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Research Paper

Line Follower Robot Optimization based Fuzzy Logic Controller Using Membership Function Tuning

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Abstract

The study was aimed to measure the performance of Fuzzy Logic Controller (FLC) on Line Follower Robot (LFR). FLC output is a deviation value of Pulse Width Modulation (PWM) to determine the rotational speed of the left and the right wheel. As input variables are current and previous line sensors. Tuning was applied to input and output variables in each membership function (MF) to conduct the best performance. This study used triangular membership function that consists of three MF. Mamdani Fuzzy Inference System (FIS) is used using nine rules. The result obtains that after MF tuning, the performance of the LFR settling time is 0.63s faster compare to that without tuning.

Keywords: *Fuzzy Logic Controller, Line Follower Robot, Mamdani.*

1. Introduction

Line follower robot (LFR) is an electronic system that can follow lines, where the line is visible or invisible. Generally, a line is a predetermined path that can be detected by the sensor[1][2]. LFR has a wide implementation in many different areas such as hospitals[1][3], restaurants[4] and as household devices[4]. LFR requires a certain way to move along the line, some of it is bang-bang control, PID method[5], or intelligent approach methods[6]. One of common LFR controlling based on intelligent approach methods is FLC [6][7][8][9][10][11][12][13]. This study exploits the performance of embedded FLC on LFR to reach its settling time. Settling time is the time required for the response to reach and remain within a specified tolerance limit around the steady-state value.
FLC consists of the following four elements[14]:

1. A rule-base, which contains the quantification of fuzzy logic from an expert linguistic description of how to achieve good control.
2. An inference mechanism, which emulates expert decisions in interpreting and applying knowledge of how best to control the plant.
3. A fuzzification, which converts the controller input into information that the inference mechanism can be easily used to enable and apply rules.
4. A defuzzification, which turns the inference mechanism into actual input for the plant.

The commonly used technique for defuzzification is the centroid method[14]. Using the centroid algorithm shown in Equation (2), where n is the number of sample elements, x_i is the elements and $\mu(x_i)$ is the MF value paired withx_i. In this experiment, input and output variables use both triangular membership functions, as in Equation (1). Triangular curves depend on three parameters a, b, and c [15]. **Fig. 1** shows triangular membership functions.

$$f(x;a,b,c) = \begin{cases} 0 & \text{for } c < x < a \\ \dfrac{x-a}{b-a} & \text{for } a \le x < b \\ \dfrac{c-x}{c-b} & \text{for } b \le x \le c \end{cases} \qquad (1)$$

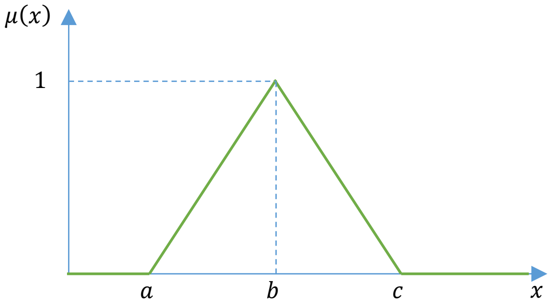

Fig. 1: Triangular membership function

$$x' = \frac{\sum_{i=1}^{n} x_i \cdot \mu(x_i)}{\sum_{i=1}^{n} \mu(x_i)} \qquad (2)$$

2. Experimental Details

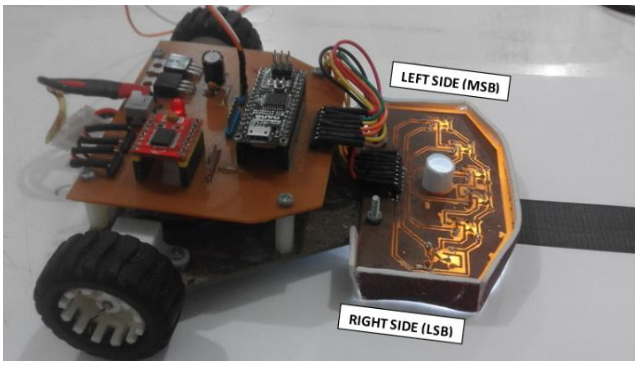

Fig. 2: Line follower robot prototype

LFR diagram is shown in **Fig. 3** consist of three part of main hardware; it is line sensor, Arduino Nano, and motor driver. The line sensor is built from the six-sensor array with distance between sensors of 2 cm. Each sensor connected to an ADC canal which goes through to the fuzzification section. The crisp value of line sensors reading has a universe of discourse (UoD) that specified from 0 to 10.

