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CONTROL OF AUTONOMOUS MOTORCYCLES BY MEANS OF TRAJECTORY TRACKING AND BALANCE STABILIZATION

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ABSTRACT

An autonomous motorcycle is a two-wheeled vehicle that can move without human intervention. It uses a combination of sensors, cameras, and algorithms to detect its environment and make decisions on how to move. This paper shows the comparison between the control of an autonomous motorcycle using fuzzy logic and an LQR counter controller built in Matlab and implemented in an embedded system with a microcontroller. The trajectory tracking and balance stabilization of a prototype built for this purpose is performed. It is determined how the LQR control has a good behavior in front of the fuzzy logic control in front of the impulse response represented in changes of angle in the stabilization.

Keywords: *Autonomous Motorcycles, Trajectory Tracking, Balance Stabilization, Fuzzy Logic, LQR*

1. INTRODUCTION

Single-track vehicles, such as motorcycles and bicycles, offer greater agility and versatility, making them particularly suitable for off-road terrain such as deserts, mountains, and forests [1]. Their performance is superior to that of two-track vehicles in such environments. In addition, the low weight of motorcycles brings notable advantages, such as high energy efficiency and rapid acceleration. A mathematical model has been formulated and control algorithms for the autonomous motorcycle have been designed in the paper [1].

This mathematical model for motorcycles presents significant advantages compared to other models found in the literature. Unlike multibody dynamics models, which are highly complex and unsuitable for control system design, simple inverted pendulum models, such as the one employed in [2], fail to capture all the dynamic characteristics of the motorcycle system, such as underactuation and non-holonomic constraints.

The model employed in this paper presents simplifications compared to the multibody dynamics model but retains the nonholonomic constraint properties of the system. Therefore, the model provides sufficient accuracy of the system and is tractable for control system design purposes. We have expanded this model to take into consideration the motorcycle trajectory and the caster angle, which are important geometric parameters in motorcycle dynamics and are not considered in [1].

The control algorithms ensure asymptotic tracking of the desired trajectory provided by the motion planning module. The integration of motion planning, trajectory tracking, and balance control of the autonomous motorcycle is demonstrated by numerical simulations and embedded implementation of LQR controls and fuzzy logic in a prototype. In addition, experimental tests of the proposed algorithms are performed on a real motorcycle prototype.

The remainder of the paper is structured as follows: Firstly, a review of related work is provided in Section II. Section III details the mathematical model of motorcycle dynamics. The design of both the LQR and fuzzy logic control system for trajectory tracking and equilibrium stabilization control is presented in Section IV. Section V showcases the numerical simulation results of the autonomous system. Lastly, the conclusions of the numerical simulation and the implementation of the embedded system are presented in section VI.

2. BACKGROUND

Technological advancement in the field of autonomous vehicles has generated a growing interest in the development of advanced control systems for single-track vehicles such as

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motorcycles [1]. However, despite previous efforts in this field, there are still significant challenges that need to be addressed to achieve efficient and safe control of autonomous motorcycles [2].

The main objective of this research is to investigate and compare two control approaches, using fuzzy logic and a linear quadratic regulator (LQR), for trajectory tracking and balance stabilization in an autonomous motorcycle [3]. In addition, it seeks to evaluate how these approaches address specific challenges associated with motorcycle dynamics, such as non-holonomy and underactuation [4].

The modeling and control of bicycles or motorcycles represent a challenging task. There is an extensive body of work investigating the stability and dynamics of these vehicles. For example, Sharp [3] discusses mathematical models of a motorcycle with a rider using the Lagrange equation. Likewise, Sharp [4] studies the motorcycle model with multibody dynamics using Simulink and Matlab dynamic simulation packages.

Hara et. al. in [3] presented the development of autonomous driving technology for motorcycles, highlighting the lack of comprehensive studies in this field. The stability of motorcycles at low speed is addressed, without making significant structural changes. A SPACAR-based model is introduced to obtain a linearized non-skid motorcycle model, and a speed-dependent programmed gain control is applied. The gain scheduling method is improved compared to previous studies, and experimental responses showing stable driving at 1.5 km/h are obtained.

