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Development of Image Processing Based Line Tracking Systems for Automated Guided Vehicles with ANFIS and Fuzzy Logic

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ABSTRACT

Automated Guided Vehicles (AGVs) are robotic vehicles with the ability to move using mapping and navigation technologies to perform tasks assigned to them, guided by guides. Using sensor data such as laser scanners, cameras, magnetic stripes or colored stripes, they can sense their environment and move safely according to defined routes. The basic requirement of motion planning is to follow the path and route with minimum error even under different environmental factors. The key factor here is the most successful detection of the guiding structure of a system moving on its route. The proposed system is to equip a mechanical system that can produce very fast outputs and autonomous motion as a result of combining different algorithms with different hardware structures. In the line detection process, the wide perspective image from the camera is designed to be gradually reduced and converted into image information that is more concise but representative of the problem in a narrower perspective. In this way, the desired data can be extracted with faster processing over less information. In this study, the image information is divided into two parts and planned as two different sensors. The fact that the line information was taken from two different regions of the image at a certain distance enabled the detection of not only the presence of the line but also the flow direction. With the fuzzy system, the performance of the system was increased by generating PWM values on two different hardware structures, loading image capture, image processing processes and driving the motors. In order to determine the membership function parameters of the fuzzy system for each input, the ANFIS approach was used on the data set modeling the system. The outputs produced by the ANFIS model were combined into a single fuzzy system with two outputs from the system rules framework and the system was completed. The success of the algorithms was ensured by partitioning the task distribution in the hardware structure. With its structure and success in adapting different technologies together, a system that can be recommended for similar problems has been developed.

Keywords: Automated guided vehicles, Line following, Image processing, Fuzzy logic systems, ANFIS.

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Introduction

Science and technology are sets of values that model human life and define its standards on an incredible scale with the changes they continually bring about. In the world's scientific development adventure, there are such processes encountered as technological leaps that tend to radically change the way of life, habits and order. Intelligent Autonomous Systems (AOS) are among the most prominent of these leaps that have the potential to trigger these trends [1]. AOSs based on artificial intelligence are defined as having the ability to make decisions and perform tasks independently by adapting to changing environmental conditions. While performing many tasks, classical systems are handed over to AOSs that have the ability to make decisions on their own, can take situations according to changing environmental conditions, develop the ability to act in accordance with the tasks they undertake, and interact with other environmental systems. They also pave the way for innovative technological revolutions or developments and can perform tasks autonomously without the need for human intervention [2, 3].

AOSs are capable of creating innovative uses in robotics, transportation, logistics, retail, healthcare, manufacturing and many more. In robotics, examples include autonomous robots for tasks such as automated assembly lines, hazardous material handling and exploration in environments unsuitable for humans. In transportation, self-driving cars and autonomous drones have the potential to improve safety, efficiency and convenience. In healthcare, smart systems can help diagnose diseases, perform surgeries and provide personalized treatments [4, 5].

Automated Guided Vehicles (AGVs) are robotic systems used to automatically move loads in a given area or to perform tasks assigned to them under guidance. AGVs usually have the ability to move using mapping and navigation technologies. Using sensor data such as laser scanners, cameras, magnetic strips or colored stripes, they can sense their environment and identify obstacles, corridors and target points. In this way, they can move with safe guides based on set routes [6] and perform a variety of tasks such as moving materials, flowing materials to storage racks or between machines, managing inventory, or moving medical supplies in a hospital environment [7]. Grand View Research (2017), a market report forecasting the period from 2018 to 2025, focuses on the potential growth opportunities of AGVs, noting that the future growth of AGV systems is driven by the emergence of flexible manufacturing systems, increasing demand for customized AGVs, and the adoption of industrial automation by SMEs [8].

The main consideration in controlling AGVs operating indoors is orientation, which is a combination of positioning, route tracking and wayfinding [6]. Guidance is defined as the ability of the AGV to choose its route and decide on the start-finish path, and aims to find the shortest feasible route and follow the correct path to the destination. The AGV moves with the presence of navigators to guide it along its defined route. Wan. et al. summarized smart factories as a model in which production efficiency is increased through the use of digital technologies in production processes, production processes are automated, and data collection and analysis concepts are included in the processes.[9]. Smart factories use AGVs to transport materials or equipment, increasing productivity and reducing the cost of material handling. Navigation systems applied in AGV technology are usually fixed path and free range type [9]. Typically, in such structures, paths exist as physical guides on the ground and positioning is guided by sensors that detect the guide. These predefined paths are marked on the ground using marking methods such as ground painting, magnetic striping, etc., or buried in the ground using a wire. The AGV does not actually know its position in the territory map, it just stays on the path. Mobile robot guidance based on landmarks is widely practiced worldwide and is an important sense-making for a mobile robot capable of navigating on a predefined path or towards a designated destination using a line, landmark or mark as a reference point.[10]. The focus of the present study is on the line following guide task, which is realized by using an imaging system (camera), interpreting the instantaneous images (image processing) by an expert system (fuzzy system) and completing the task.

The AGV is the main component of the structure in which it operates, for example a flexible production line, and it performs its task by moving in structures that are considered intelligent, without any human intervention other than planning. It picks up a load, an unfinished product, a piece of equipment, etc. from a defined starting point and transports it to a different point for the ongoing stages. AGV systems are available in different structures designed for different tasks [11, 12]. Four main guidance methods are commonly used in AGVs: laser signals, line tracking, magnetic dot or stripe tracking and barcode tracking guidance [13, 14]. In the line tracking method, the scenario is brief; the AGV will follow a pre-loaded path in the work area. The route is determined by drawing lines of different colors on the ground surface, drawing magnetic tape or burying a wire in the ground. The sensor system attached to the robot detects the existing or planned structures on the route and the device follows the path to reach the desired destination. Table I shows a comparison of these methods in terms of installation cost, ease of installation, complexity, flexibility, ability to deviate from the route, efficiency and ease of expansion for the system. [15].

Table I – Comparison of guidance systems.

Guidance System	Laser Signals	Line Following	Magnetic Tracking	Barcode Tracking
Installation Cost	Moderate	Low	High	Low
Ease of Installation	Moderate	High	Moderate	High
Complexity	High	Low	Moderate	Low
Flexibility	Low	High	High	High
Ability to Deviate from Path	High	Moderate	Low	Low
Efficiency	High	Moderate	High	Moderate
Ease of System Expansion	Moderate	High	High	Moderate

A project by Ishikawa et al is one of the first similar studies. A camera-mounted AGV is designed for navigation use in an industrial or factory environment [16]. The AGV is trained to recognize and respond to different possible line shapes captured by the camera and is also equipped with obstacle detection systems in case of collisions. Due to hardware limitations and algorithm complexity, there are significant drawbacks for such vehicles that need to operate in real time. Processing time is the most important factor for systems such as AGVs that perform their tasks in real time, and there is a very important link between the compatibility and speed of the system components. In short, the most prominent output of the hardware and software structure that make up the system is the speed, performance and compatibility of producing results together. The basic steering circuitry of a line following AGV is generally not very complex and has light computing processes. However, by selecting the appropriate sensor combinations, it should be developed with a very high efficiency line following system that can distinguish even small color changes in the sensed environment from the color of the line to be followed.. Shah M., for ROBOCON 2016 (International robotics event), talked about the process of designing a robot line following system and explained how he designed the most optimized, efficient and high performance line following system to overcome similar problems [17]. Vo Nhu Thanh presented the development of a restaurant service robot using dual line sensors in combination with a PID control approach for a system aiming at a stable speed result. They focused on hardware, software and mathematical calculations for multidimensional line tracking. They provided a comparison of the existing shortcomings over the system they developed and provided a reference for future studies. [18].

