A Novel Low-Cost Obstacle Avoidance System for a Quadcopter UAV Using Fuzzy Logic

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***Abstract*—Modular drones are a type of open-faced UAV which are used in drone research due to their modifiability. One downside to the drone-type is the lack of built-in drone features such as the obstacle-avoidance. This paper describes the design and construction of an** obstacle **avoidance feature for the drone using a fuzzy logic-based controller. The program is designed to be modifiable in terms of input distance and output pitch and roll values as to the user's requirements. Loose bench testing was done prior to the actual indoor test in order to verify the output results. Actual indoor testing results showed a good response in terms of the fuzzy-logic controller performance. Creation and integration of a controller to regulate the flight controller output was recommended.**

***Index Terms*—obstacle avoidance, fuzzy logic control, quadcopter, ultrasonic**

I. Introduction

Drones or unmanned aerial vehicles (UAVs) are a fast-emerging flight technology that have made significant presence in military operations (e.g. surveillance, artillery), search and rescue (SAR), geographical mapping, agricultural and commercial land surveying, and even in film and arts industry. Like Global Positioning System (GPS), UAVs used to be exclusive to military applications and just presented itself to the public within the last decade, hence the fairly young research about the field. Today, improving the autonomy of these vehicles is among the fast-emerging areas in drone research alongside with hardware development. Included in this is smart navigation-both path tracking and obstacle avoidance.

Obstacle detection and avoidance in UAV automation helps a vehicle steer away and/or maneuver about a stationary or dynamic obstacle that intercepts its path. In the case of a quadcopter, obstacle avoidance is done with adjustments in its velocity, roll, pitch, or yaw or a combination of these.

The usual challenge in implementing this feature in UAVs is the heavy, expensive, and energy-consuming nature of high-grade sensors necessary for obstacle detection. Wagster et al. underscored the usage of off-the-shelves sensors that are available in typical electronic shops [1]. A one-meter-range sonic sensor was selected in the study because of its small payload and cheap cost. Obstacle avoidance was implemented with two lateral sonic sensors on a robot vehicle that tried to center the vehicle in between obstacles using a push algorithm. In a similar study, Rapidly Exploring Random Trees (RRT) was used to integrate the push algorithm and the forward-facing sensor [2]. RRT is designed to efficiently search non-convex, high-dimensional spaces by randomly building a space-filling tree. Kala established that fuzzy logic has simpler computations over RRT since the vehicle speeds that it governs are based on fuzzy rules, while the other has a little too high complexity for its multiple attempts to compute collision-free speed

Another method that is typically used in obstacle avoidance is the artificial potential fields (APF) where a robot is assumed to move in an abstract artificial force field, the variation of which describes the structure of the robot's environment. Jia and Wang explained the disadvantage of this method with its tendency to get caught in local minima, causing the subject vehicle to fail [3]. This is due to the fact that the APF basically acts as a fastest descent approach. Cohen and Sabo made simulations and comparison between APF- and fuzzy logic control (FLC)- guided UAVs [4]. The APF performed with overall failure rate about six times that of the FLC. The APF committed failures that went to about a third of the total cases while the FLC finished at five percent failure rate.

Dong et al. combined model-based control with FLC to navigate a UAV past stationary and moving vehicles [5]. The model-based controller was derived assuming that the vehicle has no prior knowledge of the environment except its GPS coordinates. A two-layered fuzzy logic controller then was used to make the UAV track its path while avoiding the fixed, but unexpected obstacles. The sensor inputs were fed in as random values and the desired output values were obtained. Simulation showed that the proposed method was effective but costly. Other studies that uses quadcopters for task implementations are shown in [6-10].

In this paper, a novel low-cost obstacle avoidance system for a quadcopter drone using fuzzy logic is

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presented. Four low cost ultrasonic sensors were used to provide distance from the obstacle to the drone as the input to the FLC. The behavior of the drone is streamed and the activation of the FLC is done in the ground station via wireless internet connection. Using a Raspberry Pi 3 computer, the drone is allowed to steer away from obstacles according to pitch and roll values as relayed to the Pixhawk flight microcontroller. A hierarchical control structure was used in building the fuzzy rule base of the system to reduce the size of the association matrix. A push algorithm was also adapted to allow the drone to always position itself at the center of two obstacles in opposite directions.

