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Research Paper

Fuzzy Decision Based Modeling of Rheostatic Brake System for Autonomous Land Vehicles

Semir Sünkün*[1], Berke Oğulcan Parlak[1], Alper Yıldırım[2], Hüseyin Ayhan Yavaşoğlu[1]

[1]Mechatronics Engineering, Yıldız Technical University, Istanbul, Turkey

[2]Mechatronics Engineering, Marmara University, Istanbul, Turkey

(semir.sunkun@yildiz.edu.tr, boparlak@yildiz.edu.tr, yildirim.alper@marmara.edu.tr, hayhan@yildiz.edu.tr)

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Abstract— The most fundamental characteristic of autonomous vehicles (AVs) is their autonomy. However, due to the dynamic operating environment of the vehicle, their control algorithms may make imprecise, approximate, and unreliable decisions. Therefore, there is a need for the creation of more robust driving algorithms, notably consistent obstacle avoidance algorithms. Occasionally, the vehicle must come to a complete stop in order to avoid obstacles. In this situation, the engine brake control of the car can be engaged. In this study, a fuzzy model was proposed to effectively brake autonomous land vehicles, with an electrical braking system known as rheostatic braking. Since a rheostatic braking system (RBS) is employed, the input values of the fuzzy controller for this designed modeling are vehicle speed and ground slipperiness, and the output value is the rheostat resistance value. In the developed fuzzy controller, Mamdani inference and Aggregation methods were utilized. In addition to these two methods, the fuzzy controller also provides the output of the centroid, bisector, average of the maximum, smallest of the maximum and largest of the maximum sharpening methods to the user. Finally, using the Python programming language and the Tkinter library, the graphical user interface displays the linguistic expression and membership degree of the user's inputs, the final fuzzy output graph, and the exact outputs from all clarification methods (GUI).

Keywords : *Fuzzy Logic, Autonomous Vehicles, Rheostatic Braking System*

1. Introduction

The most basic characteristic of AVs is their ability to act autonomously. However, since the vehicle's working environments are real and dynamic, they can act by making flawed, approximate and unreliable decisions. In order to work in real environments, AVs must be able to achieve their determined goals despite unexpected changes. For this reason, AVs that can avoid possible dynamic or static obstacles have been proposed. Autonomous land vehicles can be divided into wheeled, legged and humanoid. Of these, the ones with wheels are the most efficient in obstacle avoidance action. Given their easy applicability and reliability, wheeled mobile vehicles have gained a large place in the manufacturing industry. There are many different types of wheeled vehicles. These can be categorized as vehicles with parallel fixed-wheel differentials and omnidirectional wheels.

Avoiding obstacles sometimes means that the vehicle stops when it encounters an obstacle. In order to stop the vehicle, the engine of the system must be braked. The motor can be braked mechanically or electrically. Mechanical braking is provided by hydraulic-pressure driven brake shoes. Therefore, the effectiveness of mechanical braking is contingent upon the brakes' physical condition. As the brakes degrade over time, the braking system's effectiveness can diminish. Electrical braking permits the maintenance of efficient braking performance.

Electrical braking can be accomplished in three ways: rheostatic or dynamic braking, plugging or reverse current braking and regenerative braking. Plugging braking is not preferred in this study because it is generally used in heavy works such as elevator systems and machine tools. Despite the fact that regenerative braking appears to be the best option for its energy recovery capability, it may not be preferred in some low-range applications due to its increased production cost and system complexity. On the other hand, RBSs are straightforward to implement with DC motors. Additionally, it requires less maintenance and has a high degree of dependability. Because of these factors, a rheostatic braking system was selected for this study.

During rheostatic braking, motor armatures are connected to the supply line. The rolling wheels turn the engine armatures and the engines begin to act like generators. Loading the generator circuit with resistance causes the generators to slow their turns. By changing the resistance value here, motors can slow down at a high rate. Figure 1. shows the application of the RBS for an armature-controlled DC motor.