In the proposed study, a method that uses a combination of image processing, artificial intelligence and fuzzy logic technologies for guidance tracking is proposed. The PWM values of the motors that steer the AGV are generated by the fuzzy system. The input parameters of the fuzzy system are obtained instantaneously by image processing, divided into RoI fields and presented to the system as sensor data. The parameters (membership functions) of the fuzzy system are trained by ANFIS over the data set in which the routing pattern of the system is defined. The requirements of the overall system are designed to produce high performance considering the real-time operation of the AGV system. The images taken by the camera include steps such as detecting the line, extracting information about the line and generating commands for the AGV to follow the line. A fuzzy logic control system is developed to control the position and movement of the AGV on the line and evaluates various input data to determine where it is on the line and how fast it should move, and generates the appropriate outputs PWM outputs. ANFIS is trained on the dataset to determine the fuzzy logic parameters that will produce the most optimal outputs.

Material and Methods

The basic requirement of motion planning in AVG or mobile robot systems is to proceed with minimum error in path planning and route following even under different environmental factors. The key factor here is the most successful detection of the structure that is the guide of a system moving on its route. The main problem encountered in sensing with optical or magnetic sensors is that the signals they send are reflected according to the properties of the surfaces they hit and the system works according to different situations in this reflection. For example, infrared sensors have operating principles such as Planck's law of radiation, Stephan Boltzmann's law and Wein's displacement law because they reflect part of the light incident on a colored surface. In the case of a white surface, the light is completely reflected. But if light falls on a black surface, it is completely absorbed due to the absorption of the black color. This principle is used in the design of infrared sensors. When light falls on normal or regular surfaces it bounces back to the photodiode, whereas when it falls on a black object it is absorbed; therefore, no light ray is captured by the photodiode. Difficulties in accurately detecting reflected signals with different tones or distortions, or in instantaneously determining differences in threshold values according to ambient variations, are important factors in the success of such systems. However, the most obvious advantages of these systems are their simple structure, response generation and data transmission speed. In recent years, technological and theoretical advances have offered many advantages to system developers, especially the powerful computing capacities and low cost of small-sized computers with very fast data processing capabilities. These benefits have enabled more computationally intensive algorithms to be used at low cost in systems that require fast response times. In the positioning process, an AGV is evaluated on its ability to use the image information it receives from the camera, to make intelligent decisions, to quickly evaluate situations and to see in real time.

Image processing is the combination of different methods to obtain the desired information with algorithms to be used to solve the problem determined on real-world images transferred to digital media. Image processing is also used to process the visual data taken with cameras and to produce outputs that will make decisions based on these data in a digital environment. Environment detection is an identification technology that helps a robot understand its environment. When combined with the image processing method, firstly, using a camera with a digital image capture element, the surrounding images are processed using image processing algorithms and the environment is tried to be perceived. In this way, robots can perceive their surroundings and adjust their movements accordingly. The important distinction here is that AGV or robot systems are equipped with algorithms capable of detecting image information and processing it to produce target output. In order to specialize the systems in line following processes, it may be preferable to develop the expert systems approach using fuzzy logic methods and to use this combination as the eyes of the systems in order to obtain fast results [19-20].

Fuzzy logic is a theory developed for solving problems involving uncertainty [21] and focuses on the possibility of a quantity taking values within a range, rather than on the possibility of a quantity taking exact values. Fuzzy logic is also used in expert systems. Expert systems can be used in decision-making processes using methods such as fuzzy logic.

Image Processing Basics:

An image is represented by its dimensions (height and width) based on the number of pixels. This pixel is a point on the image that receives a certain shade, opacity or color. Usually an image is represented in one of the following forms: Grayscale (a pixel is an integer with a value between 0 and 255, where 0 is all black and 255 is all white), RGB (a pixel consists of 3 integers between 0 and 255, the integers represent the intensity of red, green and blue), RGBA (an extension of RGB with an additional alpha field representing the opacity of the image).

Image processing is the process of converting an image into a digital form and performing certain operations to extract some useful information from it. The image processing system usually treats all images as 2D signals while applying certain predetermined signal processing methods [22]. There are five main types of image processing:

Visualization - Finding objects that are not visible in the image

- Recognition - Distinguish or detect objects in the image
- Sharpen and restore - Create an enhanced image from the original image
- Pattern recognition - Measuring various patterns around objects in an image
- Import - Browse and search for images from a large database of digital images that resemble the original image. Basic Image

Processing steps can be listed as follows:

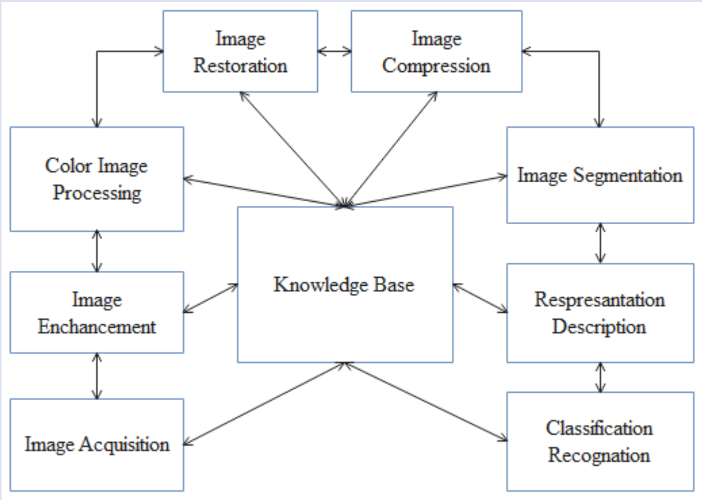


Figure 1. Image processing steps.

These steps represent a basic image processing process. However, different steps and techniques can be used depending on the application.

Fuzzy Logic(FL)

Fuzzy Logic based on multivariate logic, probability theory, genetic algorithms and artificial neural networks, it introduces the concept that deals with the degree to which events occur rather than the probability of occurrence Prof. Zadeh describes FL as "a technique close to a human with a high mechanical IQ". The initial idea of FL started with "everything is a problem of gradation" proposed by logicians in the 1920s. Jan Lukasiewicz, who worked extensively on logic in the 1920s, worked on principles showing that propositions can take fractional values between the binary values 1 and 0. In the light of this work, Lotfi A. Zadeh of the University of California published his seminal paper "Fuzzy Sets". Lotfi A. Zadeh developed an arithmetic for fuzzy sets by applying Lukasiewicz's logic improvements to all elements of a set [23]. The basic logic here is about the degree to which events occur rather than their probability. Probability and fuzziness, which seem to be close concepts, are actually quite different concepts. Probability measures the likelihood of an event occurring, while fuzziness measures the extent to which an event will occur, the extent to which a condition will exist.

Fuzzy logic, in essence, enables the realization of processes identical to human thought and helps to explain or assist in modeling uncertain and imprecise events that are frequently encountered in the real world. In classical logic, any proposition is "true" or "false". However, when modeling events in the real world, it is necessary to determine to what extent it is true or false. The fuzzy set approach performs graded data modeling by using linguistic structures such as a little, little, medium, low, low, much, more, many. Thus, it enables the production of results that are closer to natural, realistic and expressive in modeling events.

In classical binary logic, an object (element) either belongs (is a member) or does not belong (0 or 1) to a set, and such sets are called crisp. FL, on the other hand, creates a more convenient approach to logic that matches real-world data (everyday expressions) by representing the binary concepts that sharp logic restricts to precise concepts with softer determinants such as less short/less long, slightly slower/slightly slower or faster [24]. More precisely, a classical (sharp) set determines the relation of an element to itself by assigning 0 or 1 values to its elements.

