, the training of the network and the fuzzy system. The third section presents the results and their analysis and finally the fourth section presents the conclusions reached.

2. RESEARCH METHOD

The application of automatic control of an intelligent traffic light requires it to be able to interact with the environment according to the characteristics of vehicular flow. Given that it seeks to prioritize the passage of vehicles to ambulances, the automatic identification of these is essential, for this a deep learning network based on region proposal network (RPN) as the faster R-CNN, but using a ResNet-50 architecture [25], [26] is trained through transfer learning. This allows to identify and localize the ambulance within the scene. To control the time duration of each traffic light state, when an ambulance is detected, a fuzzy inference algorithm is used, which, as stated in the state of the art in the introduction, is one of the traffic control algorithms that stands out for its efficiency and versatility [27], [28]. Both parts of the algorithm are presented below.

2.1. Ambulance detection

For training, a database of 100 ambulance images is used. A data augmentation process is applied to the database by means of reflection operations on the vertical axis and translation, obtaining 300 images in total. A distribution of 80% of the images are used for training the network and the remaining 20% for validation. Figure 1 shows a sample of the database used.

The training of the network was performed at a learning rate of 0.001, for 30 epochs and 250 iterations. This process takes about 16:59 minutes on a 2.80 GHz Intel Core i7 computer with NVIDA Gforce GTX 1050 8 GB GPU. Figure 2 illustrates on the left the training process where for the 220th iteration already reaches 100% accuracy, on the right is the ratio of accuracy versus recall obtained.

Figure 3 shows the result of learning the network for ambulance detection. Figure 3 on the left shows a case of high vehicle flow with partial occlusion of the ambulance, which reduces the confidence level of the detection to 0.69. To avoid confusion with normal vehicles, the results of the network are thresholded at a confidence level greater than or equal to 0.6. For the cases where the ambulance is captured complete as seen in Figure 3 center and right, it is observed that the confidence level is quite high, overall, for these cases is greater than 95%.

Figure 1. Sample ambulance database

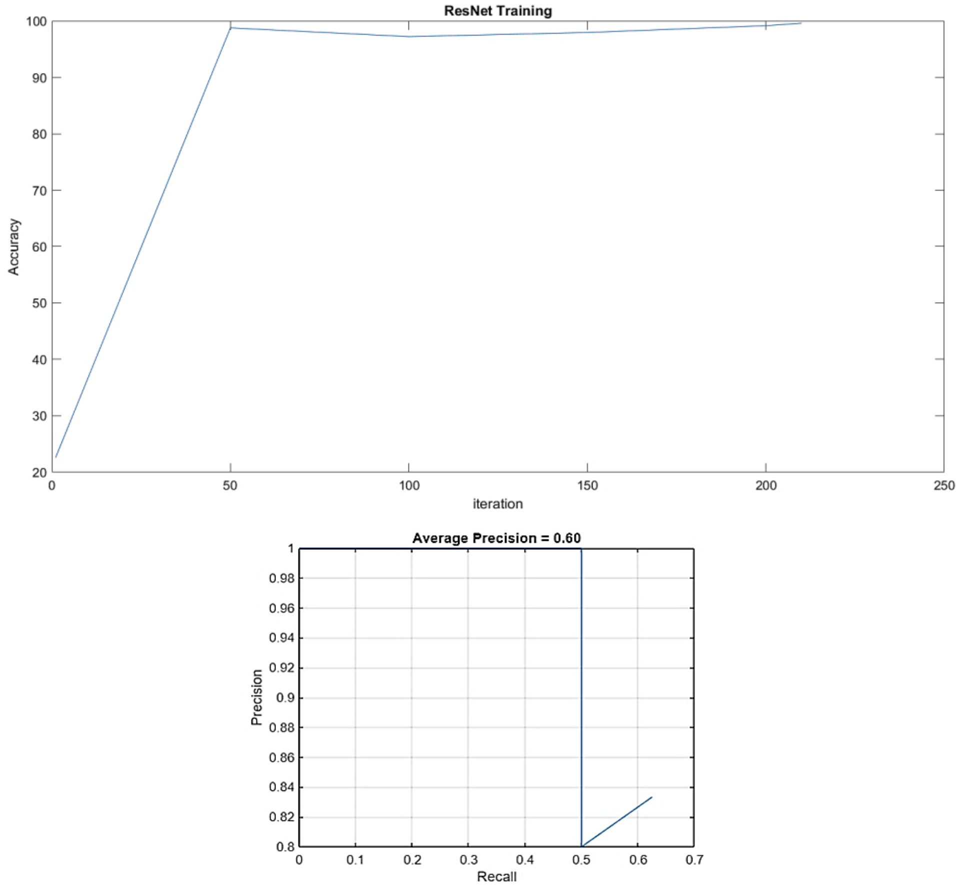

Figure 2. Result of the network training process

Figure 3. Ambulance detection using faster R-CNN

2.2. Traffic light control

The timing control for the light change of the proposed intelligent traffic light is performed by means of a fuzzy system. The fuzzy algorithm is the best option given the nonlinearity of the system, since it cannot predict when an ambulance will appear or under what traffic conditions. Which makes it difficult to establish an associated mathematical model [29], [30].