II. Obstacle Avoidance Controller Design

Fig. 1 illustrates the sequence in which the obstacle avoidance of the UAV is implemented. Each of the four ultrasonic sensors mounted on the vehicle takes the vehicle's distance from the obstacle, d_i where i = 1, 2, 3, and 4, as the input to the controller. If one of the distances goes below the threshold value for obstacle proximity, the FLC is activated. Distances are processed inside the fuzzy logic computing unit to determine how much roll, α, or pitch, β, the vehicle should move with, in order to secure a safe distance from the obstacle. The Raspberry Pi computer gives this value, either through a telemetry serial connection or Universal Serial Bus (USB) connection, to the Pixhawk flight microcontroller, which is responsible for the behavior or attitude (e.g. velocity, heading angle, etc.) of the vehicle during flight.

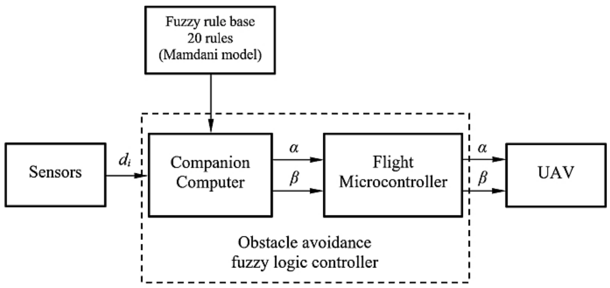


Figure 1. Obstacle avoidance system diagram of the UAV

A. Design of Fuzzy Algorithm

Fig. 2 shows the Gaussian membership functions (MFs) used to transform the crisp input values to the system that is the distance between the vehicle and the obstacle. The maximum obstacle distance at which the remote control of the vehicle is overridden by the fuzzy control is set at 180 cm. The universe of the distance variable was divided into five fuzzy sets namely Very Near, Near, Middle, Far, and Very Far. Listed below is the assignment of mean distance value for each of the fuzzy sets.

Very Near	0 cm
Near	45 cm
Middle	90 cm
Far	135 cm
Very Far	180 cm

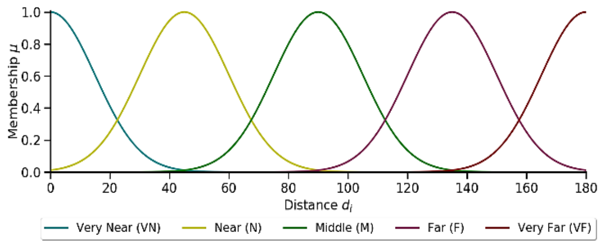


Figure 2. Input membership functions

Triangular MFs were used to classify the output angle into its fuzzy set. A maximum of 8° for both roll and pitch angles was used in creating the output membership functions. Same range of angles was used for both pitch and roll of the vehicle because of its symmetrical structure. This means that the inertias of the vehicle, each with respect to roll- and pitch-axes, are practically the same. Ten fuzzy sets were made to accommodate both positive and negative angle response of the UAV. The output membership functions are summarized in Fig. 3.

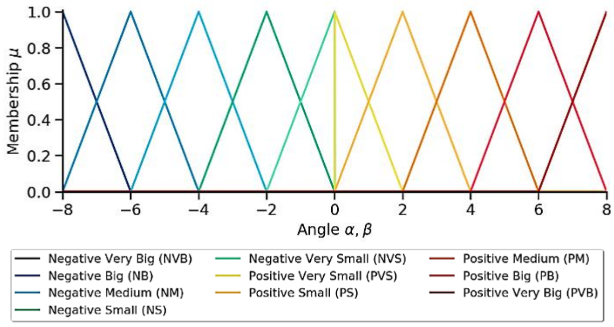


Figure 3. Output membership functions

The method of centroid, particularly the center of gravity (CoG), is used to defuzzify the output of the control system. In CoG method, the value of the centroid is taken where a vertical line would slice the aggregated areas into two equal masses. Ross [6] gives CoG as

$$x^* = \frac{\int x \cdot \mu_{\underset{\sim}{X}}(x)\,dx}{\int \mu_{\underset{\sim}{X}}(x)\,dx}. \tag{1}$$

B. Hierarchical Controller Structure

A non-hierarchical fuzzy-associated memory (FAM) controller would have fuzzy rules of form:

if (Left Distance is Too Near) and (Front Distance is Medium) and (Right Distance is Far), then (Roll is Positive Big) and (Pitch is Positive Small), etc.