In classical set theory, a set determines the relation of an element to itself by assigning a value of 1 or 0 to the element to which it belongs. In other words, if the element takes the value 1, it belongs, and if it takes the value 0, it does not belong. As can be seen in Figure 2a, a temperature of 20 degrees is considered "hot", whereas according to binary logic and the classical set, a temperature of 19.5 degrees is considered cold. It is obvious that the boundaries of this approach are strict and lack flexibility, and it is also obvious that many real-world problems are difficult to model with this structure due to the lack of such strict boundaries.

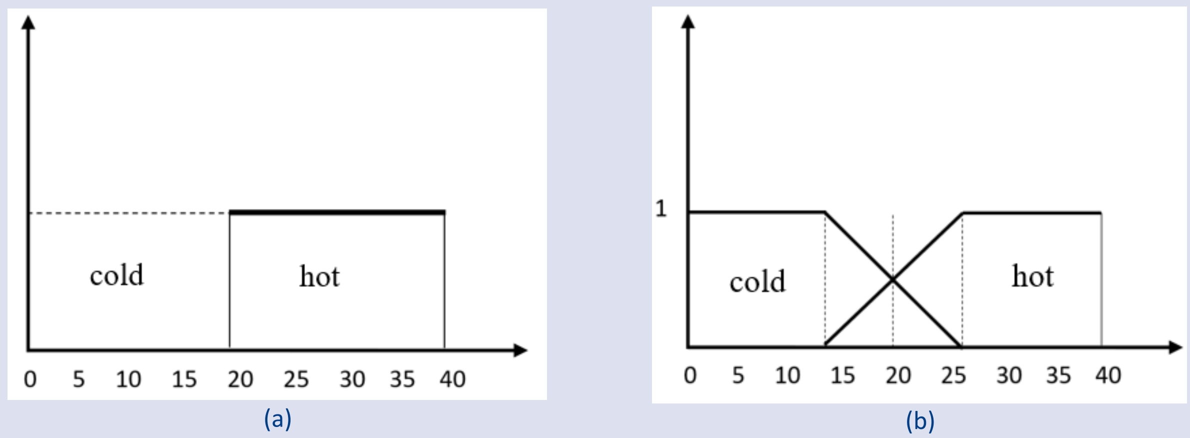


Figure 2.(a) Classical set theory, (b) Fuzzy set theory.

Classical set theory was developed by the German mathematician George CANTOR (1845-1918). In this theory, an element is either an element of the set in question or it is not (Figure 3-a). There can never be partial membership. If the membership value of the element is 1, it is a full element of the set, and if it is 0, it is not an element. In other words, in classical sets, the membership values of the elements are {0,1}.

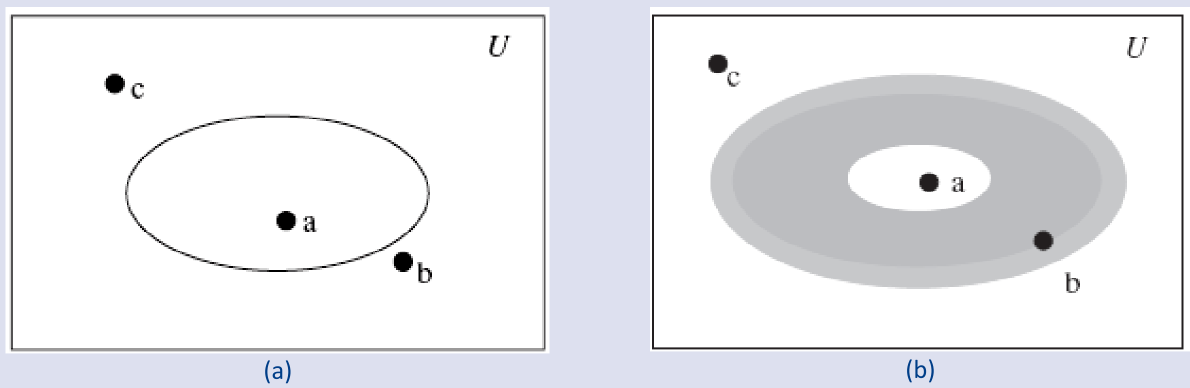


Figure 3.(a) Classical set boundaries, (b) Fuzzy set boundaries.

A classical set can be expressed as $A=\{x \in U \mid p(x)\}$. Here A is the classical set, P is the property of the set and U is the space to which this set belongs. The characteristic function, $\mu_A(x): U \rightarrow \{0,1\}$, is defined as '1' if x is an element of this set and '0' if it is not. In fuzzy set theory, the characteristic function, known as the membership function, represents a more generalized structure. Figure 3-b shows the expression of a fuzzy set with a venn diagram. Here the element 'a' is the definite element of the fuzzy set. The membership degree of this element is expressed as 1. If element 'c' does not belong to the fuzzy set, its membership degree is considered as 0. The element 'b' is a member of the fuzzy set at a certain degree (level). This membership is expressed by a membership degree in the range [0,1]. The degree of membership function is important.

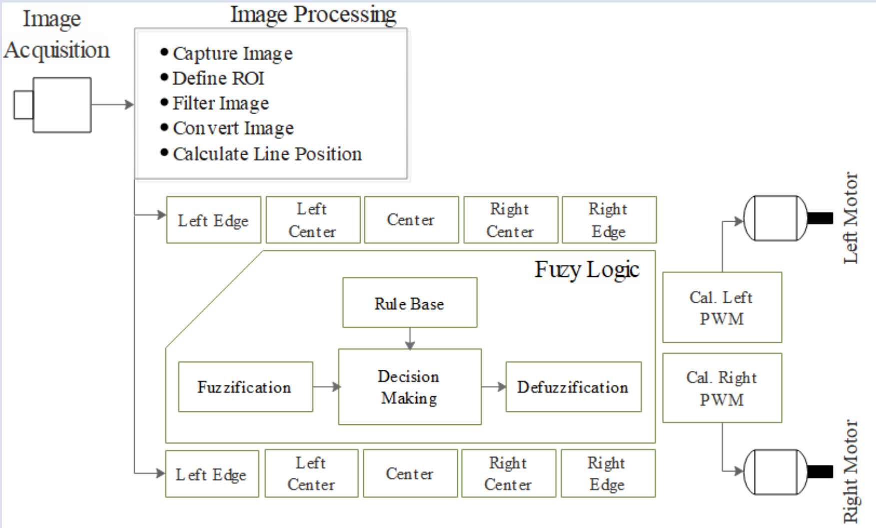
ANFIS-Adaptıve Network-Based Fuzzy Inference System

ANFIS, It is a hybrid approach that combines the ability to learn and parallel computation, which are the most basic features of Artificial Neural Network (ANN) theories, with the ability of Fuzzy Logic (FL) models to infer inexact structures. Developed by Jang [25], this theory has been widely used in problems in different disciplines such as classification, grouping, control and time series analysis, and in particular in modeling nonlinear functions, prediction of chaotic time series [26]. In order to model the pattern hidden in the data, it uses the expert insights and experience of the UN and the learning capabilities of the ANN. Successfully models functional structures that can be expressed in different forms and converges to the functions of the structures at acceptable rates [27, 28]. The training process of ANFIS, one of the machine learning approaches, depends on the ability of the data set to represent the problem (all inputs and outputs). It learns system behavior from a data set of real measurements and is a more flexible computational tool than conventional statistical methods, especially for nonlinear functions [29]. One of the most obvious disadvantages of ANNs, which derive their power from their ability to learn, is that the learning results are presented with very large parameter sets, which makes it difficult to express the results in words. The basis of the UN is that it mimics the thinking structure of the human brain, as in natural languages. As it is known, it cannot learn the rules by itself, as a result, it needs guidance from experts. At this point, the neural fuzzy logic approach comes into play. The neural fuzzy logic approach offers the idea of combining ANN learning processes with the views of a BM expert system.

