Development of a fuzzy logic-based method for estimating the flight path of an unmanned aerial vehicle (UAV) required for the unmanned traffic management (UTM) system

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The purpose of this article is to provide a solution for estimating the trajectory for UAVs, using the intelligent control with fuzzy logic. Fuzzy logic, which is based on the theory of fuzzy sets, allows the linguistic description of the laws of command, operation and control of a system that can be managed by the soft computing. Working with complex and nonlinear systems it can often be seen that as their complexity increases there is a decrease in the significance of the details in describing the overall behavior of the systems. One of the consistent arguments for approaching through vague sets and logic methods the description of the laws of command and operation of systems is that of the ease of use of linguistic expressions, of the use of words. In this article, we propose a Unmanned Traffic Management System (UTM) architecture for an unmanned traffic management system for detecting the trajectory of unmanned aerial vehicles (UAVs) based on fuzzy logic. The performance of the fuzzy system, evaluated in terms of prediction error and the number of targets (drones) lost by radars, and the comparison with that of a system using a Kalman filter demonstrate the effectiveness of the fuzzy system. The generalization of the use of the fuzzy system for any type of target depends on the development of automated approaches for determining the most appropriate rules and membership functions.

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1. Introduction

In recent years, the use of drones / unmanned aircraft system (UAS) has increased significantly in all directions - commercial and personal applications, with millions of aircraft registered in Europe and the United States alone. Predictions show a steady increase, with FAA (Federal Aviation Administration) estimates suggesting that the number of unmanned aircraft registered could double by 2025 [1]. This rapid increase in the traffic of unmanned aircraft used more and more frequently in the commercial area, brings new challenges. As airspace capacity is limited [2] and the increase in the use of unmanaged air traffic can lead to insecurity and potential critical situations through the use of drones, especially entertainment drones, near Critical Infrastructure areas. For these reasons, it has become necessary to develop unmanned aerial traffic management system (UTM) architectures in order to ensure the maximization of the use of airspace, but also the safety of Critical Infrastructures [3].

The principles that currently apply to radio-electronic (radar) research can also be applied to UTM. Actions of detection, interception, analysis of communications and electromagnetic radiation and especially the ability to determine the trajectories of drones evolving at high speeds in an uncontrolled environment, measurements can often be severely disturbed and unable to provide relevant data to UTM systems [4-8]. For these reasons, in recent years, various systems for drone detection have been developed, but these methods still have limitations, which makes identifying compromise solutions relevant.

The use of classical methods, based on Boolean logic, which are not able to operate with imprecise notions, can provide erroneous data, which can jeopardize the success of detection actions. Therefore, it is necessary to use methods that allow great flexibility in describing input variables, that exceed the limitations imposed by Boolean logic and that allow logical reasoning with multivalent logic variables capable of taking any value in the range [0,1].

Fuzzy logic, which is based on the theory of fuzzy sets, allows the linguistic description of the laws of command, operation and control of a system. In working with complex and nonlinear systems it can often be observed that with the increase of their complexity a diminution of the significance of the details in the description of the global behavior of the systems is observed. A detailed description of the behavior of a system is often not only unnecessary, but even counterproductive [9-11]. One of the consistent arguments for approaching by the methods of sets and vague logics the description of the laws of command and operation of systems is that of the ease of use of linguistic expressions, of the use of words.

Although such an approach may seem inappropriate, it often proves to be superior and much less laborious than a rigorous mathematical approach [12,13]. The main argument in favor of fuzzy set theory, which is a generalization of classical set theory, is to excel at operating with vague, imprecise concepts that arise from the lack of a clear transition from belonging to a certain class to not belonging. In classical set theory, a clear distinction is made between the notion of belonging and the notion of non-belonging of an object to a given set. Thus, there is no partial membership in a set and no means of expressing such a situation. For example, a tree may belong to a set called the "biosphere," while a rock may not belong to that set. We will continue to call such sets crisp sets. The theory of vague sets highlights the fact that there are extremely few rigid sets. For example, defining a rigid set called the "biosphere" may have difficulty including the notion of "coral," which is often considered a lifeless limestone. Fuzzy logic admits the partial belonging of an object to a set; thus, the gradual transition between total membership in a given set and total non-membership in the same set is allowed. Partial membership in a certain set simultaneously implies partial non-membership in that set.