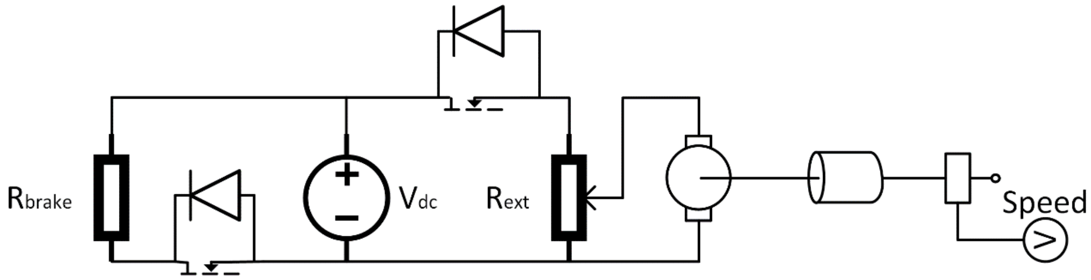

Figure 1. RBS for armature-controlled DC motor

Rheostatic brake system can be used for all wheeled vehicles. This has broadened its application. In addition, the rheostatic brake system provides different braking rates for varying resistance values, making it ideal to use fuzzy logic (FL) controllers. With the use of artificial intelligence, an intelligent braking system has been created. Thus, this braking system has become a ready-made method for different AV applications (obstacle avoidance, path planning…).

The subject of AVs navigation has long been a challenge. Obstacle avoidance is insurance to safely reach the destination from the vehicle's starting point. The obstacles that the AV may encounter can be dynamic or static. The problem of detection and prevention of obstacles in practical applications is very important (Bao & Zelinka, 2019). Many algorithms have been proposed to solve this problem. Examples of these are the gap method (Sezer & Gokasan, 2012), artificial potential field method (Lee & Park, 2003) and particle swarm optimization (Chen & Li, 2006) algorithms. For algorithms using artificial intelligence, the genetic algorithm (Tu & Yang, 2003), FL (Zadeh, 1988), neural network (Zelinka & Lampinen, 1999) and self-organizing migrating algorithm (SOMA) (Zelinka, 2004) can be counted.

In the artificial potential field technique, the target is represented by an attracting artificial potential, whilst the obstacles to be avoided are represented by a repulsive artificial potential. As a result, no impediments are struck as the vehicle approaches the target. The disadvantages of the artificial potential field method are summarized in (Koren & Borenstein, 1991). However, the main disadvantage of this method is local minimums. This happens when all of the vectors and the target point from obstacles cancel each other out, making it impossible for the vehicle to get to the target. There are specific studies (Castaneda et al., 2008; Chengqing et al., 2000; Shimoda et al., 2005) to avoid local minimums, but none offer guarantees. Likewise, since the particle swarm method is a kind of optimization method, it has the same problem. There are certain advantages and disadvantages in the SOMA method. SOMA generally converges to the global minimum, but may have problems if the initial population spread does not satisfactorily cover all parts of the area studied (Kadlec & Raida, 2011). Usually, it converges quickly but tends to converge early if the algorithm remains at a local optimum.

The biggest issue with the Genetic Algorithm method is that the map must be given to the system beforehand in order to generate the path. Additionally, it is time-consuming to process and creates smooth trajectories that are challenging to implement in real time. Neural networks, another artificial intelligence method, do not require maps and can make instant decisions. However, in labyrinth-like situations, the vehicle may take the incorrect path and be unable to reach the target (Engedy & Horváth, 2009).

On the other hand, FL control was chosen in this study. It is rule-based, not learning-based like artificial neural networks. Since it does not require a full mathematical description of the problem, it can be studied on a larger scale. Due to its abstraction ability, it better tolerates noisy input data. For these reasons, an FL-based control has been applied.

The most common braking mode of electric vehicles is the coordination of regenerative braking and frictional braking (Xu et al., 2019). If the electric vehicle's kinetic energy can be transformed into electrical energy with the help of the regenerative braking system and then transferred to the storage unit while the vehicle is braking, the energy efficiency of the electric vehicle will be enhanced and its range will be increased (Pan et al., 2016). Recovering energy to increase a vehicle's range is advantageous for autonomous vehicles. However, the weight and complexity of the regenerative braking system, the cost of manufacturing and assembly, and the cost of maintenance may be significant drawbacks for certain applications.