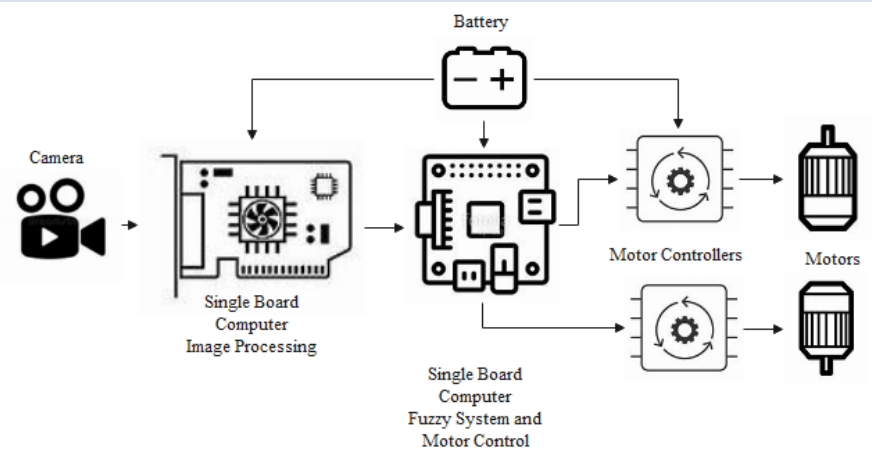
In the theoretical background of this idea, BM controllers are introduced into the system with two different adaptations: structural and variable tuning. Structural tuning consists of setting up the BM rule structures such as the number of variables to be present in the system, the number of rules and the separation of the definition spaces of each input-output parameter. The determination of the rule structure that fits the requirements must be accompanied by the determination of the controller parameters. In the variable/parameter setting part, the centers, widths and slopes of the membership functions and the weights of the BM rules are calculated [30].

Theory and Calculation

The development of autonomous systems or object detection based systems based on environment analysis with camera images is the basis of many academic and theoretical studies. [31-34]. Camera images provide comprehensive visual information about the position, shape, size, color and motion of objects or environments. In particular, using this information, an automated system or artificial intelligence model can successfully analyze the environment. This detailed information can enable detailed analysis of environments and create a more comprehensive perception feedback. The real-time nature of camera images is almost the most fundamental factor in applications that require fast response. In recent years, thanks to advances in deep learning and artificial intelligence technologies, systems have been trained with large amounts of image data from camera images and more qualified identification capabilities have been developed. In the light of all these explanations, it is an accepted fact that environment detection of the autonomous line-following system, which is the subject of this study, using a camera is an appropriate method[35]. The camera can flexibly detect and process color, shape and location information of real objects in the environment in harmony with the environment. The real-time nature of the images allows the system to react quickly to instantaneous changes and information. The flow given in Figure 4-a is a visualization that briefly summarizes the theoretical structure, data flow and processing processes of the proposed work. The hardware architecture of the system is shown in Figure 4-b. The system input information is obtained by taking camera images with an SCB (Single Board Computer) that performs image processing processes on the Linux operating system. These data, which are generated as numerical values, are transferred to another SCB, which is also responsible for the movement of the motors, via the I2C [36] communication protocol. Fuzzy analysis algorithms are also operated on this second SCB to control the system operation by generating coefficients for the PWM signals required for the version control of the motors.



(a)



(b)

Figure 4.(a) General architecture of the system, (b) Hardware implemantation of system.

The line following model of the AGV will consist of two basic steps. In the first step, the presence and position of the line with the camera image will be determined by image processing steps. In the second step, the line information will be processed by the expert system to manage the motor systems that control the vehicle's orientation Figure 4.

The key factor in the proposed system is to acquire, process and quickly transfer the image selected as a guide for route tracking to the system in a semantic way. Real-time image processing is the process of perceiving and organizing digital images with a limited and fast time constraint. It is often used in applications that require fast and accurate responses, such as digital cameras, machine vision, surveillance and biomedical imaging. Some of the key factors of real-time image processing are: computational complexity, frame processing speed, real-time hardware implementation and real-time software optimizations. These factors affect the quality and reliability of real-time image processing applications, as well as the trade-off between speed and accuracy.

Images taken at 320x240 pixel resolution from the camera placed on the front of the AGV system at a distance of approximately 20 cm from the ground and at an angle of 15^0 forward are divided into areas of interest as shown in Figure 5. Here, no processing is performed on the image parts corresponding to Out of Interest (OoI) areas. In this way, image processing time is significantly reduced. By detecting the presence and position of the line on the image information in the parts determined as Region of Interest (RoI), input data will be generated for the algorithms of the model that will guide the AGV system as it moves forward.

[OoI : Out of Interest , The image detected by the camera is divided into four segments horizontally (Figure 5), two of these segments are not included in the calculations and processing, this approach reduces the number of data to be processed. RoI : Region Of Interst is the image range corresponding to the segments detected and separated by the camera and all processes are performed from the data in this range].

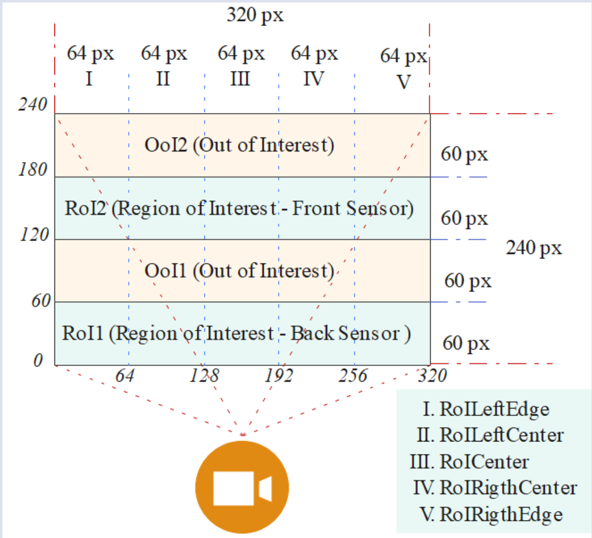


Figure 5. Camera image segmentation.

For the prototype vehicle used in the modeling of the system, the segmentation in the camera field of view is at the pixel ratios given in Figure 5. These ratios can be updated according to different designs or situations, and since the system will be dynamically configured, it is capable of responding to such update situations (from this part of the study onwards, the system will be analyzed with reference to these ratios in the explanations about the structure). The flow given in Table 2 describes how the line image will be used to generate data to be used for training expert systems.

Table 2 – Determining line input value

Capture camera image OoI (Out of Interest) extract parts from the image information { OoI_1 [60 pix-120 pix, 0 pix -320 pix] range OoI_2 [180 pix-240 pix, 0-320 pix] range } RoI (Region of Interest) take the parts from image information { Front Sensor -> RoI_1 [120-180 pix, 0-320 pix] Back Sensor -> RoI_2 [0-60 pix, 0-320 pix] } define as For Each RoI { Image processing, filtering Detect line, center_point =(First pixel + last pixel)/2 send the point value to the expert system }

RoI fields are actually sensors where the input values for the Fuzzy System are generated, and the system continuously scans these fields to generate the input values of the system that will control the AGV movement Figure 6.

