Developed Blimp Robot Based On Ultrasonic Sensors Using Possibilities Distribution and Fuzzy Logic

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***Abstract*—In this paper, we present obstacles avoidance and altitude control algorithms based on fuzzy sets and possibilities distributions to control the blimp's complexity and main behaviors of the system. The fuzzy knowledge base is designed empirically to introduce two-layer fuzzy logic controllers which have the ability to reduce the ultrasonic sensor uncertainties and to estimate the shortest distance between the blimp and the objects. Finally, the results of the experiments show the algorithm is improving the performance of the blimp to avoid obstacles safely and maintain at a certain altitude.**

***Index Terms*—blimp, airship, avoid obstacles, fuzzy control, altitude, UAV robot**

I. Introduction

Some of the most difficult applications for robotics are the unknown environments such as search and rescue, surveillance and environment monitoring. Autonomous navigation of unmanned vehicles in unstructured environments is a multidiscipline and attractive challenge for researchers. Recently, the unmanned airship becomes focus interest increasingly because of its advantages such as long time hovering, much less energy consumed and cost efficiency which made them ideal for exploration of areas [1]-[2]. However, an important navigation problem is automatic control of altitude and horizontal movement. A second important navigation problem for the blimps is obstacle detection and collision avoidance.

In recent years many researchers have developed airships robotic systems and studied the control of their behavior. The nonlinear dynamic model of the low altitude airship with six degree of freedom is introduced and the flight conditions and the balance between forces and moments acting on the airship is analyzed [3]. In order to develop airships it is important to control the stability. One of the stability theories used is the Lyapunov's theory which analyzes the stability and test the robustness to verify the controller performance [4]. Intelligent control that uses various computing approaches like neural networks and fuzzy logic is also used to control the main behaviors of the blimp. For example, the fuzzy logic with soft computing control systems has been applied to control the propulsion and steering system [5]. However, the tracking system is never mapped the specified things for airship.

The use of solar energy as a renewable source of power for such outdoor blimp is also under consideration for some researches [6]. A few researchers have designed an autonomously controlled indoor blimp and an action-value function for motion planning based on the potential field method to evaluate the blimp effectiveness in a simulated environment [7]-[8]. The Neural Network control approach is also used to control the blimp in especial purposes by collecting the sensor data for the environment and implement the multiple rules for the control strategy then the blimp have ability to avoid the obstacles [9]. In fact, it needs more experiments for training data to improve the intelligent control. However, most of these researches do not deal with the sensors behaviors during the navigation. Therefore, we introduce how it is possible to model these drawbacks by the possibility distribution (PD) and fuzzy sets. We design the fuzzy knowledge base experimentally. First, we test the ultrasonic sensor's behaviors. Second, we study the effect of the blimp's angle view and the distance between the blimp and the detected objects. Then, the fuzzy control takes as input the data provided by the ultrasonic sensors and delivers information for eventual obstacles or information about altitude in respect to blimp's position.

In this paper, through an empirical study, the fuzzy sets approach to control the navigation of blimp robot is explained in details. The approach is not only applicable to the blimp robot, but also to any other robots.

II. The Blimp System

The flying robot characteristics have some restrictions considering its hardware. Indeed, for any blimp system if the envelop volume get higher, the ascending force will increase and as a result the higher the possible payload. For our blimp system, the goal was to minimize the weight of the needed hardware equipment as soon as possible and to develop appropriate control algorithms for flying robot which are highly sensitive to outside influences to operate as a fully autonomous robot. The main components are shown in Fig. 1 which shows

Manuscript received October 20, 2012; revised December 22, 2012.

doi: 10.12720/joace.1.2.119-125

gondola onboard unit (GOU) with all the electronic components necessary to control the three motors.

A. The Main Unit (MU)

The processing control unit is the core of the system and it is distributed among Atmega microcontroller which handles stability control and maintaining blimp attitude set points. Our chosen for this microcontroller depends on its ability to interface with other components in the system.

B. Inertial Measurement Unit (IMU)

As a flying robot the Bryan angles (roll, pitch, and yaw) are required and to obtain these angles an inertial measurement unit (IMU) was used. The accelerometer data along with the gyroscope data about all three axes will be taken into contexts, allowing the blimp to know its attitude along with its distance traveled at any point in time.