Various alternative types of braking methods are suggested in the literature due to the aforementioned reasons. One of them is the plugging braking. In this approach the armature connections are switched around, which causes the motor to turn in the other direction. The advantages and disadvantages of this method are examined in (Godfrey & Sankaranarayanan, 2018). According to this study, the braking system provides fast braking, but energy consumption is high.

Rheostatic braking involves cutting off the motor's supply, reversing the field connections, and connecting a rheostat in series. To guarantee that the current going through the field winding will flow in the same direction as previously, the field connections are switched around. The braking effect is easily controlled by changing the resistance connected across the field. Additionally, taking into account the speed of AVs, RBS should be chosen in the low speed range and regenerative braking in the high speed range (Günay et al., 2020). In this study, an RBS was chosen due to its controllability and effectiveness at low speeds.

For the modeling of the RBS system, the FL was preferred because of its advantages such as being rule-based, not requiring a purely mathematical definition of the problem, and better coping with noisy data of FL. Identifying the system's inputs and outputs is the initial step in implementing FL. Slipperiness and vehicle speed, two significant elements affecting braking, are given as input data to the FL model in the braking system. On the other hand, RBS's resistance value is determined using the model's output. The creation of membership functions for the chosen input parameters comes next. Following this stage, the model's lower and upper bounds were established, and certain rules were developed.

2. Methodology

Finding the system's inputs and outputs is the first step in applying FL to it. A closer look at the braking system of the vehicle reveals two important factors affecting braking; slipperiness and the speed of the vehicle. In contrast, the output of the model was chosen as the resistance value for the RBS. The fuzzy model for the proposed system is shown in Figure 2.

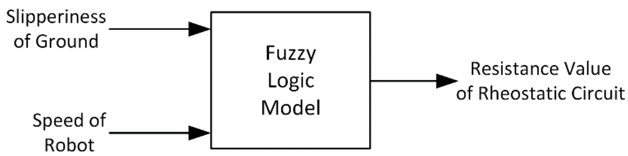

Figure 2. Fuzzy model for proposed system

Slippery measurement can be done with a digital slip meter. This device measures the static friction coefficient of the ground. Therefore, the static friction coefficient of the existing ground has been determined as the first entry. This value ranges from 0 to 1 and values close to zero indicate high slippery, while values close to one indicate high friction. The speed of the vehicle was taken as the second entry. The maximum value of the speed was determined according to the 282 km/h speed of Robocar, the fastest AV in the world. In contrast, a 100 kΩ resistor was chosen for the output of the model. The membership function numbers, names, lower and upper limits of all parameters are therefore chosen according to the impact of the input and output parameters on the problem to be represented. Figure 3 and Figure 4 both illustrate the membership functions for the input and output parameters, respectively.