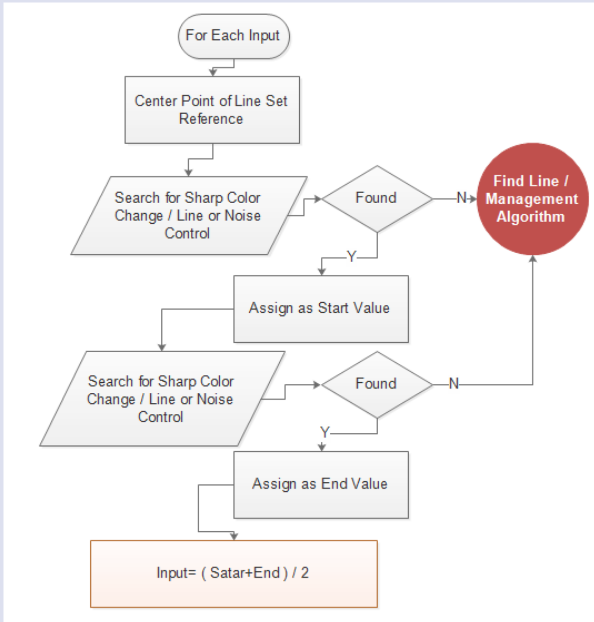


Figure 6. Determining the values of sensor1 and sensor2 variables.

With the algorithm given in Table 2, the pixel values of the approximate midpoint of the line corresponding to the RoIs are obtained. These values constitute the definition ranges of the Fuzzy Logic system as defined in Table 3.

Table 3- Input values expert system definition ranges

LeftEdge	LeftCenter	Center	RightCenter	RightEdge
0-64	64-128	128-192	192-256	256-320

In summary, the steps to be followed when developing a Fuzzy System are: creating linguistic variables, creating membership functions and creating a rule base. The system input of the line tracking algorithm is the flow of the camera image, which is two-dimensional in the non-linear RGB color space. According to the pixel values of the position of the lines perceived by the system's eye on the image, the linguistic variables for input were represented by 5 different values as "LeftEdge, LeftCenter, Center, RigthCenter, RigthEdge" and their ranges were determined as given in Table 3 . Likewise, the output linguistic expressions of the PWM values that will determine the movement rates of the right and left motors were determined with 3 different expressions as "Back1 (-1) , Constant (0), Forward1 (+1) " and the coefficient values were determined as shown in Table 4.

Table 4- Output values fuzzy definition ranges

Back1 Vel.	Constant	Forward1 Vel.
-1	0	1

Summary study of the model; The image taken as 320x240 pixels instantaneously in Figure 7 will be divided into areas of interest and subjected to image processing processes as shown in the flow given in Table 2 and Figure 6.. In the developed system, the image taken at the determined resolution ratios is divided into 5 columns of 5x64 pixels and 4 rows of 4x60 pixels. The images in the 1st and 3rd rows of these rows will constitute the source for the data input of the system. RoI1 targets the pixel range (0-60 lines) and RoI2 targets the pixel range (120-180 lines). The remaining parts are excluded from the process. The 60 pixel range is chosen because of the line thickness, which should be changed for different resolutions and structures, or these parameters should be determined dynamically, as in the development of the proposed model.

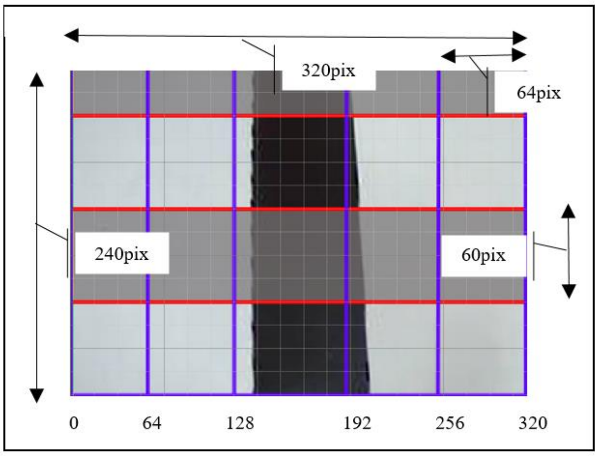


Figure 7. Camera view - identifying areas of interest.

The pixel values obtained by image processing from the snapshot taken with Figure 7 will form the inputs for the control of the Fuzzy System as given in Table 3. Figure 7 illustrates a snapshot of the screen, segmented and represented by a grid. On this sample image, the pixel value at which the line starts and the pixel value at which the line ends are instantaneously determined by the image processing programme as 132 and 200, respectively, and transferred to the relevant part of the system. The method of calculating the midpoint of these values is summarised in Table 5.

Table 5- Sample line position calculation

RoI1	
Star→132. pix.	=(132+200)/2
End→ 200. pix.	=166
RoI2	
Start→134. pix.	=(134+190)/2
End→ 190. pix.	=162

The width of the line will vary in proportion to the distance of the camera from the image. However, since the midpoint of the line is considered the target value, the line thickness is not a decisive factor. Given the fps (frames per second) of the camera and the speed of the car, the line will be close to its previous position in the next image. During the analysis of the search for the start and end points of the line, the presence of the line is verified by applying intermediate image processing algorithms to prevent possible noise-induced errors. The values generated by the image processing steps will feed the input values of the Fuzzy Control system shown in Figure 8.

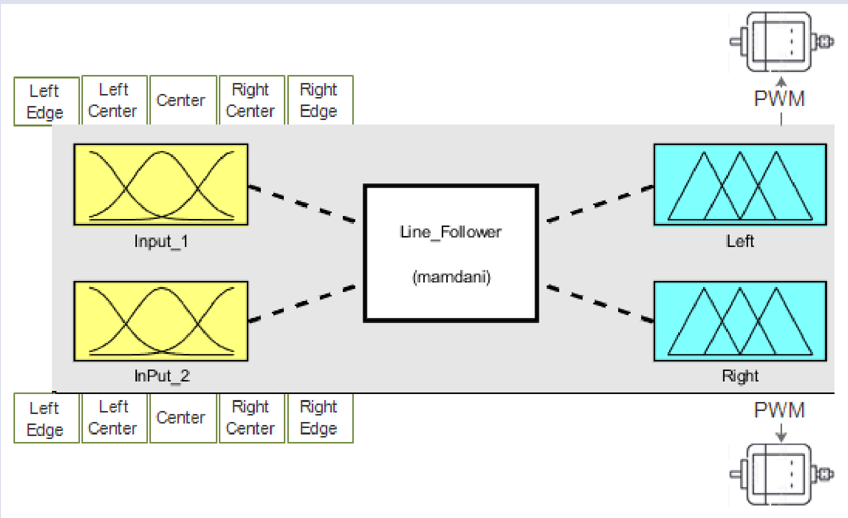


Figure 8. Fuzzy system architecture

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The effective factor on the success of the systems using fuzzy logic is to determine the membership functions in a structure that will best model the accuracy and performance of the system. Membership functions indicate the degree to which an input value belongs to a set in fuzzy logic systems and are based on fuzzy set theory. Systems designed with the right membership functions can model the input values more precisely and produce more accurate results. Therefore, it is of great importance to determine the membership functions accurately [23] [37] [38]. In general, the selection of fuzzy membership functions takes into account properties such as suitability to the data, expressiveness, validity, interpretability, ease of computation, adaptability and generalization. However, each problem and application area is different and sometimes the most appropriate membership functions should be determined by trial and error methods or expert opinions. There are different structures of membership functions used in the literature [37]. The determination of the membership functions for each system input was performed using the ANFIS approach over a database containing the pattern of the motion modeling of the system. In this way, a process that requires expert behavior was identified using artificial intelligence, based on a pattern, and an intelligent system was used instead of trial and error or past experience. Sample data of the data set used for training the ANFIS system is shown in Table 6. For different input values, the PWM output parameters to be generated for the motors were determined.