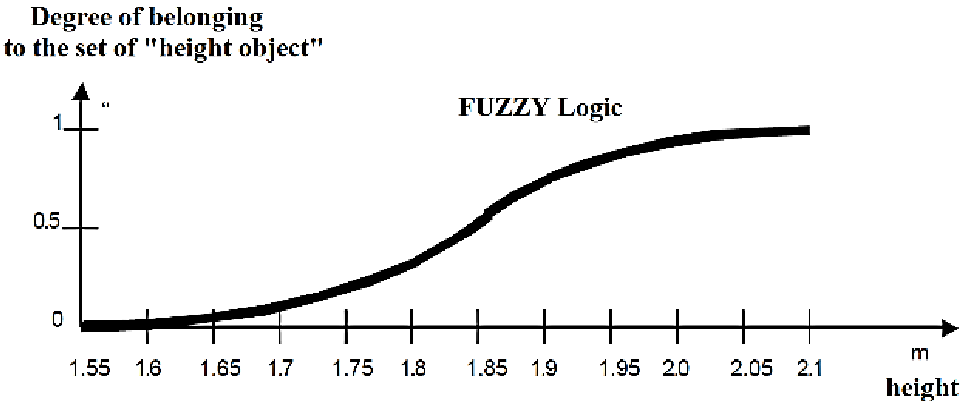


Fig. 1. Representation Fuzzy logic that allows partial membership in the defined set, being characterized by the gradual transition from "low" to "high"

The generalization characteristic of the classical set theory is given by the fact that the fuzzy set theory allows both total membership and total non-membership (of course, not simultaneously). It is obvious that we can use fuzzy logic to implement rigid systems (determined by rigid sets), but the benefit of such an approach would be negligible. The force of fuzzy systems is manifested in transition situations, in the areas of partial belonging of an element to a certain set. Traditional logic recognizes only complete membership and complete non-membership and requires that an assertion be either true or false. Fuzzy logic allows the existence of partial truth or falsehood. Fig. 1 illustrates the difference. Given the premise that the transition from false to true must be gradual and that an assertion can be both partially true and partially false, a different way of approaching command and control issues must be constructed. We agree, in principle, that the world around us cannot be perceived only in "white" and "black." In fact, in most cases, the surrounding world presents itself in a multitude of shades of "gray", which, however, in practice, we assimilate with two values: "white" and "black". Fuzzy logic not only accepts shades of "gray", but also provides us with powerful tools to operate with these shades in a proper way.

2. Experimental

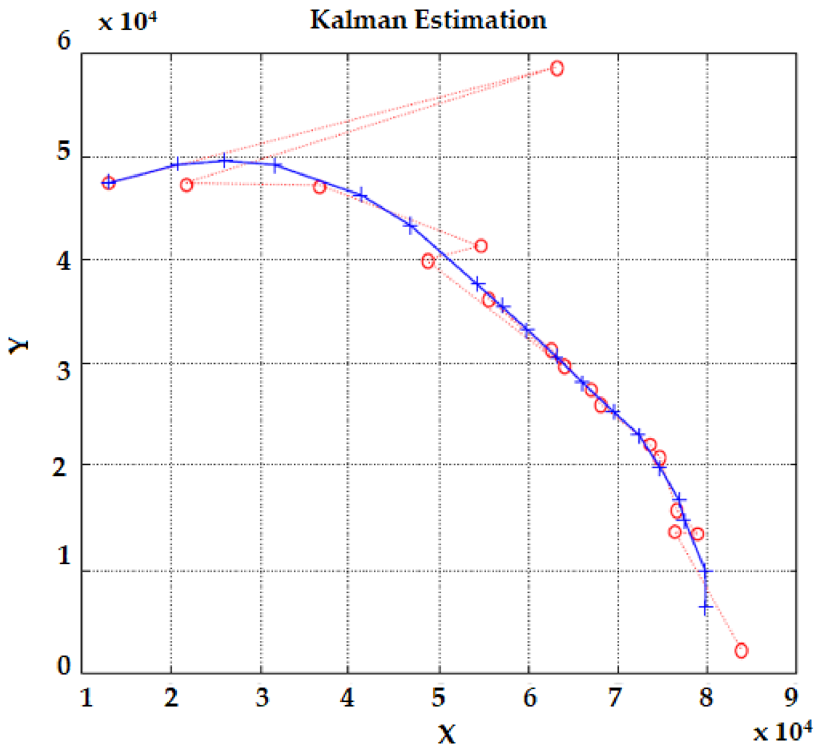
To evaluate the performance of a fuzzy tracking system, real data sets acquired within the SICOTIP project were used. Drones developed within the project were used as targets, and the data were recorded by a LIDAR (Light Detection and Ranging) radar for traffic control. The performance of the fuzzy tracking system was compared with a high-performance Kalman estimator, which takes into account cases where the target maneuvers and accelerates rapidly.