Depending on the detection of the ambulance it is required to act on the times of the traffic light states. The basis of the proposed fuzzy algorithm focuses on the bounding box of the detection through the network. Since this is greater when the ambulance is closer, as it approaches the traffic light there is a variation in the size of the bounding box which in turn refers to how fast it manages to move.

For this, a fuzzy system is established that takes as input the anchor box and how fast its size varies (reason of change or derivative). Given that the size of the images is 224x224x3, we have that due to the position of the camera in front of the panorama of the road, the maximum space it could occupy when the ambulance is very close is 50% of the image, i.e. 112 pixels. The detection by the network implies a minimum size for recognition that is validated in 37x37 pixels of the image, where the rate of change is set to a range of 75 pixels. These values give rise to the speech universes of the two fuzzy conjuncts to be used, anchorB and DanchorB, alluding to their derivative, as shown in Figure 4.

Figure 5 illustrates the output membership function. The universe of discourse ranges from 0 to 100% of the time the ambulance is detected by the network. During this time the predominant color should clearly be green, unless the ambulance is far away and moving slowly.

In general, the rule base with the described behavior is presented in Table 1. Similarly, Figure 6 shows the graph of the fuzzy system behavior, it is evident the predominance of the green state if the flow of the ambulance is constant. In this case, the defuzzification establishes the green state in output values from 35 onwards.

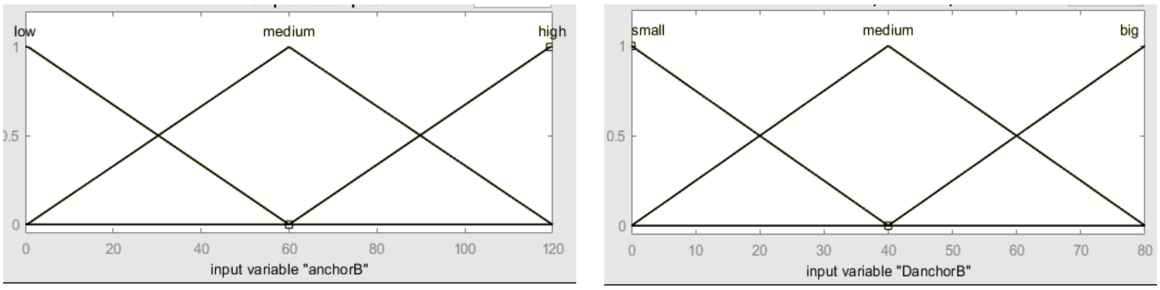

Figure 4. Input membership functions

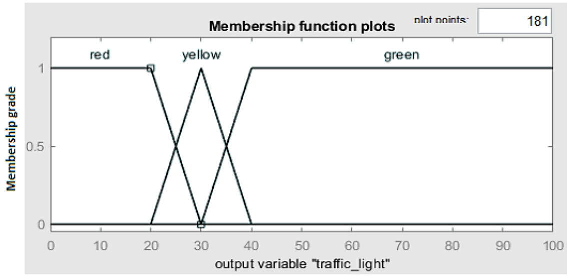

Figure 5. Output membership functions

Table 1. Base of rules

	Anchor		
	Small	Medium	Big
Danchor	red	green	green
	red	green	green
	yellow	green	green

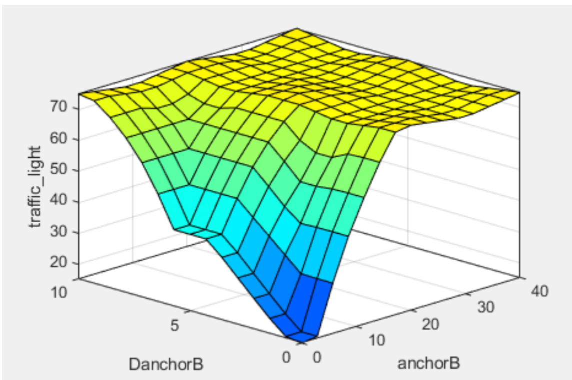

Figure 6. Graphical response of the fuzzy system

The rule base is constructed, in a general way, when the ambulance is detected. The selection of the green light should be prioritized, but given that vehicles must respond to the siren to give way, a consideration is presented against this premise, which can improve the response for the general circulation. If the vehicular flow is dense and the ambulance is close or at a medium distance the traffic light should remain on green longer, if the vehicular flow is dense and the ambulance is detected at a far distance, the time while the vehicles give way for the ambulance to pass between them can be used by giving way to the perpendicular roads, keeping the traffic light on red, case illustrated in Figure 3 in the left and central images.