Table 6- Samples data ANFIS model training

RoI1 Sensor 1	RoI2 Sensor 2	Left Motor	Right Motor
1	1	-1	1
57	57	-1	1
182	182	0	0
185	185	0	0
206	206	0	-1
210	210	0	-1
208	272	0	-1
233	297	0	-1
311	311	1	-1
320	320	1	-1
---	---	---	---

As seen in Figure 9, the fuzzy system is planned as 2 inputs and 2 outputs. The important factor here is to determine the membership functions of the inputs. Each membership function contains a curve representing each point in the specified input section. Depending on the shape of the curve, each membership function is given a specific name, i.e. triangular, bell-shaped, trapezoidal and Gaussian membership functions. There are different types of membership functions that are commonly used [39] (Table 7).

Table 7. Member ship functions

Membership Type	Description
'gbellmf'	Generalized bell-shaped membership function
'gaussmf'	Gaussian membership function
‘gauss2mf’	Gaussian combination membership function
'trimf'	Triangular membership function
'trapmf'	Trapezoidal membership function
'dsigmf'	Difference between two sigmoidal membership functions
'pimf'	Pi-shaped membership function

In order for the ANFIS model to best represent the pattern structure of the data set it is trained on, the membership functions of the input parameters should be selected in a way that reflects the effects of the input data on the model. For this reason, ANFIS models were trained over approximately 64 different combinations by taking all combinations of eight different membership functions to produce the desired results for two inputs, and the membership functions that produce the best output from the models were determined separately for each input. At this stage, statistical measures (Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), R Squared (R2) [40]) were used to test the outputs produced by the ANFIS model trained using each different combination of membership functions. While these results obtained using the Training, Test and Validation Datasets are analyzed with statistics metrics, here the main criterion for selecting the most successful ANFIS model was the results of the “Test Dataset” and the R Squared (R2) value was used as the basis and values for all datasets used in ANFIS training were generated. ANFIS is an approach designed to produce a single output. However, the proposed system should be designed with two outputs for two different motors. For this reason, the ANFIS model is trained separately for each different output. Table 8 and Figure 9 shows the best value measures produced by the trained models.

Table 8-a Right motor ANFIS model statistical metric values

Inputs	RoI1 Sensor 1		RoI2 Sensor 2
MF	gauss2mf		gauss2mf
	Data Set	Training	Test
MAPE	0.5838	0.5836	0.5067
MAE	0.0516	0.0523	0.0404
RMSE	0.1335	0.1374	0.0976
R^2	0.96	0.97	0.97

Table 8-b Left motor ANFIS model statistical metric values

Inputs	RoI1 Sensor 1	RoI2 Sensor 2	
MF	gauss2mf	gauss2mf	
	Data Set	Training	Test
MAPE	0.5512	0.5648	0.5408
MAE	0.0159	0.0158	0.0207
RMSE	0.0661	0.0678	0.0737
R^2	0.9881	0.9873	0.9844

With ANFIS, the most appropriate membership functions for the inputs were determined as "gauss2mf" based on the statistics value measures. As seen in Figure 8, the Fuzzy system is designed as 2 inputs and 2 outputs. Since the single output structure of ANFIS is not sufficient to model the system, the fuzzy model of the system was designed using the membership functions determined with ANFIS as shown in Figure 8.

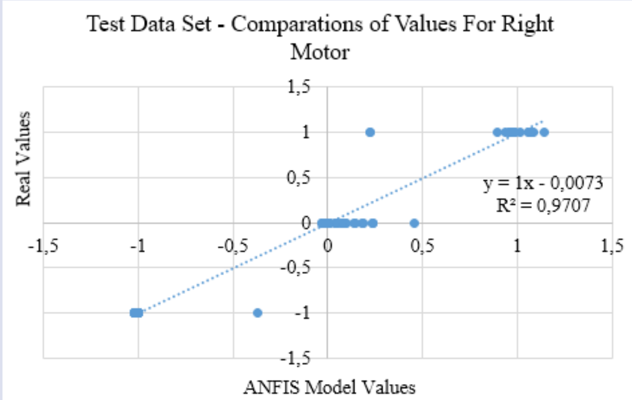


Figure 9 (a). Right motor ANFIS model comparations of test data set values.

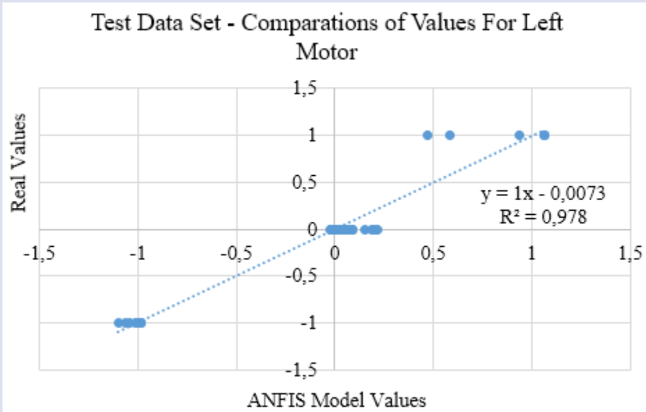
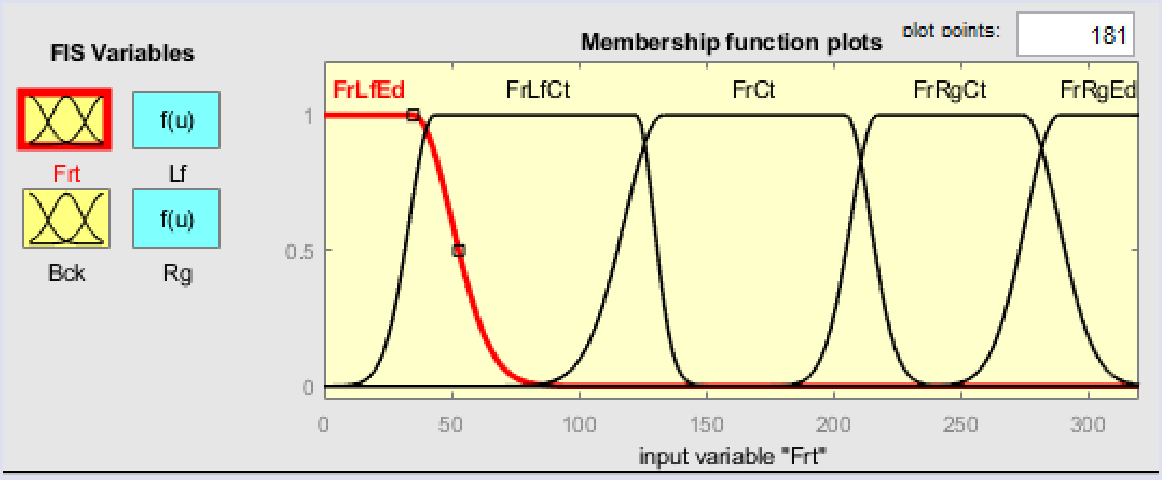


