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Distance-based fuzzy speed control applied to autonomous vehicles

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ABSTRACT

This paper proposes a vehicle speed control system based on a fuzzy proportional integral derivative (PID) controller. The controller dynamically adjusts the vehicle's speed to maintain a minimum safety distance from the vehicle ahead, using visual information obtained through computer vision techniques based on deep learning. Different neural network architectures were evaluated, including residual network (ResNet) and several versions of the you only look once (YOLO) model, for the detection and classification of vehicles using camera-captured images. The results show that YOLO performs better in real-time detection tasks, making it more suitable for assisted driving applications. Its latest version stands out for offering a better balance between accuracy, model complexity, and response time. Additionally, the fuzzy controller showed a steady-state error lower than typically accepted values, validating its effectiveness for speed regulation in intelligent transportation systems.

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1. INTRODUCTION

The advances achieved by artificial intelligence algorithms over the past decade have significantly driven the development of autonomous vehicles [1]–[3]. Among these advances, deep learning algorithms stand out, with applications including the identification of car brands and models [4], the detection of lane markings on roads to support driving assistance systems [5], tracking the actual trajectory of unmanned vehicles [6], and cabin monitoring to mitigate risks and improve comfort in autonomous vehicles [7]. One prominent category of deep learning algorithms is region-based convolutional neural networks [8], which enable both object identification and localization within images. A particularly notable example is the residual network (ResNet) architecture [9]. ResNet has several important applications in driving assistance, such as driver fatigue detection [10], vehicle recognition [11], and identification of vehicular traffic collisions or congestion [12].

Another algorithm that excels at object identification and localization using deep learning is the you only look once (YOLO) architecture [13]. YOLO has similarly been employed in vehicle detection [14] and driving assistance tasks [15]. Both ResNet and YOLO commonly utilize transfer learning techniques [16], facilitating their adaptation and customization for specific applications in various environments. Artificial intelligence has also contributed significantly to developing advanced control algorithms for systems such as vehicles [17]. Among these control-oriented techniques, fuzzy logic stands out [18], proving effective in tasks such as trajectory optimization [19], speed control [20], and object tracking [21].

Based on the state of the art, the present paper compares vehicle classification and detection using the ResNet and YOLO architectures. The aim is to implement a fuzzy logic-based speed control system that adjusts vehicle speed according to the distance from vehicles within the line of sight, based on artificial intelligence algorithms of low computational consumption. In this regard, this article makes two main contributions. First, it presents a systematic comparison between neural network architectures for vehicle detection and classification, evaluating their suitability for real-time applications. Second, it proposes the integration of the selected architecture with a fuzzy speed controller, demonstrating its effectiveness in maintaining safe distances and regulating speed in assisted driving scenarios.

This article is organized into four sections. Section 1 introduces the research topic and objectives. Section 2 details the training methodologies employed for the neural networks and the fuzzy controller. Section 3 presents the results obtained along with their analysis. Lastly, section 4 outlines the conclusions drawn from this study.

2. METHOD

The objective of this work is to propose a vehicle speed control system based on visual feedback, utilizing a fuzzy proportional integral derivative (PID) controller [22]. The system input corresponds to an adjustable proximity reference between the controlled vehicle and the vehicle directly ahead, maintaining a predefined minimum distance of 5 meters. As the leading vehicle accelerates or decelerates, the visual feedback enables automatic adjustment of the target vehicle's speed according to established fuzzy logic control rules.

In this system, feedback is provided by measuring the current distance to the vehicle ahead using a camera-based system. Vehicle identification is performed using deep learning algorithms. For this purpose, a database consisting of 300 labeled images categorized into car, motorcycle, and vehicular hood is employed, as illustrated in Figure 1. Although 300 images may initially seem like a small dataset, it is important to note that it is not intended for training from scratch. Instead, it is designed to facilitate the preliminary selection and comparison of pre-trained detection architectures within a specific operational context.