While the LFR move for the first time at the first sampling, the line sensor readings were stored to new position variable. In the next sampling, the value of new position variable was moved into old position variable, and so on for the following sampling. Both input variables have three linguistic variables which are left, right and straight which illustrated in **Fig. 4** and **Fig. 5**. The changes of both variables become the foundation to build if-then rules which illustrated in **Fig. 10** and **Fig. 11**. Output variables have three linguistic variables which is negative, zero and positive which illustrated in **Fig. 6**. Optimization is done by narrowing the universe of discourse in the straight and zero variables, which illustrated in **Fig. 7**, **Fig. 8**, and **Fig. 9**.

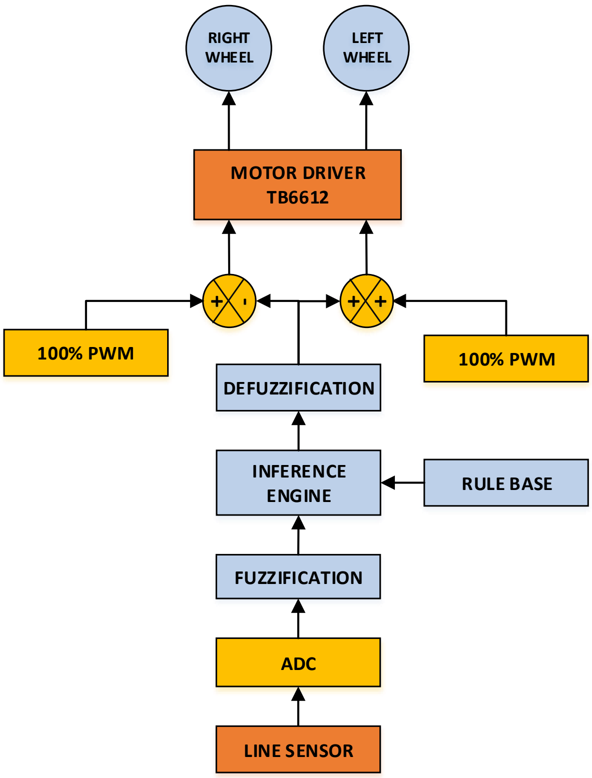

Fig. 3: Block Diagram of Line follower robot prototype

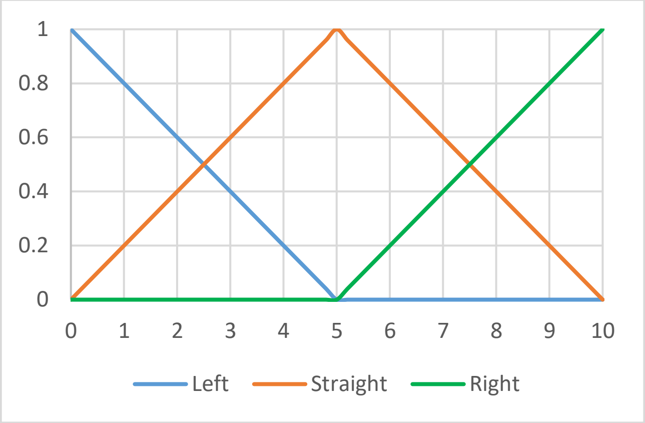

Fig. 4: Old-position variable before tuning

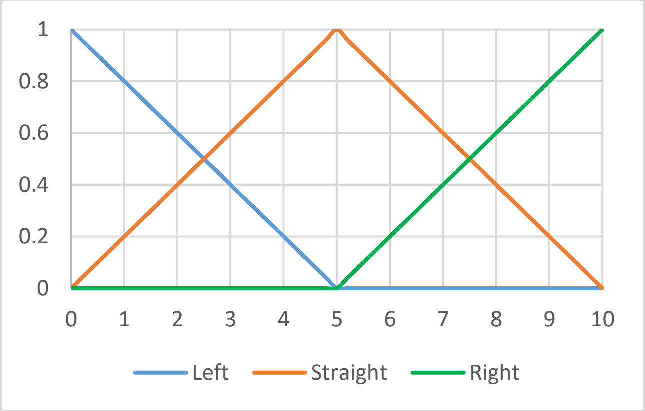

Fig. 5: New-position variable before tuning

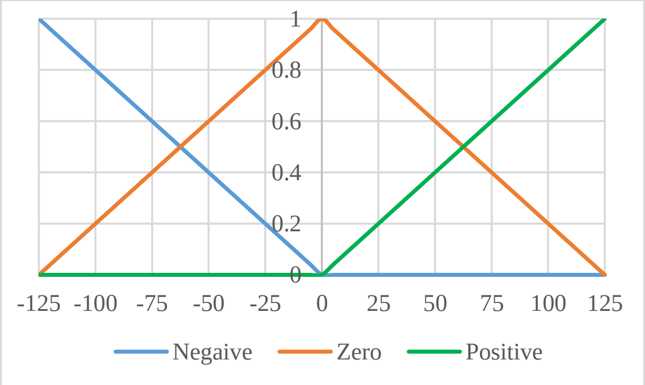

Fig. 6: Deviation variable before tuning

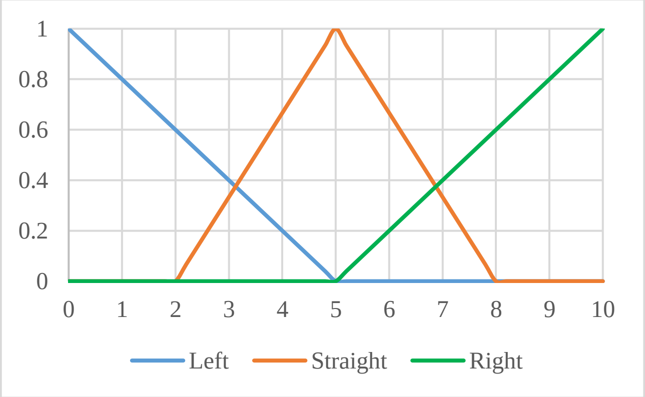

Fig. 7: Old-position variable after tuning

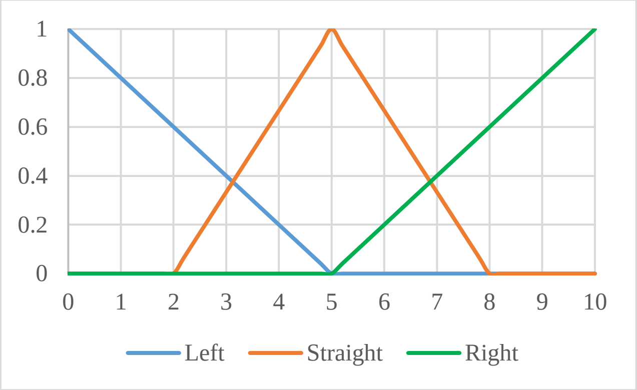

Fig. 8: New-position variable after tuning

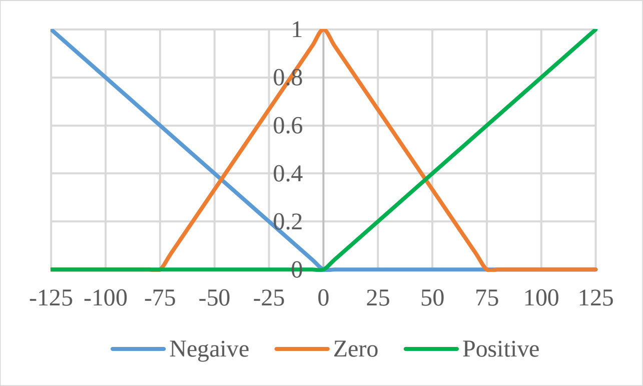

Fig. 9: Deviation variable after tuning

Of the three input-linguistic variables and the three variable-linguistic outputs, yields the following 9 bases of rules