C. Motor Drivers

They are necessary to control the speed of each motor. The drivers are based on discrete MOSFET H-bridge motor driver enables bidirectional control of one high-power DC brushed motor. It supports a wide 5.5 to 30 V voltage range and is efficient enough to deliver a continuous 15 A without a heat sink. The pulse-width modulation (PWM) is directly controlled by the microcontroller.

D. Sensors

We mounted a quarter ring with four ultrasonic sensors to gondola in (x, y) plane to be used for avoidance obstacles. The altitude distance during the flight was verification and controlled via the fifth ultrasonic sensor that is downward-facing mounted at the bottom of the gondola.

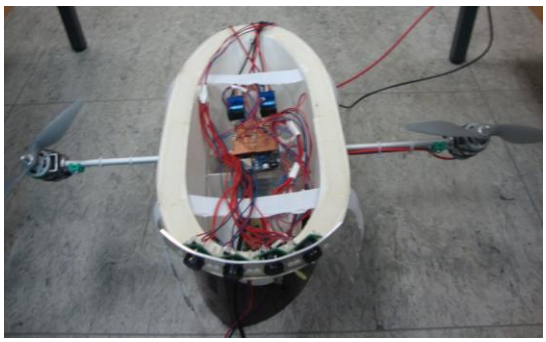

Figure 1. The gondola onboard unit (GOU)

III. Fuzzy Logic Controller

The blimp structure is demonstrated in Fig. 2. When the blimp navigates from position A toward position B with view angle β, the control system attempts to change the vectorization angle if the blimp detects an obstacle. However, the distance between the blimp and the obstacle has some uncertainties values due to sensors characteristics.

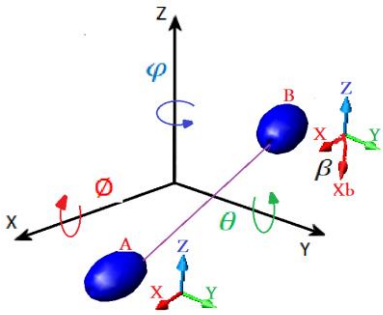

Figure 2. The blimp structure.

We implemented fuzzy logic which is derived from the fuzzy logic and fuzzy set theory that were introduced in 1965 by L. A. Zadeh [10]. Two-layer fuzzy logic controllers (FLC) have been designed and implemented. Fig.3 shows the structure of the FLC which has two sub-controllers in the first layer and two combined controllers in the second layer. In the first layer, the various inputs are classified into two input types of the sub-controllers. The fuzzy controllers in the first layer are using the proper fuzzy sets to find the shortest distance between the blimp and the obstacles. The second layer uses the outputs of the sub-controllers as the combined inputs to generate the main behaviors of the blimp. For avoidance obstacles behaviors the blimp has quarter ring with four ultrasonic sensors. The altitude distance during the flight was verification and controlled via the 5th sensor. In fact, the most well-known characteristics of sonar sensors are the uncertainties information [11]. Motlagh et al. demonstrated that fuzzy logic systems can model the uncertainties information using linguistic rules [12]. Cliff Joslyn introduced a method for construct possibility distribution and fuzzy logic from the empirical data by collecting the data and constructs the interval set statistics with random sets [13]-[16].

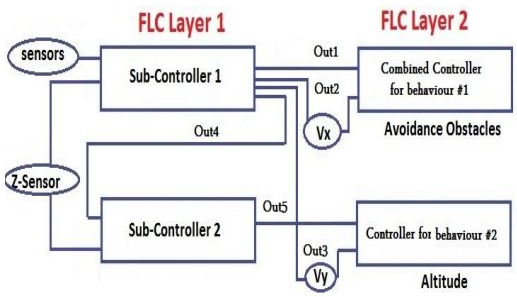

Figure 3. The structure of the FLC.