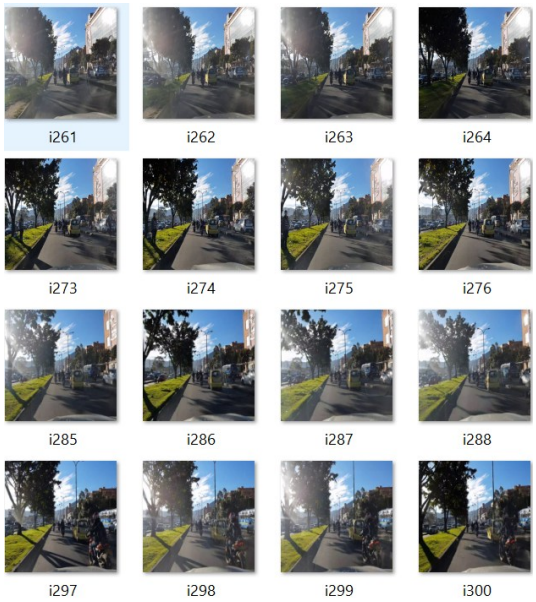


Figure 1. Database sample and experimental methods applied

Since visual feedback is necessary to identify the nearest vehicle within the captured image, a transfer-learning-based classification and localization network is utilized. Due to the relatively small number of classes (three categories), architectures such as ResNet or YOLO, which leverage transfer learning, are particularly suitable. The training methodologies for both networks are presented, providing a comparative analysis. For the ResNet architecture, given the limited number of classes, the ResNet-18 version [23] was selected, as it has the fewest learning parameters compared to the ResNet-50 [24] and ResNet-101 [25] models. Figure 2 illustrates the training behavior of the ResNet-18 network, and its associated parameters are summarized in Table 1.

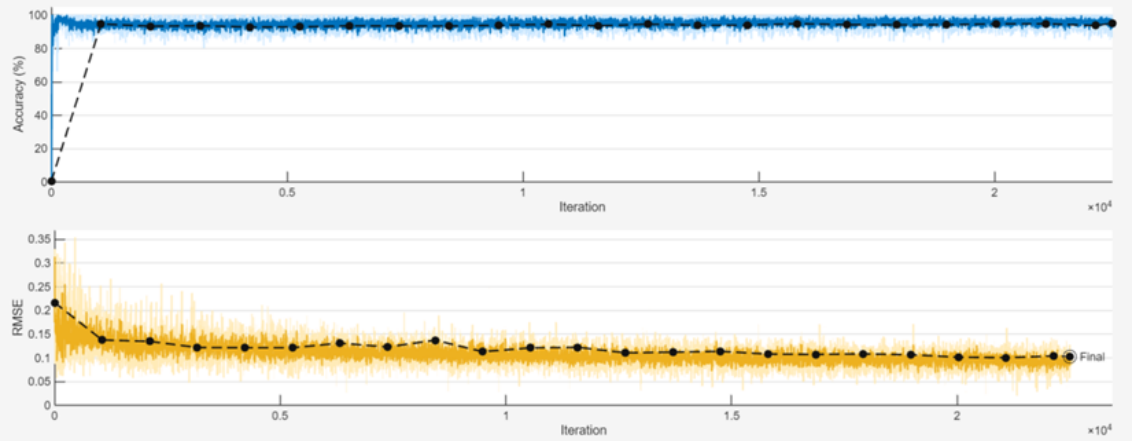


Figure 2. Training progress of the ResNet-18

Table 1. ResNet training parameters

Training parameter	Value
Input	224 × 224 × 3
Optimizer	Adam
Number of epochs	100
Learning parameters	11.7 M

For the YOLO network [26], YOLOv4, YOLOv8, and YOLOv11 are used to demonstrate their performance, digital weight, and speed of response. Figure 3 illustrates the final training performance, showing a classification accuracy of 100%, like the ResNet-18 model. The training parameters for YOLOv4, YOLOv8, and YOLOv11 are detailed in Table 2.

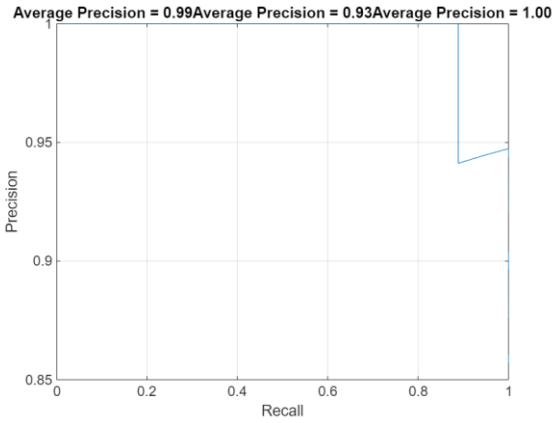


Figure 3. Final training performance

Table 2. YOLO training parameters

Training parameter	Value
Input	416 × 416 × 3
Optimizer	Adam
Number of epochs	100
Learning parameters	6.9 M