In [4] and [5], the design of speed control for a DC motor using fuzzy logic with LabVIEW software is described. A literature review of the design and implementation environment is performed, presenting the use of fuzzy logic to describe the materials and methods used. Several processes related to the idea, creation, development, and implementation of intelligent control are highlighted, as well as the results considering the application and development for this purpose.

Zheng et. Al., in [6] describes the application of control moment gyroscope (CMG) in unmanned motorcycles or bicycles to improve their stability and mobility. It highlights the importance of considering the steering mechanism in conjunction with the CMG to achieve a combined control that optimizes vehicle balance. The study proposes a dynamic model of the motorcycle and a combined control method that integrates steering and dual CMG. A simplified model is developed for the controller design, demonstrating its effectiveness through numerical examples. Simulation results show that the proposed combined controller outperforms the steering controller and the inverted pendulum-based controller.

Kung et al in [7] present research addressing intelligent intersection management in the context of connected and autonomous vehicles, highlighting the lack of consideration of motorcycles in this area. Key differences from existing management are identified and an approach using clustering and two-stage left turns with motorcycle waiting zones is proposed. This approach aims to improve traffic efficiency at intersections where vehicles are connected and autonomous, while motorcycles are not. The study presents the first model and analysis of intelligent intersection management with motorcycles, demonstrating advantages and disadvantages for their design.

Huertas-Leyva et al., in [8] present the study focuses on the braking maneuver as a critical situation for motorcycle riders, particularly due to the inherent instability of this type of vehicles. Braking experiments were conducted in emergency situations to analyze loss of control and predictive models were developed based on vehicle kinematic parameters. These models demonstrated a 100% ability to predict loss of control, and specific thresholds were identified for different levels of driver skill. In addition, the peak-mean-square ratio of roll acceleration was found to be the most robust parameter for identifying loss of control at all skill levels.

In [9] and [10] Lucci et al., described the development of a procedure to design new experiments to evaluate the feasibility of motorcycle autonomous emergency braking (MAEB) among end users. A comprehensive literature review and pilot tests were conducted using an automatic braking device on an instrumented motorcycle. The specifications and test protocol for testing the system under various riding conditions were defined, with the objective of providing broad support for the design of future experiments and serving as a reference for the design of tests of other advanced rider assistance systems.

Merkel & Winner in [11] describe the importance of considering the connection between the driver and the motorcycle when implementing autonomous motorcycle emergency braking and stabilization systems. It is emphasized that the maximum applicable decelerations should be in tune with the driver's braking readiness, and it is mentioned that autonomous systems should analyze the connection of the driver to his vehicle and his ability to adapt to changes in the vehicle state. The study identifies and evaluates measures for rider adaptation to changes in vehicle state, focusing on the relative motion between the rider's upper body and the motorcycle. Experiments show that the connection between the rider and the vehicle is more direct when the rider brakes on his own compared to an autonomous maneuver, highlighting the importance of considering the rider's anticipation and body tension when applying braking.

Bruschetta et. al. in 2020 [12] addresses the development of an effective virtual rider (VR) intended to control motorcycles during high-performance maneuvers. Control variables include steering angle, rider lateral movement, and acceleration/braking effort. The motorcycle model is represented as a plane with the ability to roll and slide in both directions (x and y), with a moving point mass symbolizing the rider and possessing lateral degrees of freedom. The controller was designed using the Nonlinear Model Predictive Control (MPC) approach and implemented using the open source MATMPC toolbox. The evaluation was carried out by co-simulation with VI-Motocycle RealTime software, specifically designed to replicate vehicle behavior with high fidelity. Tests were performed on a chicane and a lap on a challenging track to demonstrate the flexibility and evaluate the performance of the system, confirming the ability of the proposed virtual rider to handle complex maneuvers effectively.

3. MATHEMATICAL MODELING

Although there are previous works addressing the control of autonomous motorcycles, most of them focus on simplified models and algorithms that do not fully capture the complexity of real motorcycle dynamics. Moreover, few studies directly compare different control approaches under practical conditions [8], [9], [10].

What differentiates our work from previous ones is our comprehensive approach, which combines a detailed mathematical model of motorcycle dynamics with the practical implementation and comparison of two advanced control algorithms. In addition, our approach considers the integration of motion planning, trajectory tracking and balance control, which better reflects the complex interactions between these aspects in a realistic environment [11].