A. The Sub-Controllers

The main problem in the fuzzy logic is how to design the fuzzy knowledge base. We solved this issue experimentally by testing the ultrasonic sensor's behaviors and study the effect of the blimp's incidence angle and the distance between the blimp and the detected objects. First, the experiments are designed to collect the sensor data for different distances [0-320 cm] and different view angles $[4.5^o - 22.5^o]$ as shown in Fig.4,

Fig.5 and Fig.6. Then, we analyzed these data to construct PD then proposed a fuzzy knowledge base. Some definitions of the suggested model are listed below:

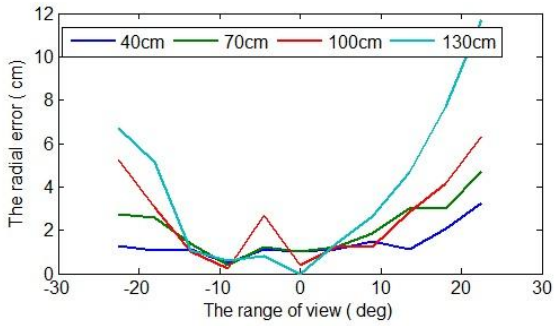

Figure 4. Frequency distribution for the data [40-130] cm.

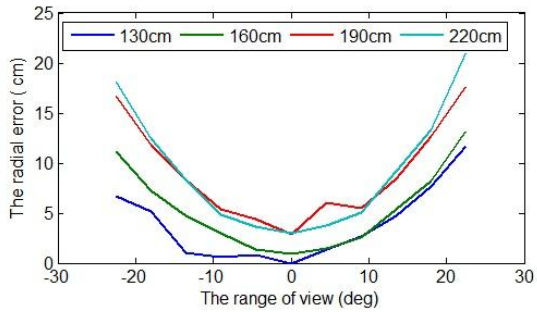

Figure 5. Frequency distribution for the data [130-220] cm.

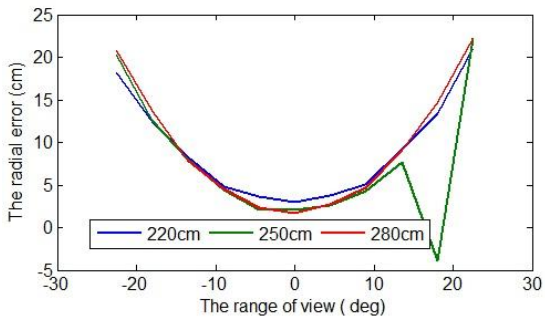

Figure 6. Frequency distribution for the data [220-280] cm.

Definition 1 (Support of a fuzzy set A): The support of a fuzzy set A is the ordinary subset of the universe X and given by (1):

$$Supp(A) = \{x \in X, \mu_A(x) > 0\} \tag{1}$$

Definition 2 (Core of a fuzzy set A): The core of a fuzzy set A is the ordinary subset of the universe X and given by (2):

$$Core(A) = \{x \in X, \mu_A(x) = 1\}\ . \tag{2}$$

Definition 3 (Set-Frequency Distribution): Given a general measurement record $\vec{A}$ and empirical focal set F^E, $C_j = C(A_j)$ is the number of occurrences of A_j in $\vec{A} \forall A_j \in F^E$. Then, a set frequency distribution is a function $M^E : F^E \rightarrow [0,1]$ as in (3):

$$M^E(A_j) = C_j / \Sigma C_j, A_j \in F^E \tag{3}$$

Definition 4 (Random Set): Given an evidence function ξ, the finite random set is given by (4):

$$S = \{\langle A_j, \xi_j \rangle : \xi_j > 0\} \tag{4}$$

Definition 5 (trapezoidal membership function): it is identified by four parameters $A = (a_1, a_2, a_3, a_4)$ where a_1, a_4 represent the support and a_2, a_3 represent the core.

Definition 6 The cores of the possibilities distribution depend on the vectors of the endpoints E, as in (5):

$$C(\pi) = [\max\{E_j\}, \min\{E_m\}] \tag{5}$$

The errors in the sensor readings depend on two main factors the angle view of the blimp's sensors and the distance between the obstacle and the blimp. For example, the two adjacent sensors S_1, S_2 with their view angles β_1, β_2 as shown in Fig.7 have three possibilities cases summarized in Table I.

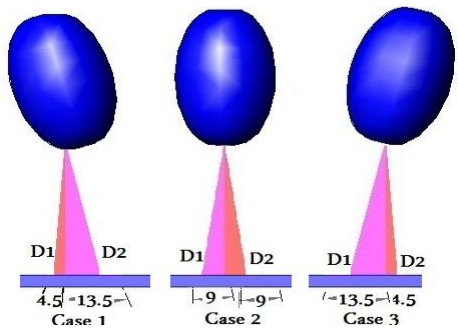

Figure 7. Possibility cases between two adjacent sensors.