To calculate the distance, bounding box coordinates from object detection are used. Specifically, the reference point is the central top edge of the detected vehicular hood box, indicated by a red dot in Figure 4. Starting from the reference point, the system searches vertically upwards, within a range of 60 pixels, for the first bounding box corresponding to a detected vehicle. The distance between vehicles is determined from the reference point and the bounding box (blue line in Figure 4) using (1) and (2).

In (1), the line-of-sight distance metric relates to the pixel distance between the reference point and the bounding box. Pf is the final pixel associated with the vehicle in front, Pi associated with the initial pixel associated with the hood, and dpx is the distance per pixel ratio that varies according to the input size of each network. In (2) relates the linear distance between vehicles starting from the fact that the DistLv measurement is not given from one point to another in a straight line. Rather, it actually corresponds from the hood height (taken on average at 1.2 meters) to the detection of the boundingBox of the front vehicle related to the ground. For vehicles a Δx corresponding to the distance from the trunk to the tires (approx 0.25 meters) is subtracted.

$$DistLv = (P_f - P_i) * d_{px} \quad (1)$$

$$DistA = \sqrt[2]{DistLv^2 - 1{,}2^2} \quad (2)$$



Figure 4. Distance calculation

To regulate the vehicle's velocity, a fuzzy PID controller was designed, operating based on the detected distance and position error. Figure 5 illustrates the output response of the velocity controller according to fuzzy inputs. Figure 6 presents the control surface graphs: on the left, the relationship between error and integral of error, and on the right, the relationship between error and derivative of error. Table 3 shows the rule base relationship utilized, where N = negative, Z = zero, and P = positive correspond to the input membership functions, and S = stop, L = low, M = medium, and H = High correspond to the output membership functions.