Using real data sets, the performances of the proposed fuzzy tracking system and the Kalman filter tracking system were evaluated in terms of the number of tracking losses (a general indicator of the reliability and robustness of tracking systems) and the mean prediction error (an indicator of the system's ability to closely track targets). It was also investigated how the recovery time after incorrect actions and the initial data affect the performance of the tracking systems. The simulation is based on a program developed in MATLAB 2022, which performs both the simulation of the behavior of a Kalman estimator and the simulation of the behavior of an α - β estimator with variable coefficients established by fuzzy means.

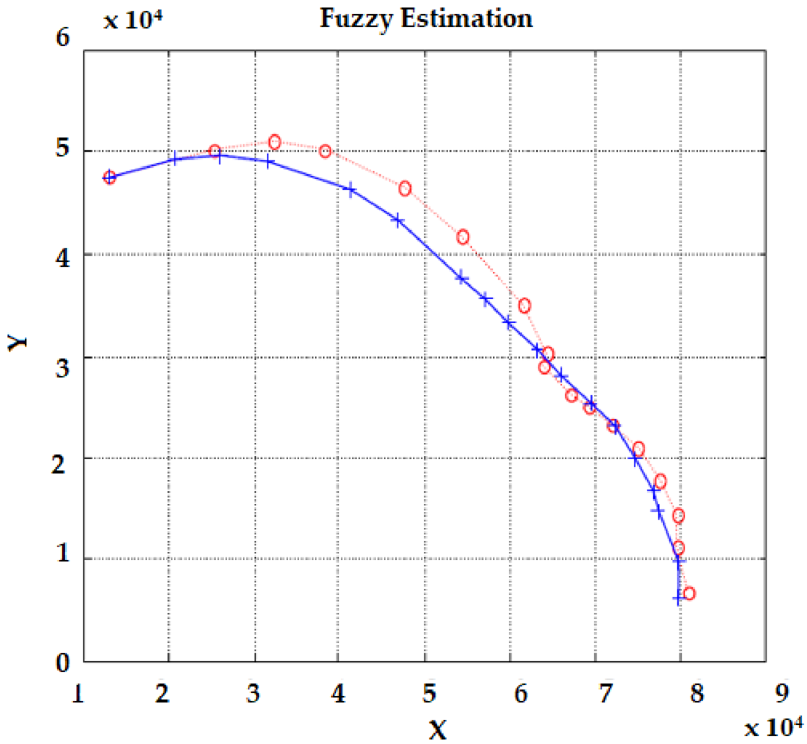
The prediction accuracy depends on how much precisely the previous and current positions of the object were measured. Unfortunately, due to parasitic echoes generated on the radio locator screen, the limitations of algorithms related to processing the signals coming from different sensors, the position of the targets can be determined only with approximation. The values measured can enhance multiple variable features and may be constrained by different initial conditions depending on the flight angle and on the position of the target towards the radar.

Research presented in article [14] on the use of fuzzy logic to track the trajectory of a target has had a major impact on research and academia. The stability of the fuzzy controller plays an important role and has been thoroughly investigated. In [15] we presented the mathematical algorithms for tracking the trajectory using fuzzy logic, below we will present only the results obtained by demonstrating the superiority of fuzzy logic over the Kalman filter. In the first situation (Fig. 2), a target accelerates rapidly and executes rapid turns. As it can be observed, the Kalman filter performs several erroneous actions in series, which increases the displacement between the current position and the predicted one by accumulating the errors from one scan to another. This low rate of response to unexpected changes in the dynamic of flight is due to the time required by the Extend Kalman estimator's response (usually during a few scans). For the target executing a 360° turn over six scans, a delay of two scans may represent a 120° angular deviation. Thus, the tendency of the Kalman system to overestimate the next position of the target is not surprising, thus resulting in loss of the target.

Fig. 3 show the performances of the two systems in another situation. A target is being tracked on an approximate linear trajectory with constant speed. There are no significant losses of the target. It can be noticed that the predictions of the Kalman system are placed on a curve in a zig-zag pattern. The system is thus dependent of noise, even if the noise level is minimum. This result demonstrates the possibility of using fuzzy logic in tracking targets in difficult conditions characterized not only by high noise levels, but also by non-uniform accelerations of the targets, sudden turns, and the lack of target observation during several successive scans during maneuvers. The results demonstrate that the fuzzy system has a high degree of error tolerance and a better recovery rate. Also, as is the case with rule-based approaches, the generalization of the use of the fuzzy system for any type of target depends on the development of automated approaches for determining the most appropriate rules and membership functions.