TABLE I. POSSIBILITIES BETWEEN TWO SENSORS

Possibilities	Shortest distance	Angle view
1	D_1	$\beta = \beta_1 + 4.5$
2	$D_1 = D_2$	$\beta = \beta_1 - 9, \beta_2 + 9$
3	D_2	$\beta = \beta_2 - 4.5$

Based on the possibility cases analysis, it is easy to represent the uncertainty in the angle view by the possibility distributions $\pi_D(\beta)$ as they summarized in Table II. Table III shows the support and core parameters for the trapezoidal membership functions. In order to reduce the uncertainty in the sensor's readings, the three membership functions for the three cases were modeled as shown in Fig.8, Fig.9 and Fig.10.

TABLE II. POSSIBILITIES DISTRIBUTION OF UNCERTAINTY IN ANGLE VIEW

Case	$\pi_D = 0$	$\pi_D = 1$	$\pi_D =]0,1[$

1	$(\beta_1 - 22.5, -\infty)$ $\cup(\infty, \beta_1 + 4.5)$	$(\beta_1 - 9, \beta_1 + 4.5)$	$(\beta_1 - 9, \beta_1 - 22.5)$
2	$(\beta_2 - 4.5, -\infty)$ $\cup(\infty, \beta_2 + 22.5)$	$(\beta_2 - 22.5, \beta_2 + 9)$	$(\beta_2 + 9, \beta_2 + 22.5)$
3	$(\beta_1 - 22.5, -\infty)$ $\cup(\infty, \beta_1 + 4.5)$	$(\beta_2 + 9), (\beta_1 - 9)$	$(\beta_1 - 9, \beta_1 - 22.5)$ $\cup(\beta_1 + 4.5, \beta_1 - 9)$

TABLE III. SUPPORT, CORE AND MEMBERSHIP FUNCTIONS

Supp A	Core A	μ_β
$[\beta_1 + 4.5, \beta_1 - 22.5]$	$[\beta_1 + 4.5, \beta_1 - 9]$	$\{4.5, 4.5, -9, -22.5\}$
$[\beta_2 + 22.5, \beta_2 - 4.5]$	$[\beta_2 + 9, \beta_2 - 4.5]$	$\{4.5, -9, -22.5, -22.5\}$
$[\beta_2 + 22.5, \beta_2 - 4.5]$	$[\beta_2 + 9], [\beta_1 - 9]$	$\{4.5, -9, -9, -22.5\}$

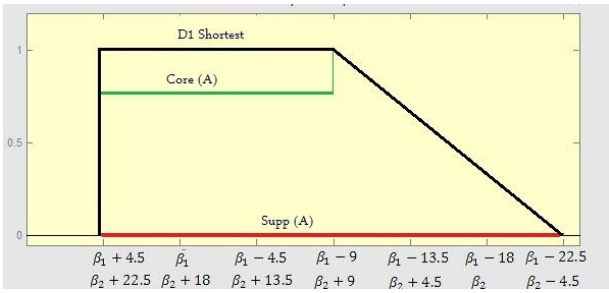

Figure 8. Fuzzy membership functions case 1

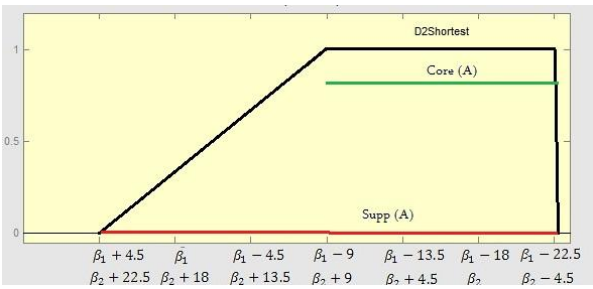

Figure 9. Fuzzy membership functions case 2

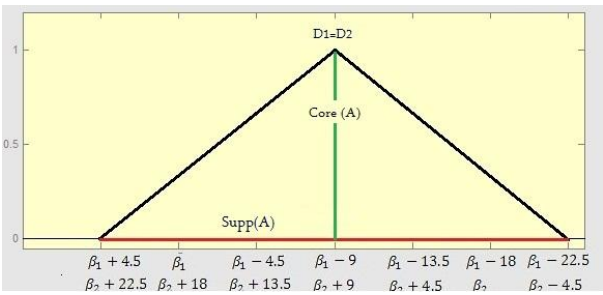

Figure 10. Fuzzy membership functions case 3.