R1: if old-position is left and new-position is left, then deviation is positive

R2: if old-position is left and new-position is straight, then deviation is zero

R3: if old-position is left and new-position is right, then deviation is negative

R4: if old-position is straight and new-position is left, then deviation is positive

R5: if old-position is straight and new-position is straight, then deviation is zero

R6: if old-position is straight and new-position is right, then deviation is negative

R7: if old-position is right and new-position is left, then deviation is positive

R8: if old-position is right and new-position is straight, then deviation is zero

R9: if old-position is right and new-position is right, then deviation is negative

The output variable deviation has a UoD value of -125 to +125 and has three linguistic variables of negative, positive and zero. The deviation value is used to reduce the PWM value of right motor and to increase the PWM value of the left motor. In this experiment, a 100% PWM value is equal to 255.

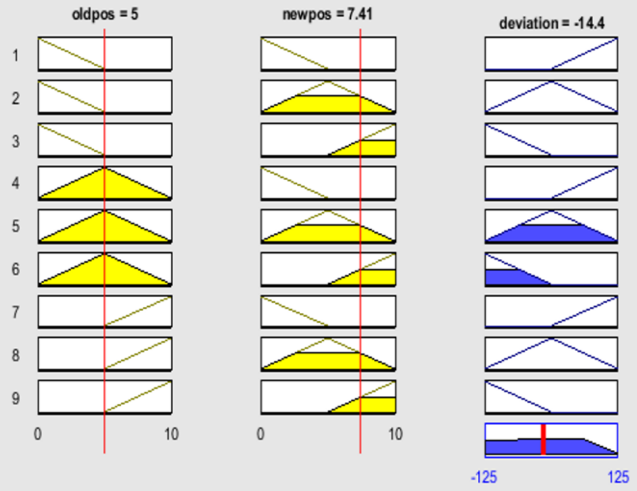

Fig. 10: Ruler based view of Fuzzy Logic Controller Without tuning

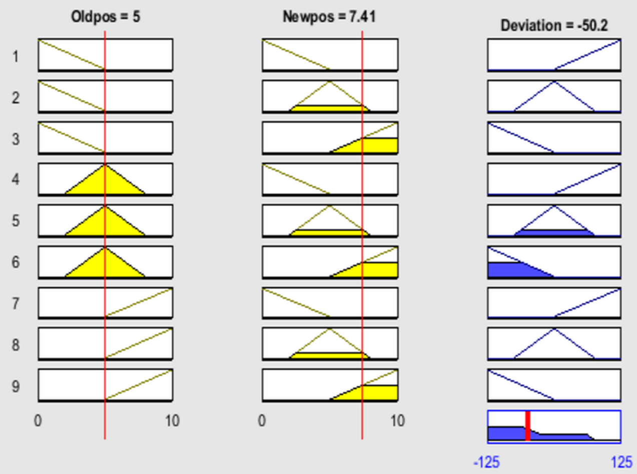

Fig. 11: Ruler based view of Fuzzy Logic Controller With tuning

Defuzzification using centroid method on aggregation result of all rules is shown in **Fig. 10** and **Fig. 11**, both before and after tuning. MF tuning is conducted through adjustment of its linguistic values. The result of defuzzification than stored to deviation variable.

For the testing purpose, the path is a black straight line with 120cm long and 2.5cm thick on a white surface. Line sensor reading was captured every 100ms and sent using serial communication. Gathered data from the acquisition, 30 data with 100ms sampling time, then processed using Excel.