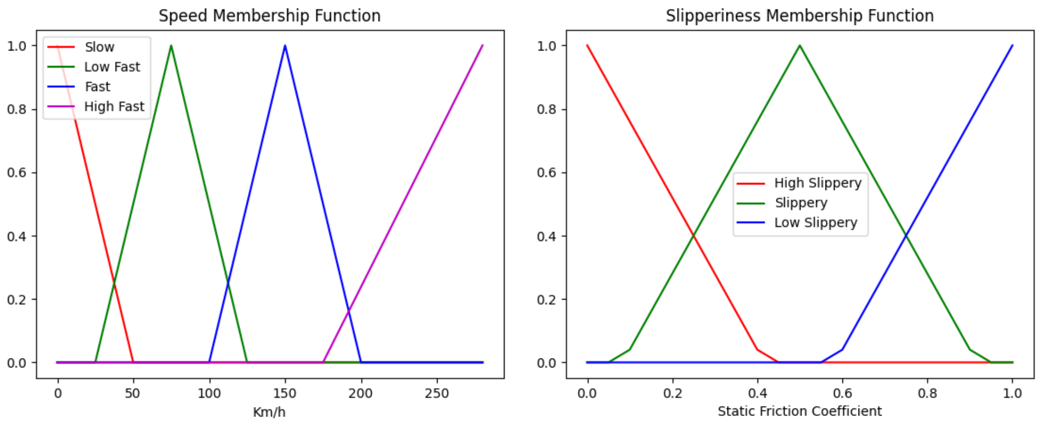

Figure 3. Input parameters membership functions

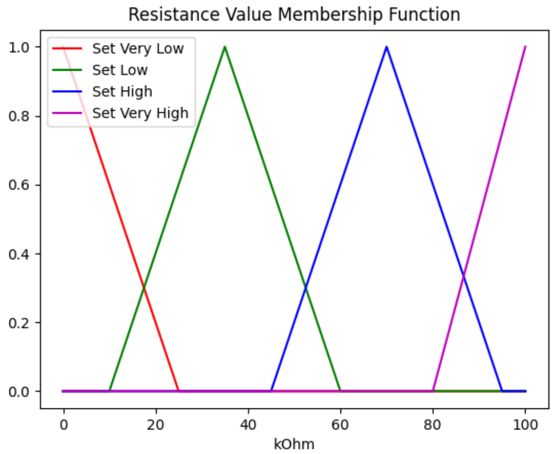

Figure 4. Output parameter membership function

Then, the twelve rules were developed to establish the necessary interactions between the system's parameters. These rules are shown in the matrix in Table 1.

Table 1. Rules providing the relationship between input and output

		Speed			
		Slow	Low Fast	Fast	High Fast
Slipperiness	Low	VL	VL	L	H
	Normal	VL	L	H	VH
	High	H	H	VH	VH

3. Results

In this study, a fuzzy model was designed to effectively brake AVs. Currently, the majority of AV brake systems are modeled according to classical logic. Therefore, even on low-slippery grounds and away from obstacles, the vehicle's braking system consumes the same amount of energy as in the critical situation of a high-slippery, close obstacle.

Thanks to this model developed based on fuzzy decision, the rheostat resistance is limited by static values (1 kΩ at low, 100 kΩ at high) in classical logic has been dynamized to take all intermediate values between 1 kΩ - 100 kΩ. Thus, it is aimed to reduce the energy consumption of the vehicle by taking intermediate values lower than 100 kΩ resistance value of the rheostat under necessary conditions. In Table 2, the exact outputs produced by different clarification methods are shown for different ground slipperiness and vehicle's speed values.

Table 2. Exact outputs of different clarification methods for different inputs

Input-1 (Dimensionless)	Input-2 (km/h)	Outputs (kΩ)				
Slipperiness	Speed	Centroid Method	Bisector Method	MoM Method	SoM Method	LoM Method
0.245	120	67.94	70.53	94	88	100
0.4	275	93.02	93.73	98	96	100
0.95	170	35	35	35	25	45
0.95	65	8.61	7.68	2.5	0	5
0.6	110	48.27	45.97	35	18	52

A GUI has been created in the application using the Python-Tkinter library. Input values which are slipperiness and the speed of the vehicle in this interface are left to the user. On the other hand, the linguistic expressions and membership degrees of the inputs, the final fuzzy output and exact outputs determined from different clarification methods are given to the user. The user also has access to the final result of the five clarification methods utilized during the clarification phase. Figure 5 depicts the graphical user interface for 0.245 slipperiness and 120 km/h sample inputs.