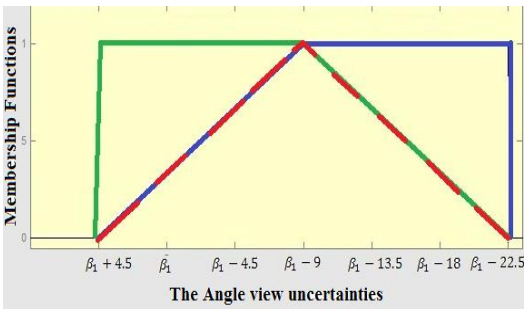

Figure 11. Fuzzy membership functions for the angle view

The final fuzzy membership functions for the uncertainties in the angle view are shown in Fig.11.

The second drawback in the readings is the radial error ε that occurs due to the beam width. In order to reduce these errors the fuzzy sets was modeled by using the frequency distributions as following:

$$\vec{A}_1 = \langle [0,1], [1,3], [0,3], [-1,4] \rangle$$

$$\vec{A}_2 = \langle [-1,4], [0,5], [2,7], [3,10] \rangle$$

$$\vec{A}_3 = \langle [3,10], [4,11], [5,11] \rangle$$

$$S_1 = \{[0,1] = 0.25, [1,3] = 0.25, [0,3] = 0.25, [-1,4] = 0.25\}$$

$$S_2 = \{[-1,4] = 0.25, [0,5] = 0.25, [2,7] = 0.25, [3,10] = 0.25\}$$

$$S_3 = \{[3,10] = 1/3, [4,11] = 1/3, [5,11] = 1/3\}$$

The vectors of the endpoints are:

$$E_{j1} = \{-1,0,0,1\} \quad , \quad E_{m1} = \{1,3,3,4\} \quad , \quad E_{j2} = \{-1,0,2,3\} \quad ,$$

$$E_{m2} = \{4,5,7,10\}, \; E_{j3} = \{3,4,5\}, \; E_{m3} = \{10,11,11\}$$

$$C(\pi)_1 = [1,1], C(\pi)_2 = [3,4], C(\pi)_3 = [5,10]$$

The supports of the possibilities distribution is:

$$Supp_{A1}(\pi) = [\{-1,0\}, \{0,1\}, \{1,1\}, \{1,3\}, \{3,4\}] \, .$$

$$Supp_{A2}(\pi) = [\{-1,0\}, \{0,2\}, \{2,3\}, \{3,4\}, \{4,5\}, \{5,7\}, \{7,10\}]$$

$$Supp_{A3}(\pi) = [\{3,4\}, \{4,5\}, \{5,10\}, \{10,1\}] \, .$$

Because the fuzzy sets and possibilities distribution have the same mathematical description, the possibilities distribution operations as shown in Fig.12 can be transferred to fuzzy sets without any changes as shown in Fig.13.

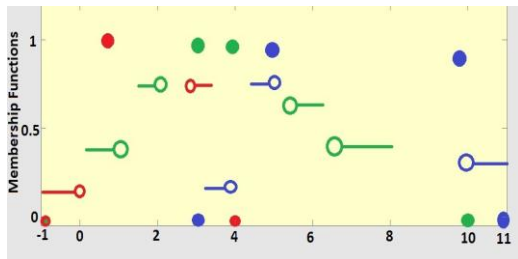

Figure 12. The possibilities distribution for radial errors

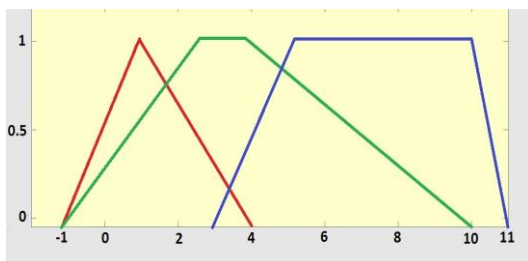

Figure 13. The membership functions for radial errors

As a result, the controller could decide which sensor has the smallest angle view with known radial errors and calculate the four Membership functions for this angle

view as given in (6). Then, rotate the reading distance (RD) to the original axis coordinate to find the shortest distance (SD) as given in (7). Finally, to estimate the shortest distance the t-norms should be used as in (8).