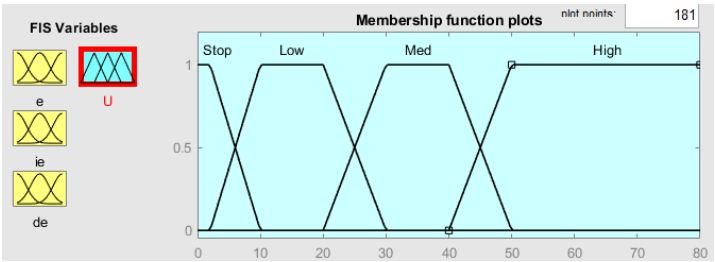


Figure 5. Output fuzzy set

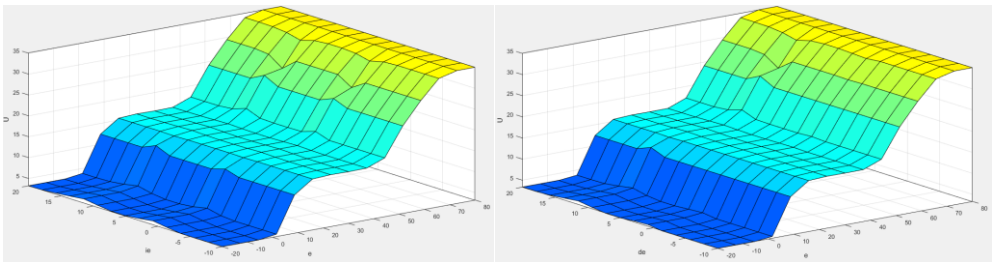


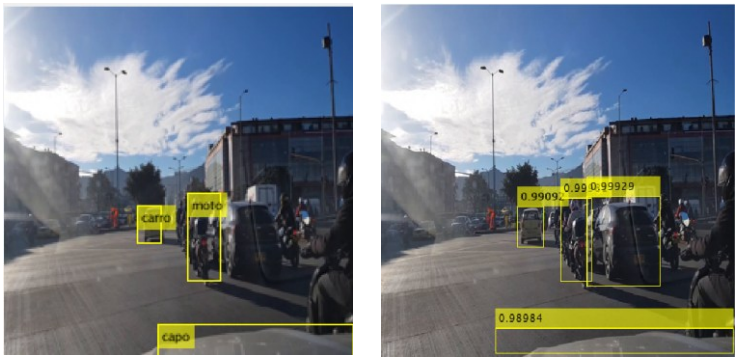
Figure 6. Control surfaces

Table 3. Fuzzy rule base

	ε	∫ε	ε̇	U		ε	∫ε	ε̇	U
1	N	N	N	S	15	Z	Z	P	M
2	N	N	Z	S	16	Z	P	N	H
3	N	N	P	S	17	Z	P	Z	M
4	N	Z	N	L	18	Z	P	P	M
5	N	Z	Z	S	19	P	N	N	M
6	N	Z	P	L	20	P	N	Z	M
7	N	P	N	L	21	P	N	P	H
8	N	P	Z	L	22	P	Z	N	M
9	N	P	P	L	23	P	Z	Z	H
10	Z	N	N	M	24	P	Z	P	H
11	Z	N	Z	M	25	P	P	N	H
12	Z	N	P	M	26	P	P	Z	H
13	Z	Z	N	M	27	P	P	P	H
14	Z	Z	Z	M					

3. RESULTS AND DISCUSSION

Figure 7 presents the vehicle identification results obtained using ResNet18 and YOLO. Figure 7(a) illustrates the vehicle identification results using ResNet, which fails to detect the vehicle positioned to the right of the motorcycle, and conversely, Figure 7(b) illustrates the vehicle identification results obtained with YOLO, where the classification result does not vary from version to version. Successfully detecting the same vehicle missed by ResNet in the example. Table 4 summarizes the performance of the networks, including their size in megabytes and classification times. The average processing time was measured across 10 different images containing three classes each, noting a variation of approximately 10% to 15% depending on the number of objects detected per image.



(a) (b)

Figure 7. Output fuzzy set for vehicle identification (a) ResNet18 and (b) YOLOv4

Table 4. Network performance comparison

Parameter	Classification time (seg)	Size (MB)
ResNet	0.243801	43
YOLOv4	0.0568	21.5
YOLOv8	0.09	6.8
YOLOv11	0.08	5.3

The YOLOv8 and YOLOv11 versions exhibit very similar responses, so the responses of the respective confusion matrices [27], [28] are evaluated to demonstrate their performance in relation to class recognition. Figure 8 presents the confusion matrices of the YOLOv8 and YOLOv11 networks. Figure 8(a) illustrates confusion matrix of YOLOv8, while Figure 8(b) shows that of YOLOv11. A slight improvement in detection performance is observed for YOLOv11, with a higher number of true positives detected.

Figure 9 illustrates the validation of the distance metrics, where the current measurement is shown at the top. A calculation error of up to ± 25 centimeters is evidenced, which in the extreme case does not impact the performance of the algorithm in terms of safety in speed control. Figure 10 illustrates the fuzzy controller test results, depicting the response of the motor's transfer function incorporating the distance-based velocity adjustment. This response is compared to the input reference distance, aimed at maintaining a constant spacing of 5 meters between vehicles.