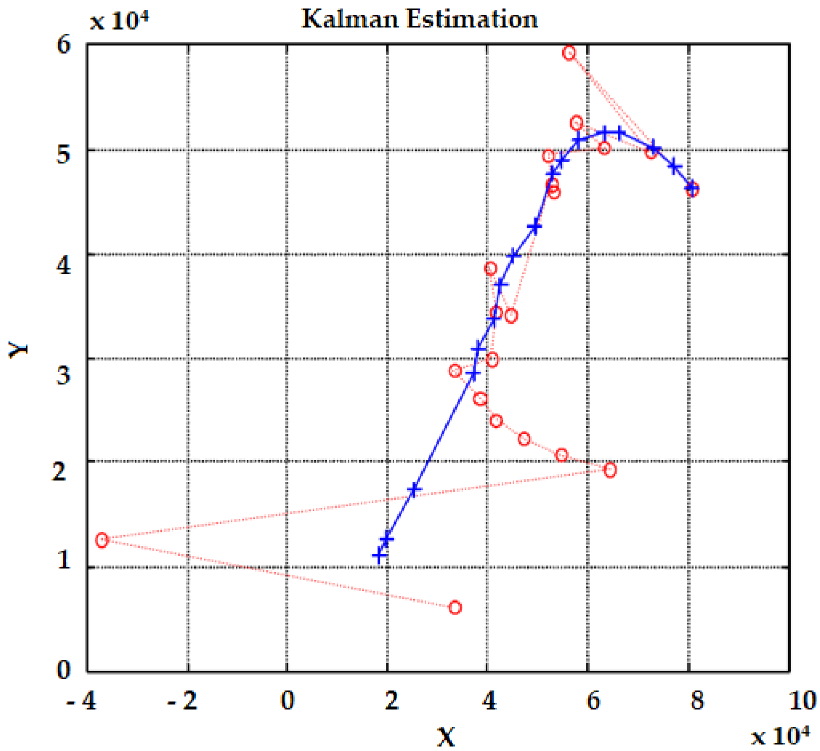


(a)

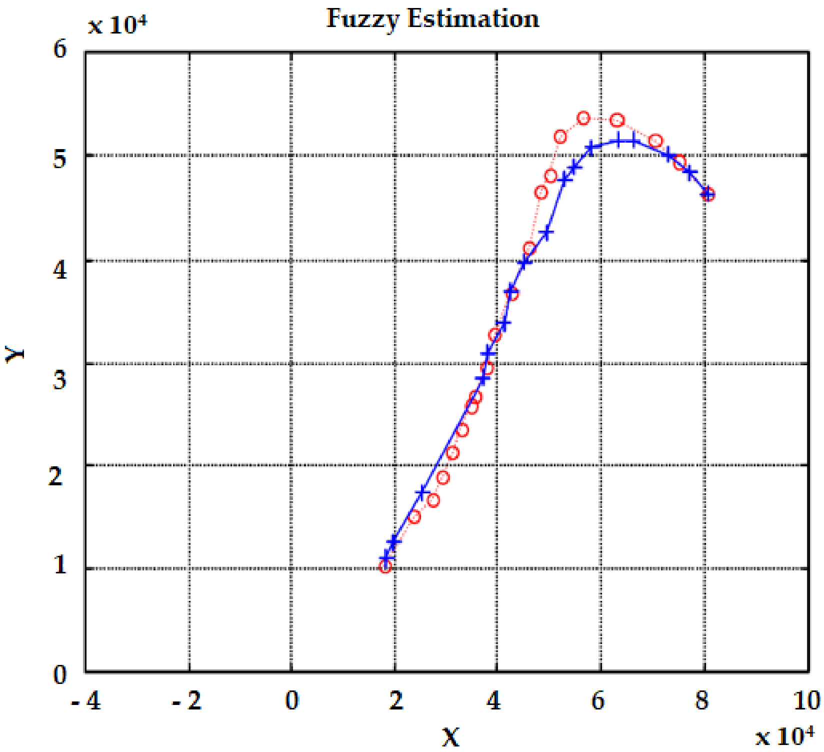


(b)

Fig. 2. Kalman filter estimation (red – real target position, blue – estimated target position) image (a) and Fuzzy filter estimation (red – real target position, blue – estimated target position) image (b) [15] (colour online)



(a)



(b)

Fig. 3. Kalman filter estimation (red – real target position, blue – estimated target position) image (a) and Fuzzy filter estimation (red – real target position, blue – estimated target position) image (b). [15] (colour online)

3. Results and discussions

To achieve the concepts described above, it is necessary to have access to means that allow the integration of intelligence at lower levels. Due to its ability to represent gradual information in a way familiar to human thinking, fuzzy logic is a powerful tool for the integration of intelligence. In particular, the way in which linguistic terms are linked to numerical quantities allows the implementation of high-level functions, such as data fusion and complex decision processes. Most implementations of distributed fuzzy systems are based on interacting distributed components that have a fuzzy rule base and communicate with other components through numerical values. The most classic solution for coding a fuzzy system is to use a high-level language. Another solution is to use dedicated hardware such as fuzzy processors.