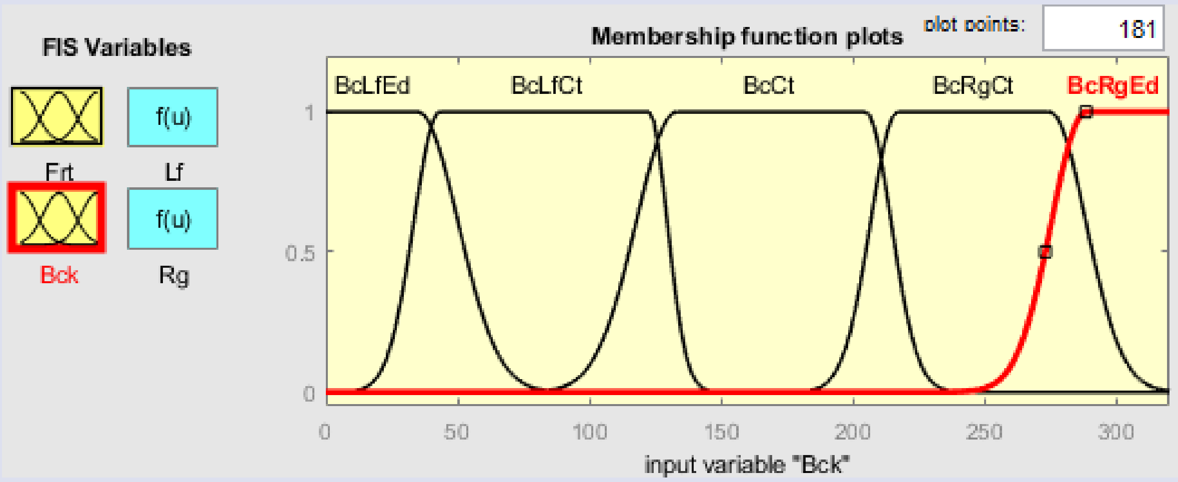
Figure 9 (b). Left motor ANFIS model comparations of test data set values.

With the step of determining the membership functions using ANFIS, a structure to determine the right and left motor PWM coefficient values with two different models was created. By combining the parameters of these two different models in a fuzzy system, the system that will manage the motion system subject to the study has been created. In the fuzzy system, the truth table given in Table 9 was used to define the rules for the right and left motors to be controlled by the inputs defined by the membership functions determined by ANFIS. The parametric values of the membership function of this structure are defined as given in Figure 10 for Sensor1 and Sensor2.



[Sensor 1]
Name='Frt'
Range=[0 320]
NumMFs=5
MF1='FrLfEd':'gauss2mf',[13.6 -22.9 15.2 35.01]
MF2='FrLfCt':'gauss2mf',[9.76 43.2 7 122.6]
MF3='FrCt':'gauss2mf',[15.2 133 9.74 204.8]
MF4='FrRgCt':'gauss2mf',[10.3 217 13.7 274.7]
MF5='FrRgEd':'gauss2mf',[13.1 288.4 13.6 344]

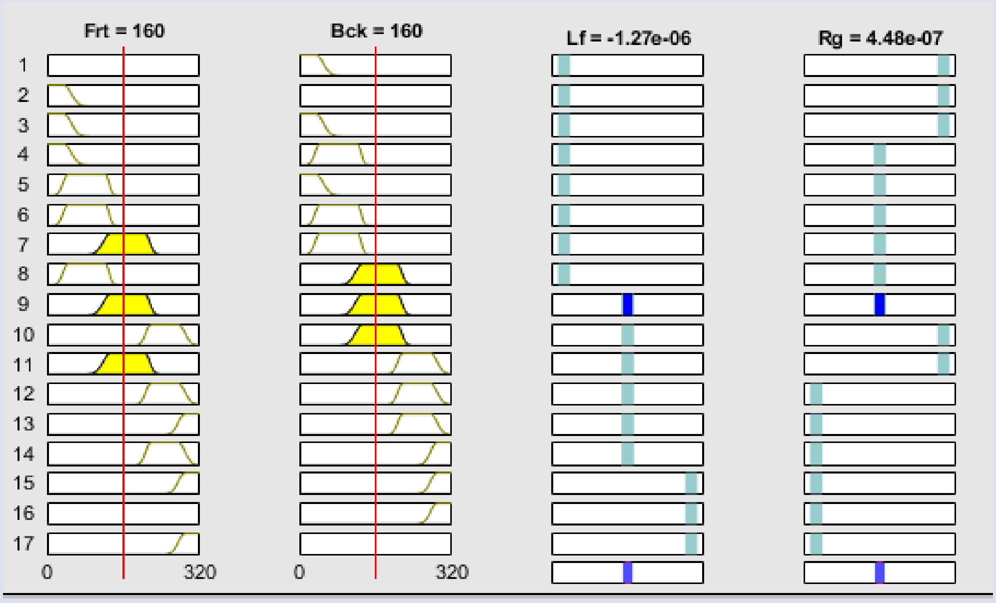
Figure 10 (a). Fuzzy input for sensor 1.



[Sensor 2]
Name='Bck'
Range=[0 320]
NumMFs=5
MF1='BcLfEd':'gauss2mf',[13.55 -22.93 15.25 26.59]
MF2='BcLfCt':'gauss2mf',[9.691 59.55 13.82 104.8]
MF3='BcCt':'gauss2mf',[15.11 136 4.178 181.5]
MF4='BcRgCt':'gauss2mf',[10.91 216.4 13.69 264.4]
MF5='BcRgEd':'gauss2mf',[13.95 295.7 13.55 343.9]

Figure 10 (b). Fuzzy input for sensor 2.

The type of membership functions and parametric settings of the membership functions were determined by training the ANFIS model. The fuzzy rules to control the motor directions with the line information (midpoint pixel values) received from the camera were developed with the verification values given in Table 6 and Figure 11 shows the structure of the defined rules.



[Motor Right]
Name='Lf'
Range=[-1 1]
NumMFs=3
MF1='BCK':'constant',[-1]
MF2='CST':'constant',[0]
MF3='RWD':'constant',[1]

[Motor Left]
Name='Rg'
Range=[-1 1]
NumMFs=3
MF1='BCK':'constant',[-1]
MF2='CST':'constant',[0]
MF3='RWD':'constant',[1]

Figure 11. Fuzzy system rules.

The comparison of the actual values produced by the developed system according to the values it receives from the inputs can be examined in Table 9 for some randomly selected values. Here, the numerical comparison of the values produced by presenting the data used in the training of the system to the Fuzzy System is given. As can be seen from the values, the system produces outputs that are very convergent to the real values.

Table 9 – Actual values - fuzzy system generated values comparison.

RoI1 Sensor 1	RoI2 Sensor 2	Left Motor	Right Motor	Fuzzy System	Fuzzy System
1	**1**	**-1**	**1**	**-1**	**1**
57	**57**	**-1**	**1**	**-1**	**0,88**
182	**182**	**0**	**0**	**0,00617**	**0,0089**
185	**185**	**0**	**0**	**0,0058**	**0,00157**
206	**206**	**0**	**-1**	**0,00121**	**-0,87**
210	**210**	**0**	**-1**	**0,0135**	**-0,81**
208	**272**	**0**	**-1**	**0,019**	**-0,79**
233	**297**	**0**	**-1**	**0,04**	**-0,99**
311	**311**	**1**	**-1**	**0,98**	**-1**
320	**320**	**1**	**-1**	**0,98**	**-1**
…	**….**	**….**	**….**		

Discussion

The goal of the designed system is to equip a mechanical system with the ability to produce very fast outputs and autonomous movement as a result of the combination of different algorithms with different hardware structures. Therefore, this system should be able to react quickly and reliably, comply with time constraints, and work in harmony with all its components to minimize latency and meet timing requirements. Unlike similar approaches, the system is designed to gradually reduce the wide perspective image from the camera in the line detection process and convert it into a more concise image information in a narrower perspective, but more concise image information to represent the problem. In this way, the desired data can be extracted with faster processing over less information. In this study, the image information is divided into two parts and planned as two different sensors. However, the system has the dynamism to work with more partitions. The fact that the line information is taken from two different regions of the image at a distance has also added the ability to detect not only the presence of the line but also the flow direction. Similar studies are weaker at this point. The performance of the system was increased by loading the image capture, image processing processes and driving the motors by generating PWM values with the fuzzy system on two different hardware structures. The computational load of the system is designed to provide fast feedbacks by loading the computational load on two different hardware. The time between the acquisition of a snapshot and the conversion of the output of this snapshot into the control commands required for the motors was kept below 0.1 s, ensuring that the planned system is within the acceptance limits.