Understanding and developing the bicycle as a dynamic system requires the application of dynamic models. A variety of models exist, both linear and nonlinear, incorporating holonomic and nonholonomic constraints. However, this research work focuses on a pre-existing bicycle platform, limiting itself to the study of specific models with rear-wheel drive and front steering. Figure 1 illustrates various measurements used to describe bicycle geometry, assigning corresponding letters to various rigid parts of the bicycle body [12].

Using a front perspective of the bicycle, the roll angle (ϕ) is defined according to Figure 2. The steering angle (δ) is depicted as shown in Figure 3. The effective steering angle (δ_{eff}), defined as the angle between the x-axis and the front wheel axis in the top view of the bicycle, is illustrated in Figure 4.

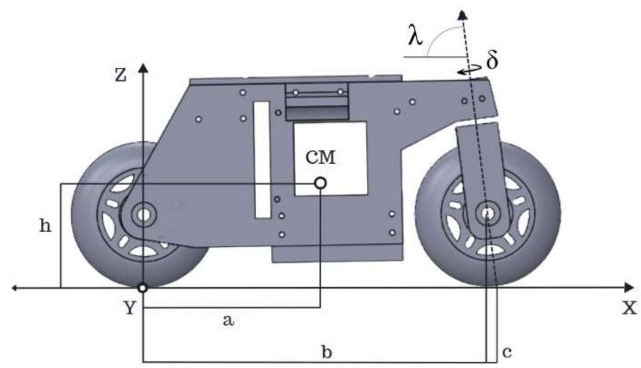

Figure 1. Profile and Dimensions of the Bicycle: A lateral Perspective.

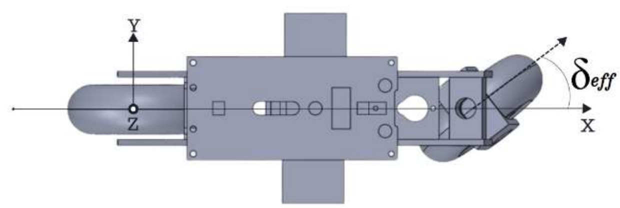

Figure 2. Overhead Perspective of the Bicycle and its Effective Steering Angle

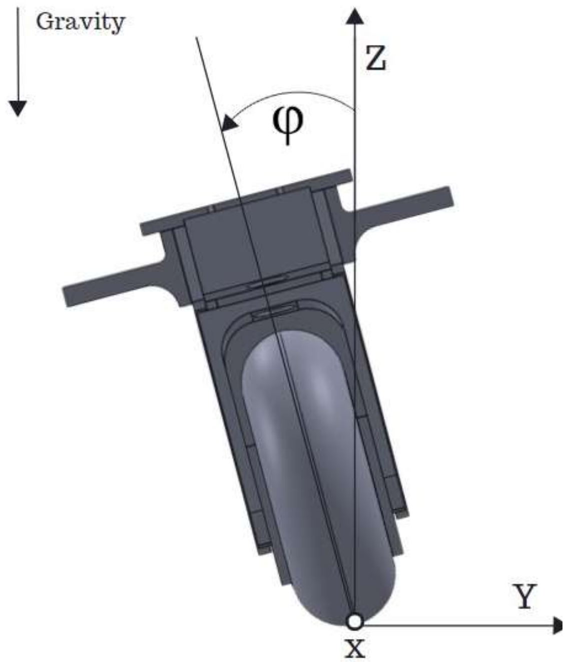

Figure 3. Frontal Perspective of the Bicycle and Roll Angle

Based on physical principles, it is feasible to develop a mathematical model describing the behavior of the bicycle. The relevant geometric dimensions are exhibited in Figure 3, with the following designations:

h: Represents the height of the center of mass.
b: Indicates the distance between the contact points of the rear and front wheels with the ground.
a: Corresponds to the horizontal distance between the center of the rear wheel and the center of mass.
λ: Describes the angle of inclination of the fork.
c: Refers to the trajectory of the center of mass.