3.1. Software implementation of FACCT fuzzy algorithms

Now we understand by the FACCT (Fuzzy Applied Cell Control Technology) language a general method of solving a certain type of problem, which can be implemented on the computer. In this context an algorithm is the absolute essence of a routine. The programming language that underlies the fuzzy machine includes, in addition to the logical part, an algebraic part. It is therefore a mixed type algorithm, organized as a finite sequence of steps, comprising several specific operations. These can be implemented in software. The form that the algorithm takes in a computer implementation is subordinated to the programming style and depends especially on the type of language. The software implementation of the fuzzy automaton can also be done based on a parallel algorithm. Parallel computing gives a new dimension to the construction of FACCT algorithms and programs. It is emphasized that parallel programming is not a simple extension of serial programming and that not all sequential algorithms can be parallelized.

In the case of FACCT software implementations, the synthesis of fuzzy automata (controllers) is sufficiently flexible, being practically a problem of emulating the typical phases of the algorithm, for the model of the given problem. The ability to program a problem is very important in this case. However, some considerations are needed, which must be taken into account when structuring a fuzzy control system, regardless of the form in which it will be implemented. The configuration of a fuzzy controller, intended to lead a process, considers the conventional decomposition of its dynamics, corresponding to the evolution strategies adopted in the modeling stage.

From the command point of view, the fuzzy controller will be structured on control channels depending on the type of dynamic controlled system: single-input / single-output (SISO), multiple-input / multiple-output (MIMO). The problem of control channel independence is analyzed in the context of the existence of the informational coupling. The interdependence of the channels is imposed by the methodology of leading the control process, taking it into account when describing the heuristic basis of the problem and in the stage of compiling the rule base.

This is important, especially in software implementation, because the way information is processed depends on the sequential operating principle and the limited possibilities to parallelize the calculations.

The possibilities of direct hardware implementation of fuzzy systems are currently a reality due to the appearance of circuits logic fuzzy (CLF), machines elementary inferences fuzzy (MEIF) for performing and circuits for generating characteristic functions with controlled membership. These microelectronic systems are found in the structure of dedicated or general-purpose fuzzy processors.

To implement the mathematical models developed for UTM applications that we present in the next subchapter, it is necessary to design each component of the structure of a fuzzy system: fuser, inference motor and defuzzification. The solution proposed for the implementation of the decision-making system is based on the classic structure of a fuzzy system with some specific modifications. The capacity of each memory block depends directly on the value range of the parameter it defines. The main advantage of the fuzzifier implemented with this method is the possibility to render some rather complex nonlinear membership functions. Another advantage is the use of memory blocks with the help of which membership functions can be defined which can be subsequently changed dynamically. The main disadvantage of the given approach is the use of a large memory capacity to define all the membership functions of the fuzzy variable qualifiers. The memory capacity used can be reduced by decreasing the value ranges. To define the membership functions and to register them in the RAM / ROM memory blocks, it was necessary to perform the procedure for adjusting them. The given procedure consists in translating the range of values to the right or to the left of the x-axis. This procedure must be performed so that the value of the input variable represents the address of the memory cell where the value of the membership function of the respective qualifier is located. Thus, the memory cells will contain the probability values for the membership functions already shifted on the x-axis and not the real values of the input parameters. In order to implement the inference engine model with reconfigurable architecture, several of the classic solutions were analyzed and then the most suitable ones were used to solve the problem in question. The concept of the generic inference engine is required to be defined in the case of solving specific problems of automatic decision-making, algorithms that can change over time. Usually, these systems are characterized by the ability to self-organize the decision-making process, which makes it difficult to design such a system and implement such a decision-making algorithm. The architectures proposed for solving these problems can be used both for the implementation of generalized decision-making algorithms and for ensuring the possibility of dynamic reconfiguration. This methodology is used to describe nonlinear or probabilistic decision-making processes. The use of configurable inference rules in the inference engine structure offers the possibility to change them over time. The use of configurable architectures in the inference engine structure, unlike specialized Fuzzy processors, excludes the redesign of integrated circuits by using FPGA (Field Programmable Gate Array) circuits that have a large number of input / output ports and only require reconfiguration of the circuit. Even the design stage of a new fuzzy kernel can be significantly simplified by using libraries of fuzzy logical elements. The generic inference engine can serve for the development of decision-making algorithms initially implemented in the conditions of insufficient data. Therefore, the use of reconfigurable inference engines offers the possibility to implement different decision-making algorithms in fuzzy systems.