$$\mu_{SD}(x) = Supp\{\mu(\varepsilon,\beta)\}, \alpha^1 < \beta < \alpha^4 \quad (6)$$

$$SD_x = [\varepsilon \pm RD]\cos(|\beta|) \quad (7)$$

$$Supp(\mu) = \sum_{\mu=1}^{4} \min(SD) \quad (8)$$

In the case where $D_1 < D_2$ and the value of reading is around 2 meters and the value of membership function from Table III is $\mu_\beta = \{4.5, 4.5, -9, -22.5\}$ with value {0, 1, 1, 0} as shown in Fig. 5. The shortest distance certainty can be summarized as below.

$$SD_{x1} = [1 \pm RD] \times \cos|4.5|, \ \mu(4.5) = 0$$

$$SD_{x2} = [1 \pm RD] \times \cos|4.5|, \ \mu(4.5) = 1$$

$$SD_{x3} = [1 \pm RD] \times \cos|-9|, \ \mu(-9) = 1$$

$$SD_{x4} = [1 \pm RD] \times \cos|-22.5|, \ \mu(-22.5) = 0$$

By using (8) we can find the shortest distance between the blimp and the object. The comparative results for model and non- model cases are shown in Fig.14. It is clear that in the model case the proposed model could reduce the errors in sensors readings with more accuracy than in the non-model case. As a result, the shortest distance between the blimp and any objects is more precisely.

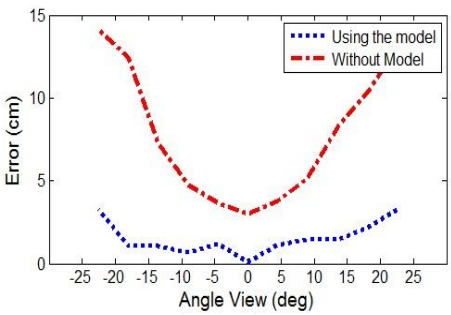

Figure 14. The comparative results for errors

B. The Combined Controllers

The most important behavior of a robot is the avoidance of obstacles. The goal of this controller was to keep the blimp at a safe distance from frontal obstacles. The collision avoidance system should cause the blimp to change the direction of main propellers motors when the front ultrasonic sensors detect an obstacle in a certain distance. For the sake of avoid obstacles, the first combined controller in the second layer used the shortest distance as an input to control the avoid obstacles behaviors. It has two inputs: first, the error which describes the difference between the required avoidance distance and the shortest distance (out1) and it has 5 linguistic variables (NH: negative high, NL: negative low, Z: zero, PL: positive low, PH: positive high). The second input is the horizontal velocity (out2 with 5 linguistic variables) and it has one output which is the vectorization angle. Fig.15 shows the behavior of this controller and the fuzzy rules for avoid obstacles behavior are summarized in Table IV.

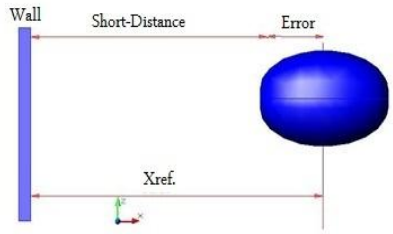

Figure 15. Behavior of the fuzzy collision avoidance controller

TABLE IV. FUZZY RULES FOR THE COLLISION AVOIDANCE CONTROLLER

Velocity	Distance Error				
	NH	NL	Z	PL	PH
NH	PH	PL	PH	PH	PH
NL	PH	PL	P	PH	PH
Z	PL	Z	Z	PL	PH
PL	PL	Z	NL	Z	PL
PH	Z	Z	NH	N	Z

Fig.16 shows the behavior of the blimp with constant horizontal velocity and 18 cm safety distance away from the obstacles. When it reaches to close obstacles, the velocity of horizontal speed reduced by avoid obstacles controller. It is clear that implemented the proposed model helps to reduce the sensors drawbacks and then it improves the avoid obstacles behavior of the blimp.