3. Results and Discussion

The performance test is shown in **Fig. 12**, **Fig. 13**, and **Fig. 14** which is without MF tuning and **Fig. 15**, **Fig. 16**, and **Fig. 17** which is with tuning. Each test was conducted five times. The default reference value is 5 of UoD which is from 0 to 10. The starting position of LFR is parallel to the line path, with the LSB of line sensor directly above the line. So that the starting point in **Fig. 12** and **Fig. 15** is (0,0) both with and without MF tuning. The LFR response time without tuning are 1600ms, 1800ms, 1600ms, 1700ms and 1500ms consecutively, while with tuning are 600ms, 700ms, 600ms, 550ms, 700ms. The average settling time is 1.64s for LFR without MF tuning compare to 0.63s with tuning.

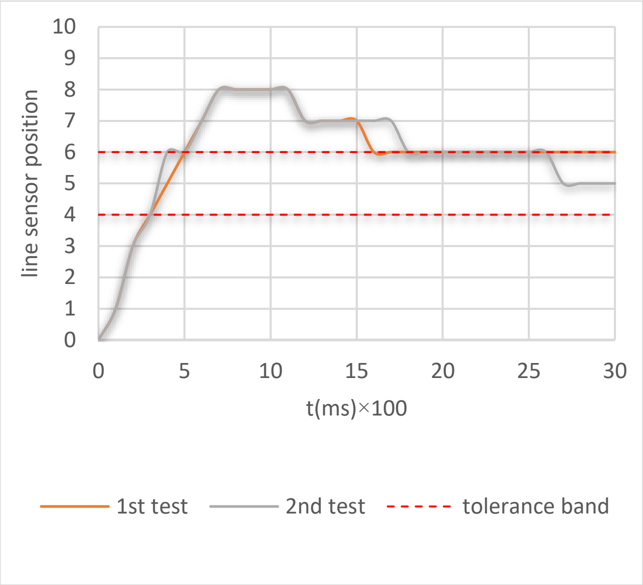

Fig. 12: LFR performance without MF tuning