Fig. 4 below shows a simple example of proportional fuzzy control.

```
declarations;
crisp x, u;
subset f,g;
varlin Error, Control;
term Z, P, N: Error;

initialisation ;
partition(Error,"Z", -1, 1, -1, 0, 0, 1);
partition(Error, "P", -1, 1, 0, 1, 1,);
partition(Error, "N", -1, 1, , -1, -1, 0);
Control=Error;
f as Error;
g as Action;
main ;

x=input(0);
f=fuzz(x);
g=0;
if f is "N" then g is "N";
if f is "Z" then g is "Z" (0.75);
if f is "P" then g is "P"
u = defuzz(g);
output(u);
```

Fig. 4. A simple example of a FACCT program.

3.2. Application of distributed fuzzy control in case of adjustment the distance between two targets

The purpose of the proposed application is to determine the control of the position of an object relative to another object. Only one fuzzy controller will be used for this application. The application uses an infrared sensor installed on the target object that provides the position to the target object. For implementation we use three cells, thus, the fuzzy sensor (cell 1), the fuzzy inference component (cell 2) and the fuzzy actuator (cell 3). The fuzzy addresses were initially established, respectively, 20 for the fuzzy sensor, 40 for the fuzzy inference, 30 for the fuzzy actuator and 60 for the supervisor (Fig. 5).

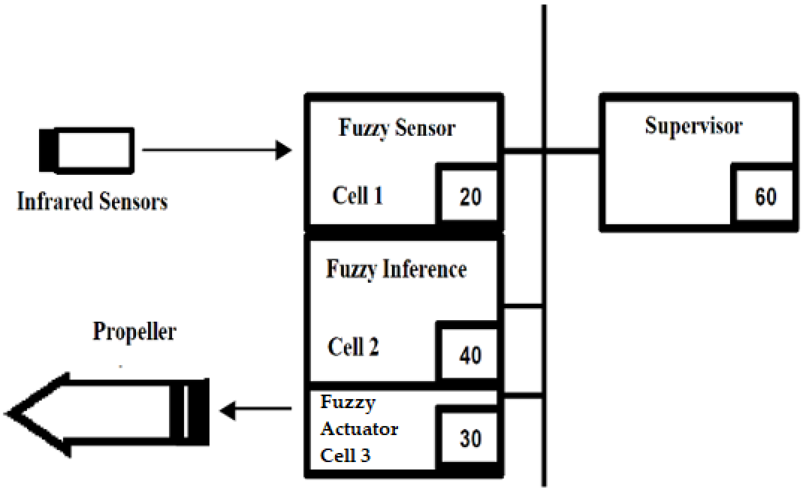


Fig. 5. Distributed fuzzy control architecture for adjusting the distance between 2 objects.

The configuration of the cells is performed by the FACCT text files transmitted by the supervisor (see Fig. 6). In cell 1, the fuzzy partition associated with the error (variable x) and the error variation (variable y) are represented by the variables *Error* and *Error_var*. The fuzzy signification associated with linguistic terms are defined by partition statements, and the set of linguistic terms is L (X) = L (Y) = {N, Z, P}. The significant terms are, negative, zero and positive. The role of cell 1 is to fuse error and error variation and transmit the results to cell 2 through the send subroutine. Telemetry reading is performed from analog input 1.

Cell 2 makes a g4 inference based on the symbolic relationships between the linguistic variables *Error, Error_var*, and *Control*. Due to the symbolic aspect of the inference, cell 2 requires only the naming of linguistic terms for each partition, this operation is performed by an instruction called *term*. The terms associated with the *Error* and *Error_var* partitions must be like the terms used by cell 1. We define the new term for the partition associated with the control action. These terms are used in the concluding part of the rules. The set of linguistic terms is *L(U) = {NB, NS, ZZ, PS, PB},* in which the terms mean big negative, small negative, zero, small positive and big positive.

Cell 3 is used for TFR (Totally Fuzzy Approach). The fuzzy signification for syntactic terms these are defined by the partition for syntax. The applied subset TFR is received in variable *f* due to the procedure *recv*. For cell 3, this subset is applied TFR and is associated with the value of 18 V.