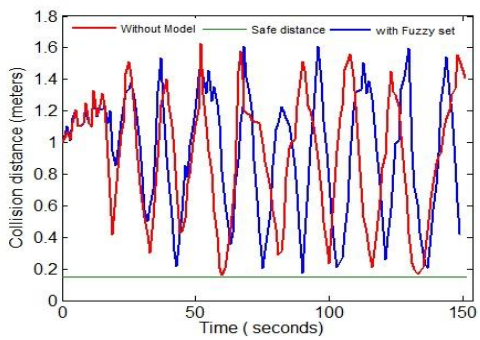

Figure 16. Behavior of fuzzy collision avoidance controller

The second combined controller is the altitude controller which has two inputs: altitude error (out5) and current vertical velocity (out3). Altitude error was the difference between the desired altitude and current shortest altitude. The change in altitude error indicates whether the blimp is approaching the reference altitude or moving away from altitude. The controller output is the voltage of main propellers. Fig. 17 shows the behavior of the fuzzy altitude controller.

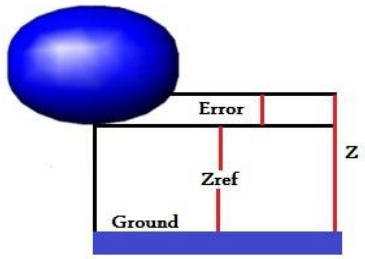

Figure 17. Behavior of the fuzzy altitude controller

After simulation studies the empirical input and output linguistic values with membership functions are defined. Fuzzy rules describe the controller behavior in terms of relationships between input and control variables are shown in Table V. A rule is usually of the type: if x_1 is A_1 and x_2 is A_2 then y is B, Where x_i and y are, respectively, input and control linguistic variables, and A_i and B are linguistic terms. The altitude controller can be described with a small set of rules, for example: If altitude error is low positive and vertical velocity is very negative then voltage of main propellers is Zero. These rules attempt to maintain the blimp at specific height. We should note that few rules have zero value to avoid continuous motor action.

TABLE V. FUZZY RULES FOR ALTITUDE CONTROLLER

Velocity	Distance Error				
	NH	NL	Z	PL	PH
NH	PH	PH	Z	Z	Z
NL	PH	PL	Z	Z	NL
Z	PH	Z	Z	Z	NH
PL	PL	Z	Z	NL	NH
PH	Z	Z	Z	NH	NH

Some experiments were carried out to check the altitude controller while the blimp starts flying from the ground to reference altitude and they led to good results with different circumstances. Fig.18 shows the comparison between the fuzzy altitude control behaviors with reducing drawbacks and without implemented the proposed model. It shows some slight oscillations and deviations in both cases but the proposed model performed slightly better than non-model approach.

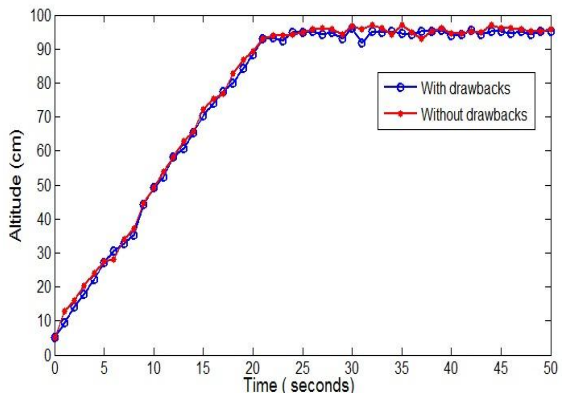

Figure 18. Behavior of fuzzy altitude controller.

IV. SUMMARIES

In this paper we have designed two layers fuzzy control to control the main behaviors of the blimp. First, we study the ultrasonic sensors characteristics and analyze them to reduce the drawbacks in the sensors readings. Then, the first fuzzy reasoning in the sub-controllers is modeled based on the possibilities distribution and fuzzy sets. This sub-controller provides us with the membership functions for the uncertainties. By combining the radial error information with the view angle information we compute the shortest distance between the blimp and the objects. This shortest distance is more precisely than the sonar reading and it can improve the main behaviors of the blimp. Then, the outputs of the sub-controllers are used in the combined controllers to generate blimp main behaviors. The experimental results showed a good performance of the blimp's main behaviors after implemented the proposed model.

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