A library of fuzzy rules was not used on the SBC, and with the logic of directly coding and loading the algorithms needed, performance degrading reasons on the board were also prevented. Thus, efficiency is increased and the average system performance is improved in terms of processing load and computation speed.

When the literature was reviewed, no similar studies were found in which the approaches summarized below, which are parts of the study, were used together.

These sections summarize

Partitioning large amounts of camera information into smaller areas of interest and using these areas as sensor information,

Determining the rules of the fuzzy system that will generate PWM coefficients from this information with ANFIS, an Artificial Intelligence method,

ANFIS is a single output system, in this study ANFIS is designed to be trained separately for both engines (with different output values for each engine with the same data sets),

As a result, the structure of these two ANFIS models is combined into a single fuzzy system with two outputs from the system rules framework.

Partitioning the task distribution in the hardware structure

It can be given. The combination of all these processes suggests an innovative approach to solving problems similar to the literature.

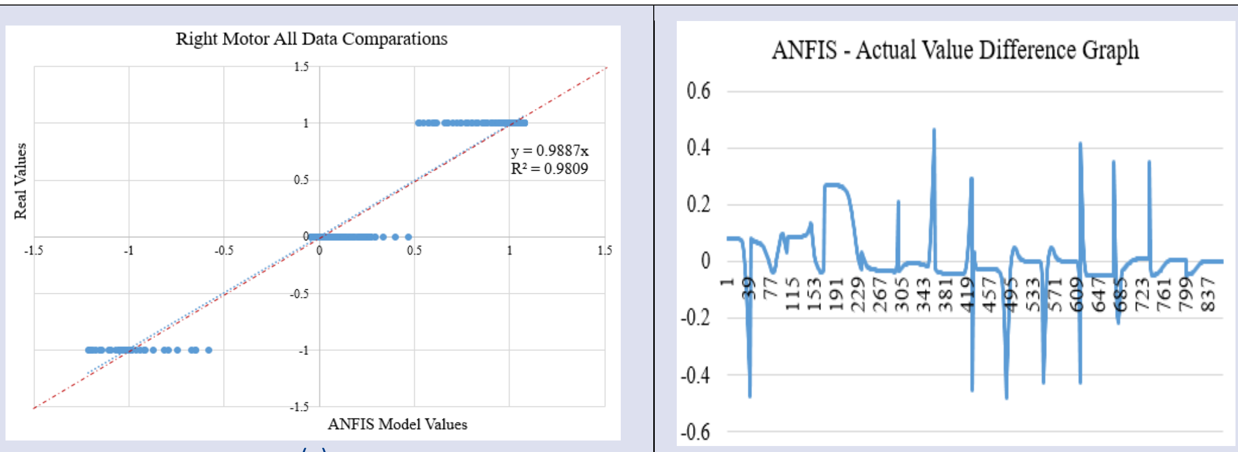
Conclusion

With the membership functions determined by the ANFIS models Table 8-a,b, the Fuzzy system is designed to produce two outputs. During this design, the accuracy or expert data of the input/output values shown in Table 10 were used.

Tablo 10- State control evaluation for fuzzy rules.

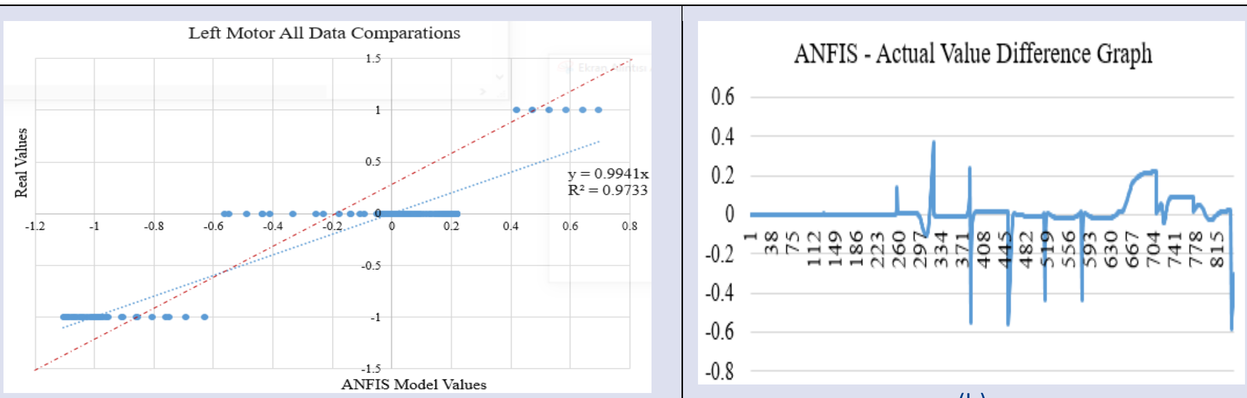
	0-64 LeftEdge	64-128 LeftCenter	128-192 Center	192-256 RightEdge	256-320 RightCenter	Left Motor	Right Motor
Sensor2						-1	+1
Sensor1	1						
Sensor2	1					-1	+1
Sensor1							
Sensor2	1					-1	+1
Sensor1	1						
Sensor2	1					-1	0
Sensor1		1					
Sensor2		1				-1	0
Sensor1	1						
Sensor2		1				-1	0
Sensor1		1					
Sensor2			1			-1	0
Sensor1		1					
Sensor2		1				-1	0
Sensor1			1				
Sensor2			1			0	0
Sensor1			1				
Sensor2				1		0	+1
Sensor1			1				
Sensor2			1			0	+1
Sensor1				1			
Sensor2				1		0	-1
Sensor1				1			
Sensor2					1	0	-1
Sensor1				1			
Sensor2				1		0	-1
Sensor1					1		
Sensor2					1	+1	-1
Sensor1					1		
Sensor2						+1	-1
Sensor1					1		
Sensor2					1	+1	-1
Sensor1							

The designs of the Fuzzy System designed within the framework of these rules are given in Figure 10 and Figure 11. Correlation graphs showing the relationship between the data generated by ANFIS and the real data for the whole data set produced by this system are given in Figure 12-a and 12-b for the right motor. Similarly, Figure 13-a and Figure 13-b are given for the left motor.



(a) (b)

Figure 12 (a). Right motor ANFIS model comparations of all data set values.
(b) Rigth motor ANFIS – all data set actual value difference graph.



(a) (b)

Figure 13 (a). Left motor ANFIS model comparations of all data set values.
(b). ANFIS – Left motor all data set actual value difference graph.

In the light of all these values and the behavior of the real autonomous system to which the model was applied, the performance of the system was accepted. Basic image processing steps were followed to keep the speed performance of the system at a higher level. It is envisaged that by using more powerful SCBs and more sensitive image processing processes, systems that are more sensitive to environmental effects can be developed with this approach.

The determination of membership functions, which is the most decisive point of fuzzy systems, was generated from the data set containing the pattern of the system with ANFIS, and thus expert opinion was made by an intelligent system. It provided an important perspective for similar control applications.

In addition, this system can be applied not only to image-based systems but also to similar systems that will follow the line using IR or magnetic information.

Conflict of interests

The authors state that did not have conflict of interests.

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