Figure 7 illustrates the final scheme used in the evaluation of the intelligent traffic light model developed. The input corresponds to the video capture of the camera associated to the traffic light. This enters the ResNet classifier, whose output is taken by the fuzzy inference system and according to the defuzzification associated to Figure 5, will activate each light of the traffic light.

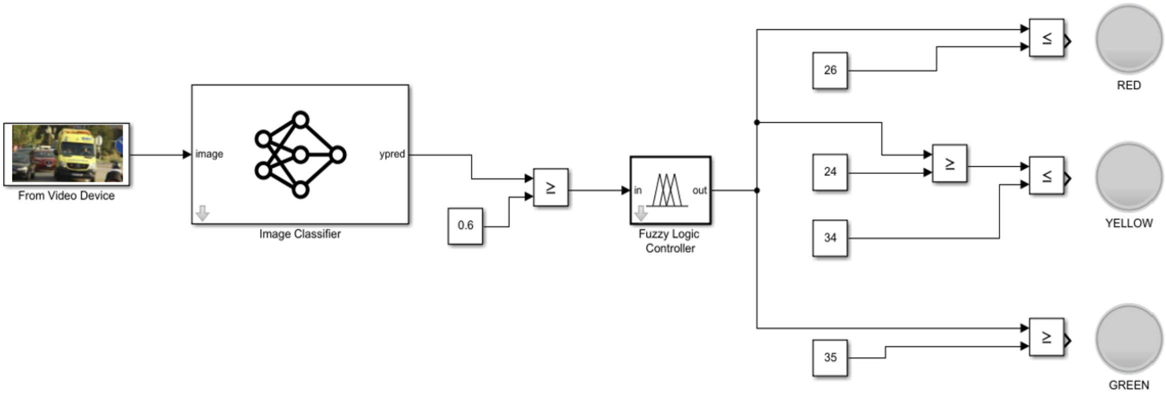

Figure 7. Graphical response of the fuzzy system

3. RESULTS AND DISCUSSION

By means of simulations carried out in the laboratory, using videos of common traffic at 30 fps and a prototype of academic traffic light by software. The performance of the exposed algorithms was evaluated, obtaining the results shown in Table 2. Taking into account that a conventional cycle goes up to 120 seconds.

Within the representative cases we have the green status at the end of the cycle where the ambulance is detected and this extends until it is not detected. The red state where with low or medium flow changes to yellow and then to green to give priority passage. The red state that with high flow and remote detection keeps the traffic light state under the normal cycle.

It was evidenced that the non-detection of the ambulance through the network generates conflicts with the traffic light times when the fuzzy inference system starts to work. That is to say, when entering the ambulance to scene, the time is governed by the algorithm of fuzzy inference, but it returns a regular cycle of semaphore, when detecting the ambulance, a tracking of this is generated until it surpasses the traffic light or it is lost in the recognition. For the second case, which was presented by occlusion of almost 50% of the ambulance within its route to the traffic light, restarting the conventional cycle and altering the priority. This problem was solved by generating a time window within the fuzzy inference algorithm. This window validated the loss of the ambulance in 10 fps. If it was not detected in that time it returned to the normal cycle.

The fuzzy inference algorithm gives a margin of greater autonomy and control over the traffic light states. Although a direct scheme against the fuzzy may seem efficient and simpler, it last can improve the results. A test of this case in the detection with a flow with high density, yielded an advantage of the algorithm of almost 50% cycle in favor of the path that must yield the priority. For the other cases no major difference is evident.

Compared to the results reported in the state of the art with similar works, it is found that by means of the training parameters of the ResNet exposed in section 2, 94% of true positives are obtained compared to 74% of those reported in [24]. One reason for this is found in the database used in the training, for our case the images come from the detection from the point of view of the traffic light, where the ambulance is in front approaching it, while in [24] side views of the ambulance are also included, which in general helps the dispersion of the learning of the network, reducing its accuracy.

Table 2. Response times

Traffic	Time average in green (seconds)
Soft	85.6
Medium	116.7
High	141.2

4. CONCLUSION

The training of the network was iterative, where the best combination of network features was exposed. The ResNet being a robust architecture takes time to converge in the training, an excessive number of epochs and a smaller learning rate significantly increase this time almost four times the exposed. Where it was concluded that it is more efficient to make test trainings with not so small learning rats and few epochs and to be increasing until achieving an efficient result. Given the fast convergence of the fuzzy inference system and the low computational cost involved, it was concluded that it is beneficial for an intelligent traffic light to use the fuzzy inference system to level the duration of cycles in both directions of vehicular flow of perpendicular roads. The integration of deep learning techniques and fuzzy systems in intelligent traffic light applications allows us to conclude that the automation of roads with emergency vehicle priority is feasible without the direct intervention of human control.

ACKNOWLEDGEMENTS

The authors are grateful to Universidad Militar Nueva Granada and Universidad de los Llanos for the funding of this project.

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