A hierarchical FAM controller would have fuzzy rules of form:

If (Left Distance is Too Near), then (Roll is Positive Big)

If (Front Distance is Very Far), then (Pitch is Positive Very Small)

From the examples above, a hierarchical system depends on fewer parameters than in a non-hierarchical system. This makes the rules easier to formulate and the system easier to test.

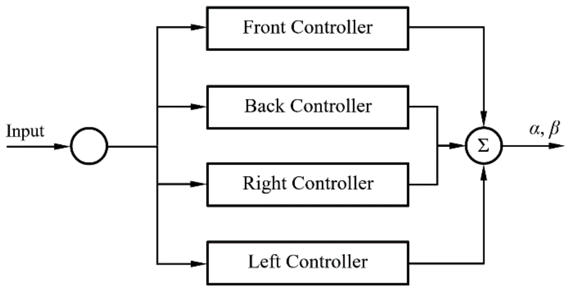


Figure 4. Structure of the hierarchical fuzzy controller

C. Fuzzy Rule Base

The decision making of the fuzzy logic control was designed according to the hierarchical control structure. With this scheme, the number of fuzzy control rules was reduced since no fuzzy operation (e.g. logical AND, logical OR) were made between two or more of the four sensor readings. In here, the decision to which direction and with how much angle the UAV should move, prior to a specific sensor reading, is independent of other sensor readings. The fuzzy rule base of our system consists of a set of IF-THEN rules that map fuzzy distance variables into fuzzy roll and pitch commands. Examples of these rules are as follows.

IF Right Distance is Far, THEN Roll is Negative Small

IF Left Distance is Near, THEN Roll is Positive Big

IF Front Distance is Very Near, THEN Pitch is Positive Very Big

IF Back Distance is Middle, THEN Pitch is Negative Medium

Seventeen similar IF-THEN fuzzy rules are listed in Table I.

TABLE I. FUZZY RULE BASE OF OBSTACLE AVOIDANCE CONTROL

Distance	Angle			
	Right	Left	Front	Back
VN	NVB	PVB	PVB	NVB
N	NB	PB	PB	NB
M	NM	PM	PM	NM
F	NS	PS	PS	NS
VF	NVS	PVS	PVS	NVS

D. Experimental Setup

The connection of the ultrasonic sensors, the Pixhawk flight microcontroller, and Raspberry Pi companion computer is shown in the schematic diagram in Fig. 5. To prevent the sensors from drawing too much current from the companion computer, a separate 9-V DC supply was designed. The microcontroller and companion computer were linked via universal serial bus (USB) connection through which the angle commands of the FLC are relayed.

The schematic diagram in Fig. 6 shows the arrangement of the four ultrasonic sensors in the cardinal directions of the drone. For initial testing, the drone was tied with loose ropes on a bench made of metal frames to confine it while it is armed and with its rotors turning. The final UAV setup is shown in Fig. 7.

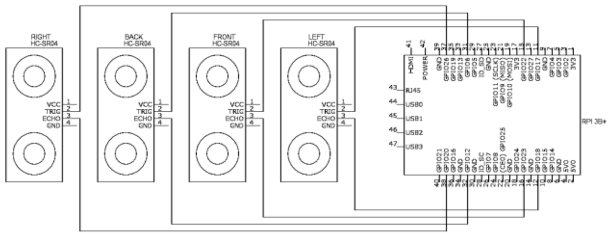


Figure 5. Schematic diagram of sensors, flight controller, and companion computer connection