Through the application of principles derived from Newton's second law for rotational dynamics, the equilibrium of the system's angular momentum around the x-axis, positioned at the contact points of the wheels, is established, as depicted in Figure 3.

$$\frac{d\,L_x(\varphi,\delta,\lambda)}{dt} = T_G(g,h,\varphi) + T_C(b,h,\delta,\lambda,v^2) + T_F(a,b,c,\delta,\lambda) \quad (1)$$

Where:
g: gravitational acceleration,
L_x: angular momentum of the system around the x axis,
T_G: torque generated by the gravity,
T_C: torque generated by the centrifugal force,
T_F: torque due to the geometry of the front fork.

After a series of simplifications, the final formulation of the mathematical model is reached as follows:

$$\ddot{\varphi} = \frac{g}{h}\varphi + \frac{a\,v\,sen\,\lambda}{b\,h}\dot{\delta} + \frac{(h\,v^2 - g\,a\,c)\,sen\lambda}{b\,h^2}\delta \quad (2)$$

3.1 State Space Model

A state space (SS) representation of model (2) can be derived using three state variables:

- $x_1 = \varphi$
- $x_2 = \delta$
- $x_3 = \dot{\varphi}$

The control input is chosen as the derivative of the steering variable, represented by $u = \dot{\delta}$ (steering velocity). When expressed in state space (SS) form, the model (2) undergoes a transformation, acquiring the following form:

$$\dot{x} = \begin{bmatrix}\dot{x_1}\\ \dot{x_2}\\ \dot{x_3}\end{bmatrix} = \begin{bmatrix}0 & 0 & 1\\ 0 & 0 & 0\\ \frac{g}{h} & \frac{(h\,v^2 - g\,a\,c)\,sen\lambda}{b\,h^2} & 0\end{bmatrix}\begin{bmatrix}x_1\\ x_2\\ x_3\end{bmatrix} + \begin{bmatrix}0\\ 1\\ \frac{a\,v\,sen\,\lambda}{b\,h}\end{bmatrix}u \quad (3)$$

To carry out the linearization of the system, the feed rate v is not considered as a state variable due to its multiplication with another state variable (x_2) and the control input. Consequently, both the system matrix A and the control matrix B become dependent functions of v:

$$\dot{x} = A(v)x + B(v)u \quad (4)$$

Since the variation of the speed v affects the plant dynamics, a real-time measurement is made, and the control input is calculated based on this measurement. And the input is defined as the derivative of δ as a function of time. In addition, the output equation is provided below:

$$y = \begin{bmatrix}1 & 0 & 0\\ 0 & 1 & 0\\ 0 & 0 & 1\end{bmatrix}\begin{bmatrix}x_1\\ x_2\\ x_3\end{bmatrix} = \begin{bmatrix}x_1\\ x_2\\ x_3\end{bmatrix} \quad (5)$$

The input is defined as the time derivative of φ, denoted as $u = \dot{\varphi}$, and represents the output vector. Equation (2) describes a second-order linear dynamical system with three real poles.

$$p_{1,2} = \pm\sqrt{\frac{g}{h}}, p_3 = 0 \quad (6)$$

The poles, which are actual numerical values, are at ±9,954 and 0 for the specific bicycle used in this project. Since one of the poles resides in the right

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half-plane of the complex plane, the uncontrolled bicycle plant is inherently unstable. To stabilize the bicycle, a LQR (Linear Quadratic Regulator) controller and a fuzzy logic controller are implemented.

3.2 Control Linear Quadratic Regulator (LQR)

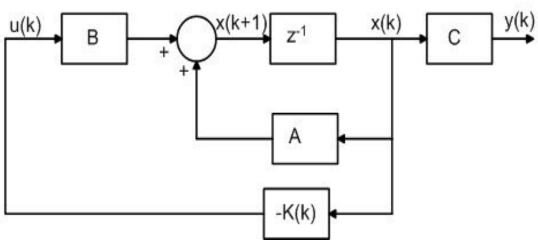

Figure 4. Block diagram of LQR control

Noting that the state space system described by equations (3) and (5) is both controllable and observable, the following control law for the motorcycle is established:

$$u = \dot{\varphi} = -Kx \qquad (7)$$

Where

$$K = [K_{\varphi}\, K_{\delta}\, K_{\dot{\phi}}] \qquad (8)$$

Introducing equations (7) and (8) into expression (3) transforms the closed-loop state space system as follows:

$$\dot{x} = \begin{bmatrix} \dot{x_1} \\ \dot{x_2} \\ \dot{x_3} \end{bmatrix} = \begin{bmatrix} 0 & 0 & 1 \\ -K_{\varphi} & -K_{\delta} & -K_{\dot{\varphi}} \\ \frac{g}{h} - K_{\varphi} & \frac{(h\,v^2 - g\,a\,c)\,sen\lambda}{b\,h^2} - K_{\delta} & -K_{\dot{\varphi}} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \\ \frac{a\,v\,sen\,\lambda}{b\,h} \end{bmatrix} u \qquad (9)$$

By incorporating expressions (7) and (8) into equation (2), the differential formulation of the bicycle control system becomes:

$$\ddot{\varphi} = \frac{bg - av\,sen\,\lambda\,K_{\varphi}}{bh}\varphi + \frac{a\,v\,sen\,\lambda\,K_{\varphi}}{b\,h}\dot{\varphi} + \frac{(h\,v^2 - g\,a\,c - havK_{\delta})\,sen\lambda}{b\,h^2}\delta$$

The cost function to be minimized by the LQR is specified below:

$$J(u) = \int_0^{\infty} (x^T Q x + u^T R u)dt \quad (10)$$

Where the matrices Q and R are defined as follows:

$$Q = \begin{bmatrix} 100 & 0 & 0 \\ 0 & 100 & 0 \\ 0 & 0 & 10 \end{bmatrix}, R = 20 \qquad (11)$$

Matrix Q reflects the costs associated with the states, while matrix R represents the cost of the inputs.

3.3 Fuzzy Logic Control (FLC)

Figure 5 shows the block diagram of the fuzzy logic controller system. The FLC is composed of four main blocks: fuzzification, knowledge base, inference engine and defuzzification.

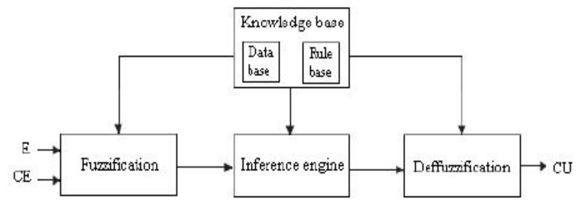

Figure 5. Block diagram of a fuzzy logic controller

There are two input variables: error in angle of inclination, denoted as $e_{\varphi}(k)$, and the velocity change error, represented as $\Delta e_{\varphi}(k)$. Both input variables are calculated at each sampling interval as follows:

$$e_{\varphi} = \varphi_{ref} - \varphi_{Out} \qquad (12)$$

$$\Delta e_{\varphi} = \dot{\varphi_{ref}} - \dot{\varphi_{Out}} \qquad (13)$$

The FLC in this section is based on the system proposed by Hara [3] and Montiel et al in [16]. This system is used as a starting point and then adapted to fit the instrumented bicycle. The FLC controller uses two inputs and one output, as seen in Figure 5. Both the input membership functions, and the output membership function are detailed in Figures 6, 7 and 8. The membership functions are tuned using a trial-and-error method.