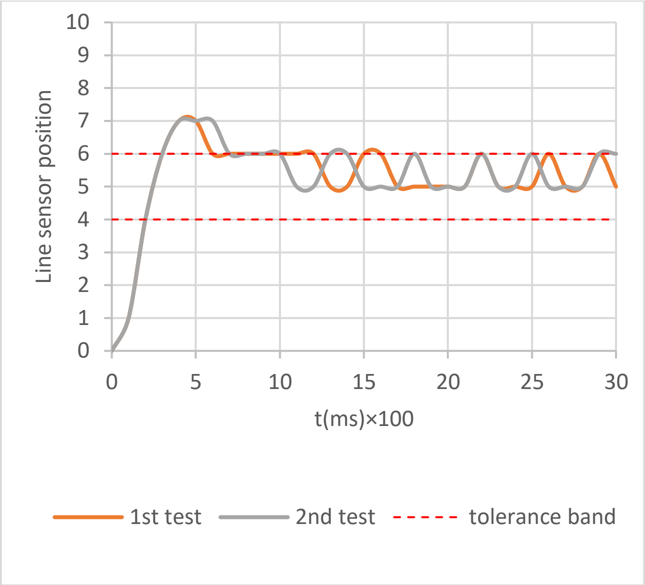

Fig. 15: LFR performance with MF tuning

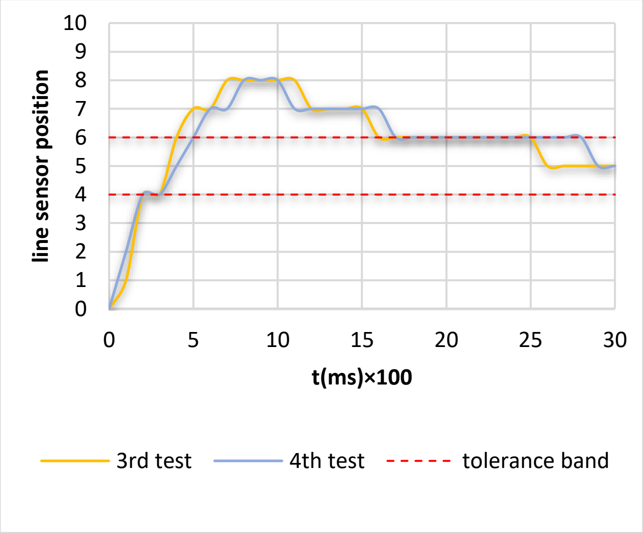

Fig. 13: LFR performance without MF tuning

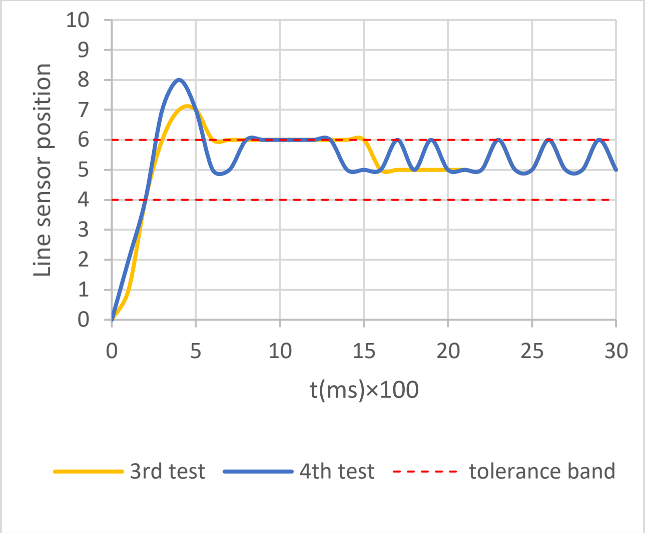

Fig. 16: LFR performance with MF tuning

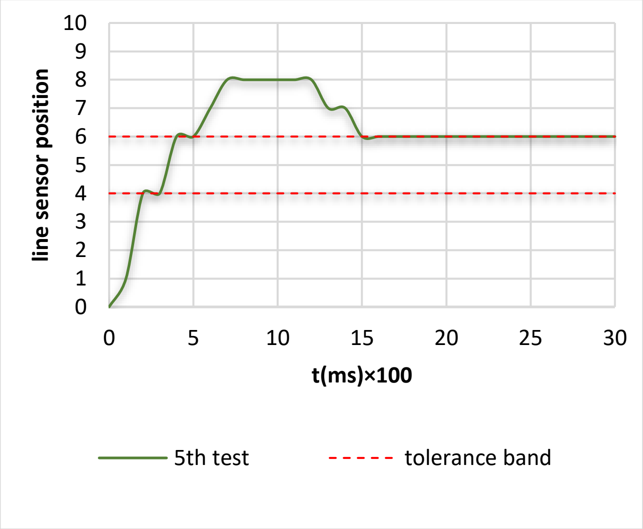

Fig. 14: LFR performance without MF tuning

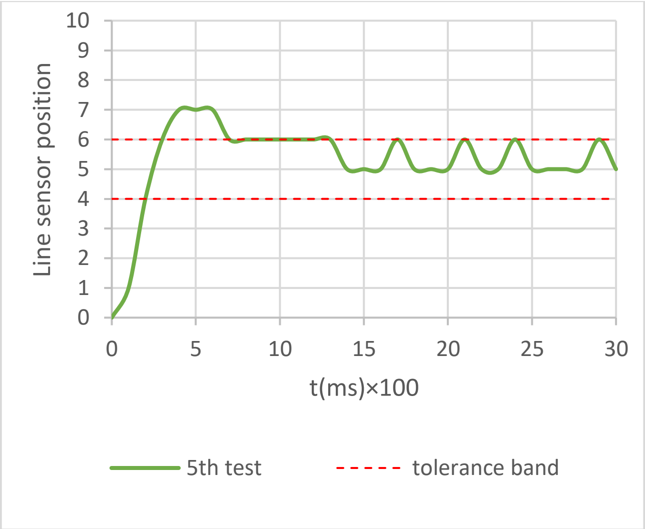

Fig. 17: LFR performance with MF tuning

4. Conclusion

It is known from the experiment that triangular MF tuning on all variables to give better result while reaching the reference point to compare to that without tuning. The future work that will conduct in order to investigate the implementation of FLC on LFR are comparing the performance of different membership functions.

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