Finally, the result obtained by the distributed fuzzy system is applied to the propulsion means which increases the speed of the first object compared to the second.

To describe the behavior of the system, the result of the feedback control is provided when the tracking object is below the minimum allowed distance and is approaching the tracked object. We assume that the error has the value x = 18 and the variation of the error is y = 3.

The fuzzy significance transmitted by cell 1 is represented in Fig. 6. According to the previous statements, the symbolic fusions of x = 18 and y = 3 are:

$$\varphi_2(x) = \left\{\frac{0}{N}, \frac{0.25}{Z}, \frac{0.75}{P}\right\} \tag{1}$$

and

$$\varphi_2(y) = \left\{\frac{0}{N}, \frac{0.85}{Z}, \frac{0.15}{P}\right\} \tag{2}$$

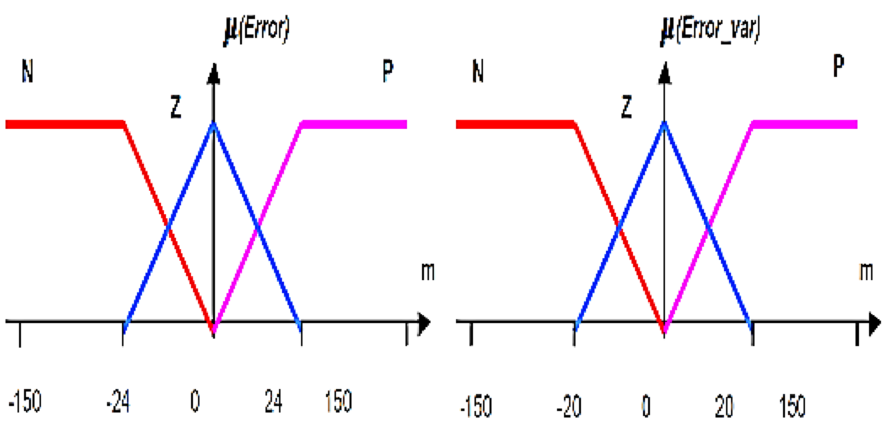


Fig. 6. The meanings of fuzzy (colour online)

Thus, the fuzzy sensor that has the address 20 for I2C (Inter-Integrated Circuit), sends two sets of information to the fuzzy inference component that has the address 40 for I2C. These sets are associated with the numbers zero and one. The message transmitted by the fuzzy sensor is shown in Fig. 7, where the bytes are represented in hexadecimal. The representation of the degrees of belonging is made in the range 0 - 255. For example, the membership degree of 0.75 is represented in hexadecimal with the value BF.

After receiving the results, cell 2 (fuzzy component of inference) realizes inference. With the fuzzy descriptions generated by cell 1, four rules are activated. The inference result is *{0 / NB, 0 / NS, 0.25 / Z, 0.75 / PS, 0.15 / PB}*. Thus, the inference fuzzy component that has address 40 for I2C transmits the fuzzy subset associated with the zero key to the fuzzy actuator that has address 30 for I2C. The transmitted message is represented in Fig. 8.

Finally, the fuzzy actuator represented by cell 3 calculates the control action that was to be applied to the propulsion mechanism. According to the definitions of fuzzy meanings in cell 3 the defuzzification result is 2 V (Fig. 9). Because there is an offset of 18 V, the control action has the value of 20 V, and the speed of the pursued object will have to increase to increase the distance between the 2 objects.

This example demonstrates the operation of a fuzzy distributed network for this control application.