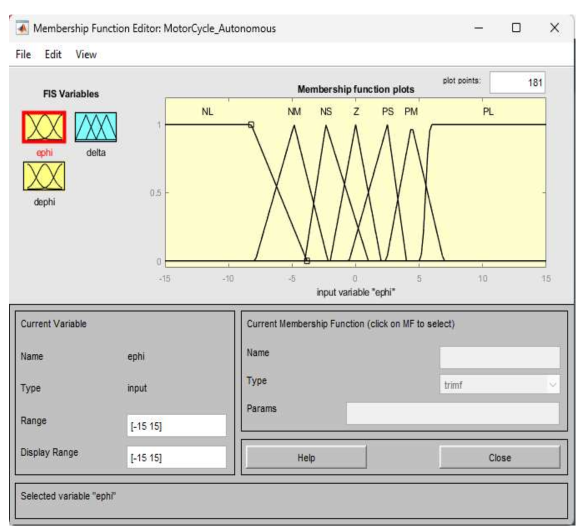

Figure 6. Membership function is the error in lean angle e_{φ}

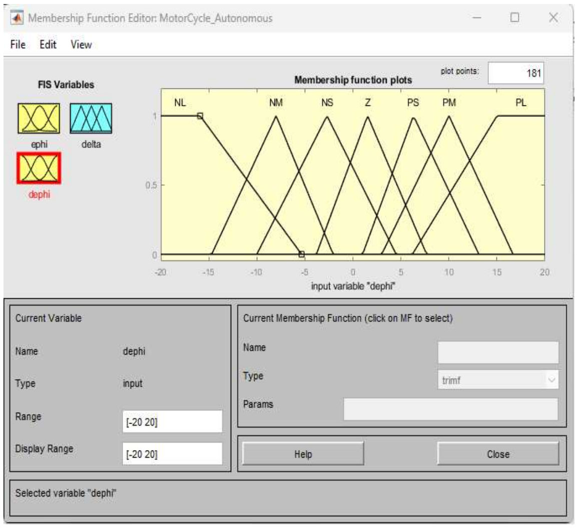

Figure 7. Membership function is the difference in lean angle error Δe_{φ}

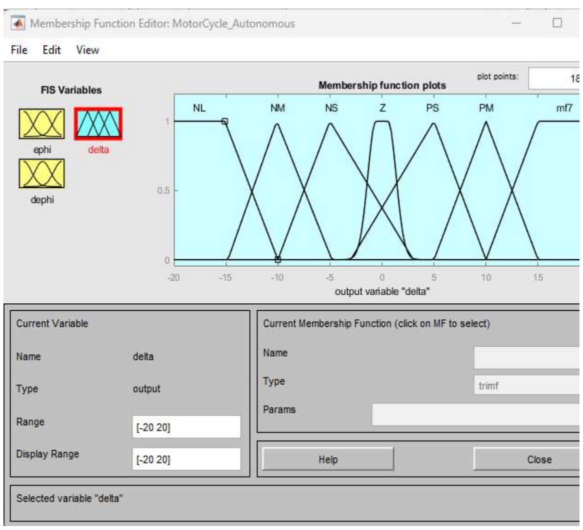

Figure 8. The output membership function is the function at the bottom of the figure, which correlates to the desired steering angle δ

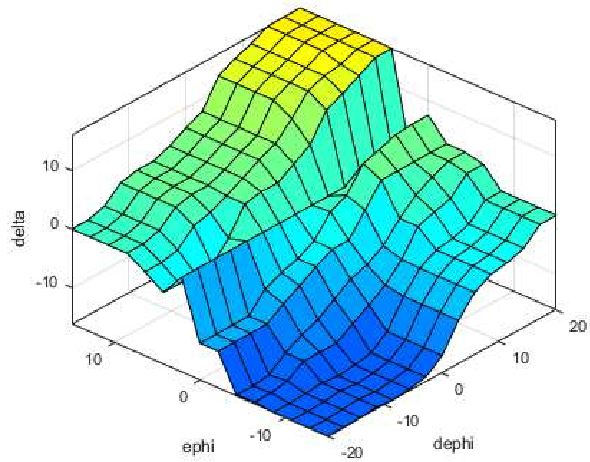

Figure 9. Surface generated from the rules given to the FLC.

4. RESULTS

The autonomous motorcycle is a two-wheeled vehicle that can move without human intervention. It uses a combination of sensors, cameras, and algorithms to detect its environment and make decisions on how to move. The study compares the control of an autonomous motorcycle using fuzzy logic and a counterbalanced LQR controller built in Matlab and implemented in an embedded system with a microcontroller. Trajectory tracking and balance stabilization of a purpose-built prototype is performed. The following shows its prototyping in SolidWorks and its final construction (see Figures 10 and 11).

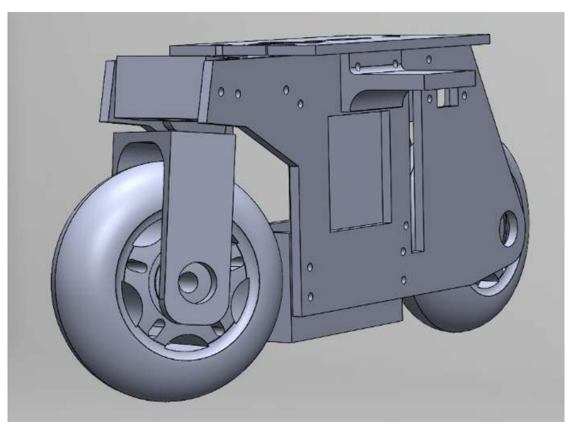

Figure 10. Design developed in SolidWorks of the prototype of an autonomous motorcycle.