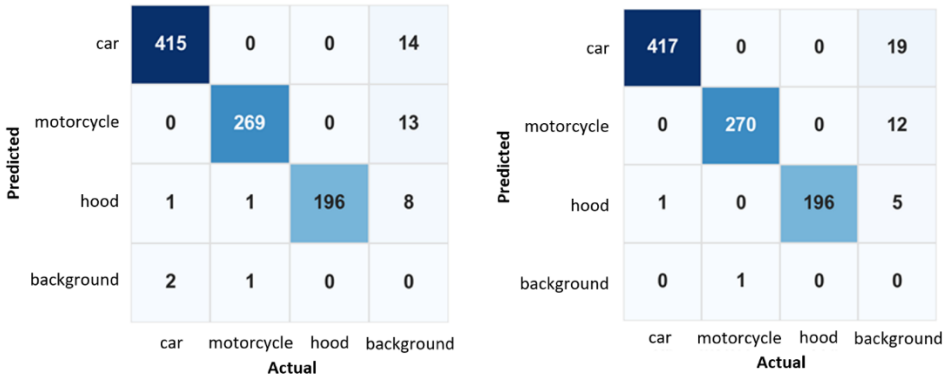


Figure 8. Confusion matrix (a) YOLOv8 and (b) YOLOv11

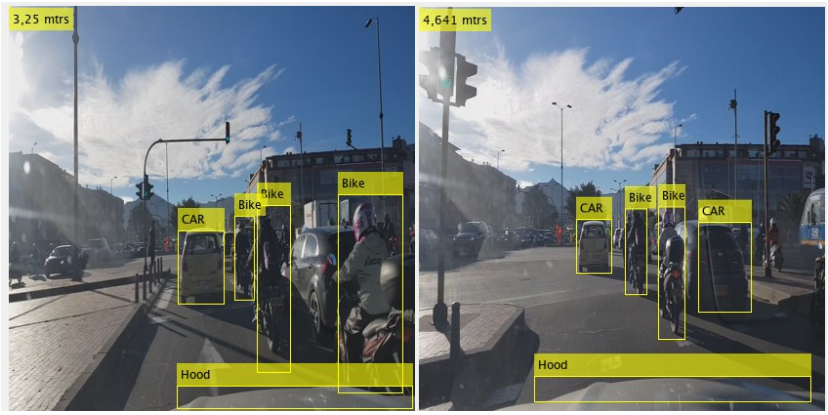


Figure 9. Controller output

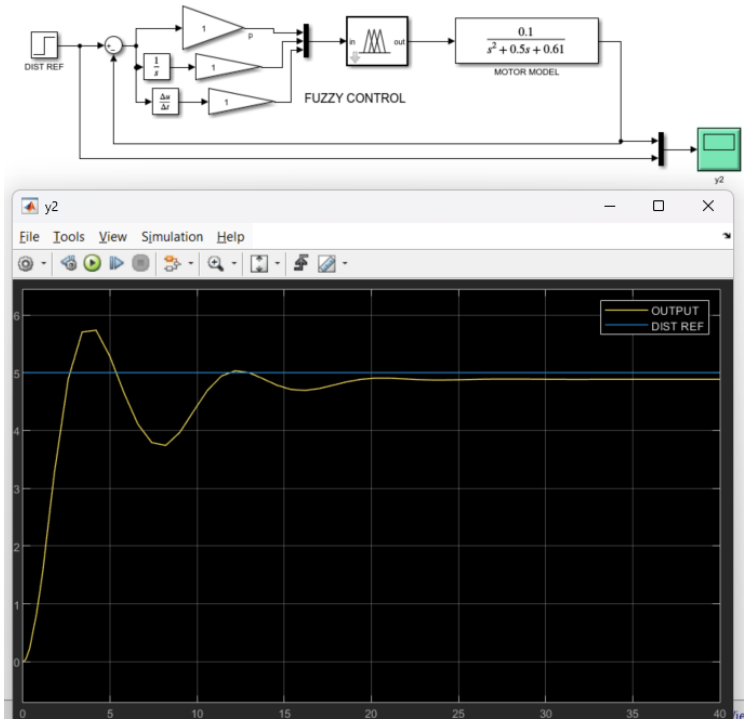


Figure 10. Controller output

The fuzzy controller responds appropriately by simplifying the control design. However, some low-light conditions still affect the detection by the network, which affects the control response. As a solution, an observation window is established by obtaining the trend in the classification of vehicle detection in the line of sight of the vehicle (relative to the hood detection), the window refers to the label obtained from the last ten samples.

4. CONCLUSIONS

A distance-based speed control system for autonomous vehicles was presented. This system is based on identifying the vehicle ahead through neural networks and, based on its distance, controlling speed using a fuzzy controller. Several neural network architectures were tested for vehicle identification, including ResNet and YOLO. Tests showed that YOLOv11 of the YOLO network offers the best performance ratio oriented towards a portable solution. The fuzzy controller demonstrates a steady-state error significantly below the typical 2% tolerance, validating its effectiveness and functionality for the intended control scenario. The results demonstrate that the proposed system can be integrated into real-time environments with limited resources. This system can be implemented in functional prototypes, test benches, simulators, and experimental vehicles. Future work includes selecting hardware architectures to test the algorithms on portable systems. It is also planned to use larger and more diverse datasets, incorporating different lighting and traffic conditions, to validate and improve the robustness of the proposed system.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Ricardo Andrés Castillo Estepa	✓	✓	✓			✓	✓	✓	✓	✓	✓	✓		
Alexander Aponte-Moreno	✓	✓		✓	✓		✓			✓	✓	✓	✓	✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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