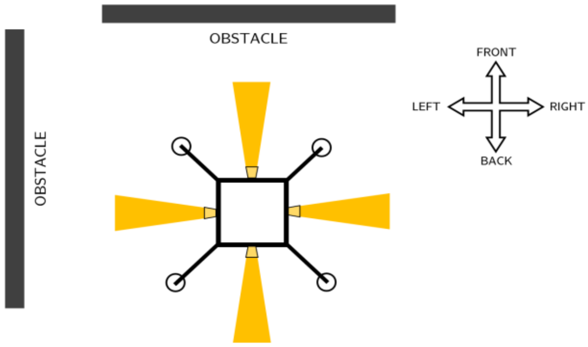
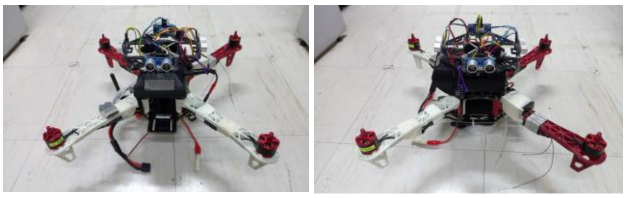


Figure 6. Diagram of UAV setup with obstacles at proximity



a. Front View b. Side View

Figure 7. Final UAV setup

III. FLIGHT TESTS AND RESULTS

A. Loose Test Bench Result

In implementing the obstacle avoidance feature for the UAV, a test bench was used to simulate the reaction of the drone. A test bench is a structural device used to test the flight capability of the drone without the risk of crashing the drone by tying it to the test bench. The drone is tied loosely to allow the drone to react when an obstacle is detected. Fig. 8 shows the setup of the loose test bench.

Figure 8. Bench test flight setup

The program was edited so that only one sensor would be working. While the program was being implemented, one of the researchers holding an obstacle would slowly approach the setup from 2 meters to 0.4 meters away from the sensors and back to the starting position. The procedure was repeated twice for each sensor and the data was recorded.

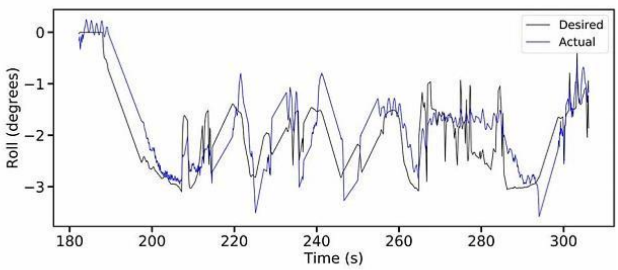


Figure 9. Trial 1 of the test bench response of the drone when an obstacle is detected by the right sensor

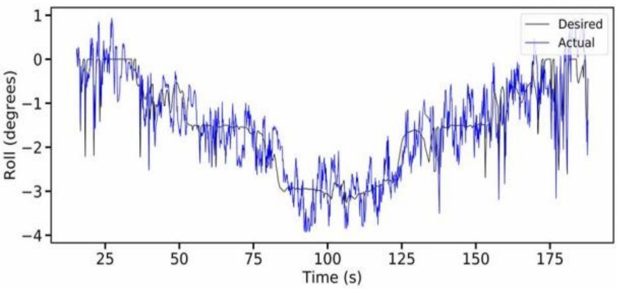


Figure 10. Trial 2 of the test bench response of the drone when an obstacle is detected by the right sensor

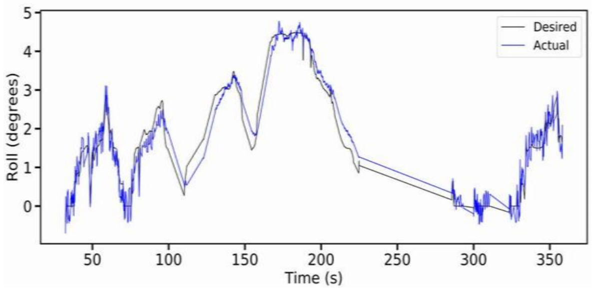


Figure 11. Trial 1 of the test bench response of the drone when an obstacle is detected by the left sensor

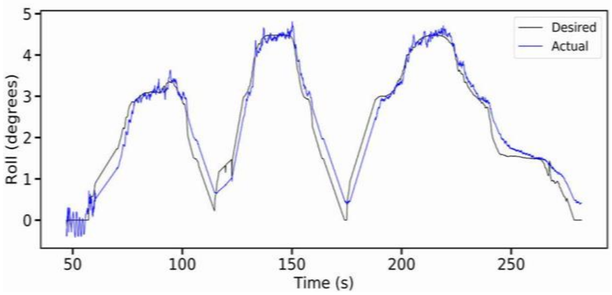


Figure 12. Trial 2 of the test bench response of the drone when an obstacle is detected by the left sensor.