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Figure 11. Final design of the autonomous motorcycle prototype

The simulation results of the two controllers under consideration, considering an estimated roll angle that differs from zero, show that the Linear Quadratic Regulatory (LQR) controller computes a non-zero steering speed input, as illustrated in the attached figure 10.

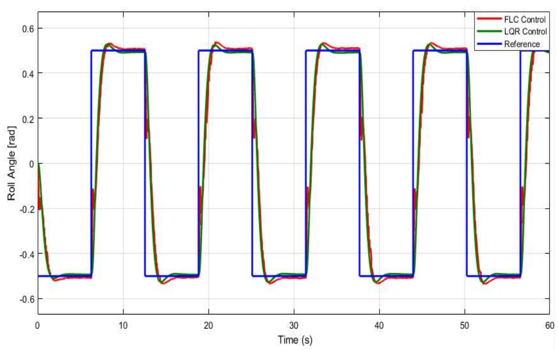

Figure 12. Simulation of roll angle behavior with LQR and FLC controls.

To evaluate the effectiveness of the LQR balance controller, an external disturbance consisting of a roll angle of $\pm 0.5\ rad$ (±28.64°) is induced to the bicycle, which is maintained for a time span of 1 second with a periodicity of 10 seconds.

The fuzzy logic controller design exhibits no performance loss in tilt angle error, and the disturbance attenuation levels now match those obtained for each individual axis. The improvement is also noticeable when comparing the principal gains of the closed-loop responses of the input disturbances in tilt angle error (e_φ, Δe_φ) (see Figure 12).

Table I. Execution Time Comparison of Control Algorithms

Controller	Mean execution time [µs]	Standard deviation [µs]
LQR	9.47093	3.762
FLC	553.251	51.775

A comparative analysis of the average execution times and standard deviation of two control algorithms: LQR (Linear Quadratic Regulator) and FLC (Fuzzy Logic Controller) can be performed. The results show that the LQR algorithm has a significantly shorter execution time with a mean of 9.47093 µs, compared to the FLC algorithm which has a mean of 553.251 µs (see Table I).

In addition, the standard deviation of LQR is relatively low at 3.762 µs, indicating a consistency in execution times, while FLC shows higher variability with a standard deviation of 51.775 µs. This analysis suggests that the LQR algorithm may be more efficient in terms of runtime and consistency compared to FLC.

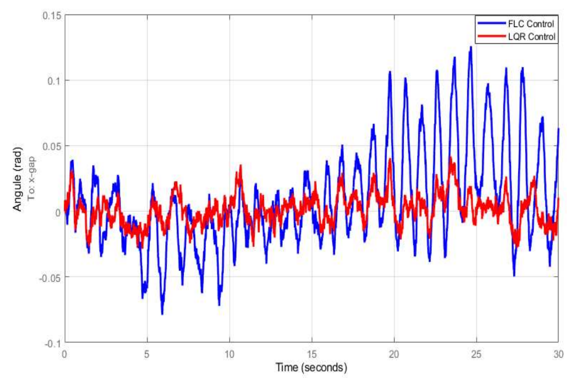

Figure 11. Comparative result of the two controllers. The blue line belongs to the FLC and the red line to the LQR.

Singular values in the context of fuzzy logic control are important for understanding and designing control systems based on fuzzy logic, allowing to evaluate their performance and behavior under different situations and conditions.