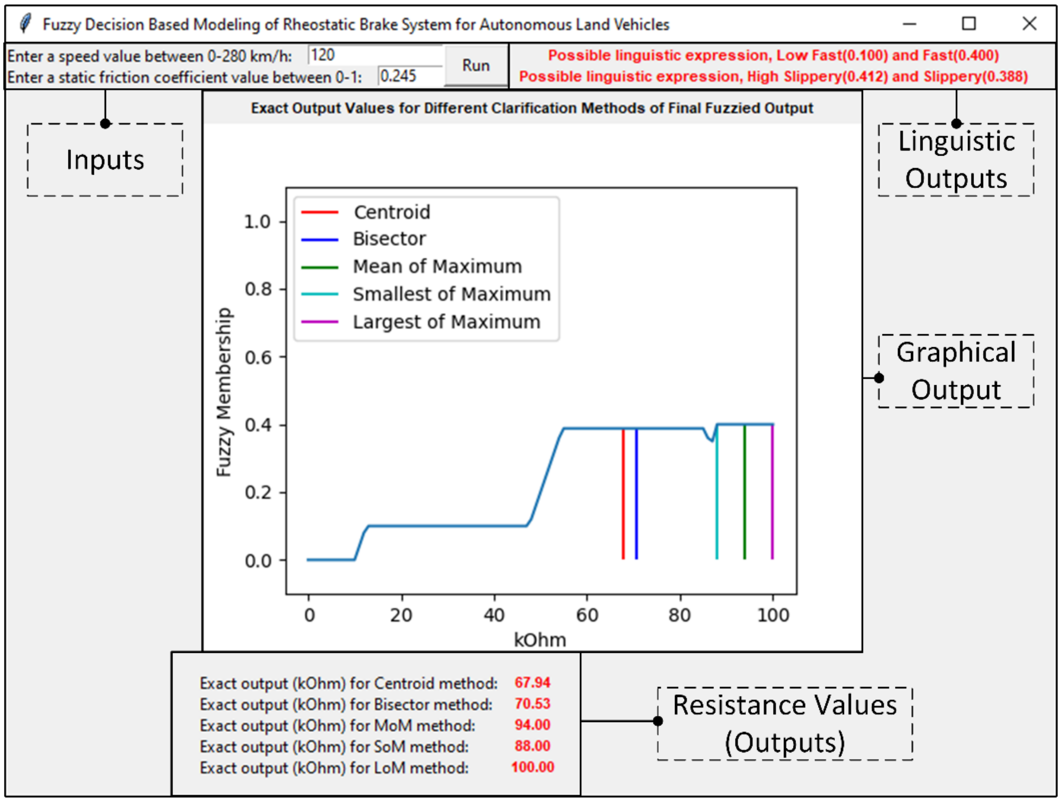

Figure 5. GUI for 120 km/h speed and 0.245 ground slippery inputs

In order to apply this developed model to real-world problems, circuits and systems that automatically detect speed and slipperiness values from outside should be placed in the relevant autonomous mobile vehicles and the infrastructure that will transfer the rheostat resistance output value produced by the system to the system must be established. Thus, the effectiveness of the developed model based on classical logic can be evaluated in the real world.

4. Conclusion

Avoiding obstacles and reaching the destination has always been a challenging task for AVs operating in real and dynamic environments. This study presents an intelligent solution for braking, one of the crucial stages of this challenging task. By combining rheostatic electric braking and fuzzy controller, a smart, efficient and practical solution has been proposed. RBS is applicable to all wheeled vehicles. This has greatly expanded its field of use. In addition, the RBS provides different braking rates for various resistance values, making the use of FL controllers ideal. As shown by the fuzzy modeling results, it provides suitable rheostat resistance outputs for different conditions and allows the vehicle to brake safely. The rheostat resistance in classical logic, which was previously constrained by static values (1 kΩ at low and 100 kΩ at high), has been dynamically expanded to take into account all values in between. The goal is to minimize the vehicle's energy usage by setting the rheostat's resistance value to intermediate values that are less than 100 kΩ when necessary.

The Python-Tkinter library has been used to build the application's GUI. The input values in this interface are left up to the user, thus the language expressions and membership levels of the inputs, the final fuzzy output, and the precise outputs determined by various clarifying techniques are all included.

While this research clearly demonstrates the positive effects of braking with fuzzy modeling, it also reveals that applications and experiments in this area need to be increased. In the future study, an experimental application of the proposed model will be conducted in order to validate the simulation results and further develop the model.

5. Abbreviations

AV	Autonomous Vehicle
DI	Dimensionless
FL	Fuzzy Logic
GUI	Graphical User Interface
H	High
L	Low
RBS	Rheostatic Braking System
SOMA	Self-Organizing Migrating Algorithm
VH	Very High
VL	Very Low

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