TABLE II. TABULATED DATA OF THE SENSORS WITH THE TRAILS AND THE CORRESPONDING RMSE.

Sensor		RMSE
Right	Trial 1	0.4034
	Trial 2	0.4403
Left	Trial 1	0.2508
	Trial 2	0.2185
Front	Trial 1	0.2728
	Trial 2	0.2814
Back	Trial 1	0.3138
	Trial 2	0.3397

The Figs. 9-12 shows the graphs for each sensor testing (right and left), the graph demonstrates the actual reaction of the drone given a desired value by the program, while Table II shows the root means square error in between the desired and actual reactions.

The left sensor exhibited the closest response with the desired value, it has an RMSE values of 0.2508 and 0.2185 for the first and second trial, respectively. On the other hand, the right sensor had the least ideal response with respect to the desired value. It has RMSE values of 0.4034 and 0.4403 for the first and second trial, respectively. Small values for RMSE are desired for it would mean that there is minimal error. However, the noise shown in the graphs above and the drone responses for both right and back sensors may be influenced by the presence of unequal tension exerted by the ropes or a possible internal issue with the flight controller.

B. Indoor Testing Result

The whole system was tested indoor, in a controlled environment, to evaluate the performance of the drone. In order to determine the differences in the reaction of the drone, three trials were done where in the roll/pitch value of the obstacle avoidance program was varied to 4, 6, and 8 degrees.

Fig. 13 shows the 4-degree roll response generated an RMSE of 0.2811 with a maximum error value of approximately 0.67 degrees from the desired. Meanwhile, the 6-degree roll value generated an RMSE of 0.4241 with a maximum error of 1 degree from the desired roll value. Lastly, the 8-degree roll response generated an RMSE value of 0.4452 with a maximum of 1-degree error. Looking at the RMSE values, it can be seen that the RMSE increases as the roll degree value was increased. However, the performance of the 4-degree and 6-degree roll values did not show much difference in terms of the aggressiveness of avoiding the obstacle compared to the 8-degree roll value. Thus, increase in the roll value error may be attributed to the aggressiveness warranted by the obstacle avoidance program of the drone that cannot be followed instantaneously by the flight controller (Pixhawk). This could be improved by tuning the microcontroller. Fig. 14 shows the actual testing using the left sensor for detection and avoidance

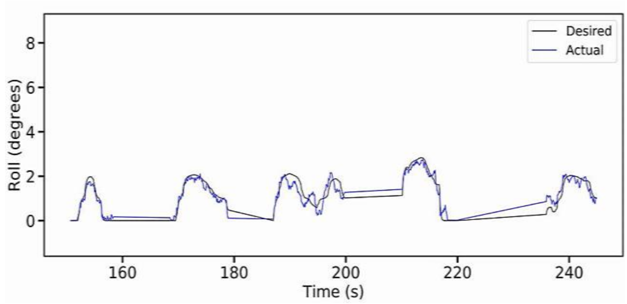


Figure 13. 4-degree in-flight response of the drone when an obstacle detected by the Left Sensor

Figure 14. Actual flight response when obstacle was detected by the Left Sensor

IV. CONCLUSION

A fuzzy logic-based obstacle avoidance control was designed and implemented utilizing low cost components. The sensors were first tested on a stationary UAV to ensure that no defect is present. A loose bench test was then conducted in order to determine if the UAV would respond to a presented obstacle. Once the avoidance feature was verified to react according to the desired output dictated by the companion computer, actual flight tests were conducted. The actual pitch and roll values obtained during flight were comparable to the desired values and the system was able to do the detection and avoidance process. In the future, a hybrid PID-Fuzzy controller can be integrated to the system in order to improve the performance of the drone.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Mr. Aniceto designed the fuzzy logic controller of the system. Mr. McGrath was in-charge of experimental design for the performance testing. Mr. Ochengco finalized the UAV setup. Ms. Regalado analyzed the results and wrote the paper. Dr. Chua conceptualized the research and determined the solutions carried out in the research paper.

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