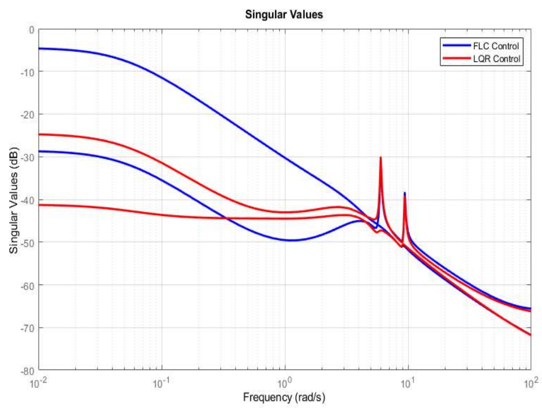

Figure 12. The singular values are observed by comparing their results in the two controllers FLC and LQR.

Table II. Analysis of controller comparison experiments

Controller	Oscillation Frequency [Hz]	Max Lean Angle [deg]	Min Lean Angle [deg]	Balancing Time [s]	Balancing Length [m]
LQR	0.6498	0.275	-0.4465	151.43	10.0
FLC	0.8227	0.683	-0.2878	36.95	10.0

The table II provides a comparison between two controllers, LQR (Linear Quadratic Regulator) and FLC (Fuzzy Logic Controller), in terms of various metrics related to the stabilization of a system, possibly a vehicle such as a bicycle, on a roller or similar surface. The data reveals that the FLC controller exhibits a slightly higher oscillation frequency (0.8227 Hz) compared to the LQR controller (0.6498 Hz), indicating faster system adjustments to maintain balance. In addition, the FLC controller achieves steeper maximum and minimum tilt angles (0.683 degrees and -0.2878 degrees, respectively) compared to the LQR (0.275 degrees and -0.4465 degrees, respectively), suggesting a greater ability to handle oscillations and maintain the system in a stable position.

In terms of stabilization time, the FLC controller shows a significantly shorter time (36.95 seconds) compared to the LQR (151.43 seconds), indicating superior efficiency in the FLC controller's ability to correct imbalances and stabilize the system faster. Despite these differences, both control configurations achieve an identical roll length of 10.0 meters, suggesting comparable effectiveness in terms of the distance traveled during the stabilization process. In summary, these findings highlight the differences in performance between the LQR and FLC controllers, with the FLC showing a greater ability to correct and stabilize the system quickly and efficiently compared to the LQR.

5. CONCLUSIONS

This section presents the final conclusions about the simulation and the actual test results. In conclusion, this study addresses the complex challenges involved in modeling and controlling single-track vehicles, particularly motorcycles, for autonomous operation. The introduction of mathematical models, such as the one presented here, offers a simplified yet accurate representation of motorcycle dynamics, accounting for critical factors like underactuation and non-holonomic constraints. By integrating motion planning, trajectory tracking, and balance control, the study demonstrates the feasibility of autonomous motorcycle control through numerical simulations and real-world experimentation.

Furthermore, the comparison between control algorithms, namely Linear Quadratic Regulator (LQR) and Fuzzy Logic Controller (FLC), sheds light on their respective strengths and weaknesses. The LQR controller, while exhibiting shorter execution times and consistent performance, may lack the agility and responsiveness demonstrated by the FLC in terms of stabilization time, oscillation frequency, and maximum tilt angles. These findings suggest that the choice of control algorithm should be based on specific requirements and performance metrics, balancing efficiency with stability and responsiveness.

Moreover, the study highlights the importance of considering real-world factors such as vehicle dynamics, environmental conditions, and sensor limitations in the design and implementation of autonomous motorcycle systems. By providing a comprehensive overview of related work and experimental results, the study contributes to the ongoing research efforts aimed at advancing autonomous vehicle technologies, particularly in the context of single-track vehicles like motorcycles.

Overall, the findings presented in this study offer valuable insights into the design, modeling, and control of autonomous motorcycles, paving the way for further research and development in this rapidly evolving field. As autonomous vehicle technologies continue to advance, the integration of sophisticated control algorithms and robust sensing capabilities will be crucial for enhancing the safety, efficiency,

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and versatility of autonomous motorcycles in real-world applications.

In summary, this study has investigated and compared two control approaches for autonomous motorcycles, providing detailed insight into their capabilities and limitations under practical conditions. Our results highlight the importance of considering the complexity of motorcycle dynamics in the design of effective control systems and highlight the need for future research to address open questions and further improve system performance in real-world environments.

5.1 Conflict of Interest

The authors declare that there is no conflict of interests regarding the publication of this paper.

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