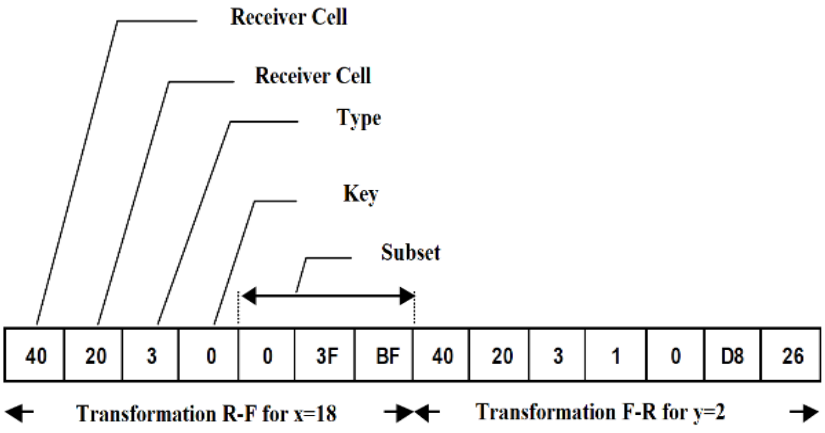


Fig. 7. The format of the message transmitted by cell 1 fuzzy sensor

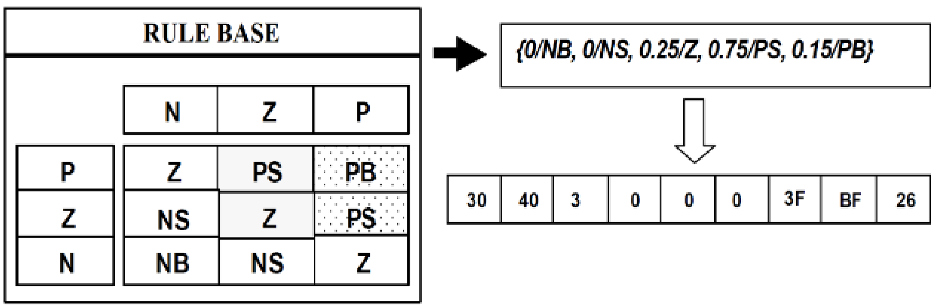


Fig. 8. The format of the message transmitted by cell 2 fuzzy sensor

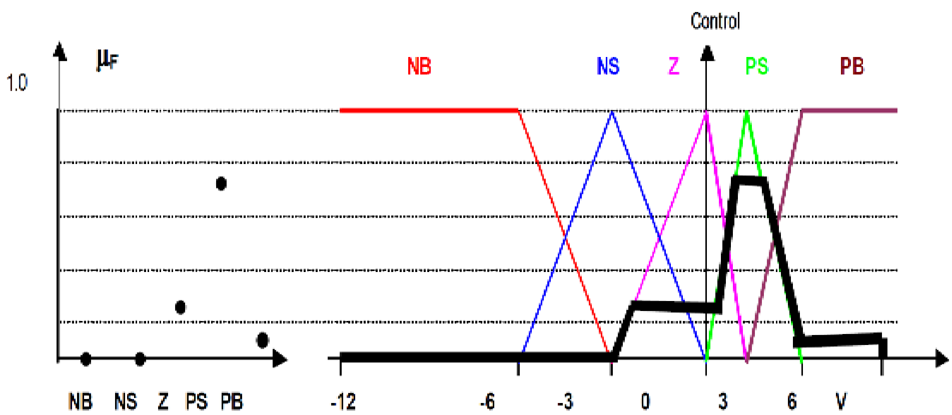


Fig. 9. The result of defuzzification (colour online)

After explaining the concept of intelligent distributed control, this chapter described the concept of fuzzy components and their definition from a hardware and software point of view. The simple way of implementing systems based on fuzzy cells was described. The configuration of the cells in the network is done by a specific language, called FACCT. FACCT files can be compiled by the fuzzy cells using a resident compiler. The cells are implemented on the structure of an INTEL D2000 microcontroller. The advantages of using a fuzzy component network do not only consist of those offered by distributed systems. It is found that fuzzy cells are easy to configure, but at the same time they provide high-level functions, such as fusion and decision processes. The network also allows the addition of components in order to increase the system performance.

4. Conclusions

The theoretical and experimental research carried out within this project (SICOTIP) led to the following conclusions:

✓ The performance of the fuzzy system, evaluated in terms of the prediction error and the number of missed targets, and compared to that of a system using a Kalman filter, demonstrates the effectiveness of the fuzzy system, which has a high degree of error tolerance and a better return rate. As is the case with rule-based approaches, the generalization of the use of the fuzzy system for any type of target depends on the development of automated approaches for determining the most appropriate rules and membership functions.

✓ From the point of view of the concept of distributed intelligent control, three types of components can be defined: Fuzzy sensors, which provide a representation of measurements as fuzzy subsets, Fuzzy actuators, which can act in a real world, depending on the fuzzy subsets they receive, and Fuzzy inference components, which can perform fuzzy reasoning. They produce new fuzzy subsets from the fuzzy subsets they received. Fuzzy components can be considered as different applications of a general component model, called a fuzzy cell. Fuzzy cells can be developed around a microcontroller that has ROM and RAM memory. Local communications can be provided by a serial interface. The configuration of the cells in the network is done by a specific language, called FACCT. FACCT files can be compiled by fuzzy cells using a resident compiler. The advantages of using a network of fuzzy components do not only consist of those offered by distributed systems. Fuzzy cells are easy to configure, but at the same time provide high-level functions, such as fusion and decision processes. The network also allows the addition of components in order to increase the performance of the system.

The main direction of further research is: the development of a compiler for the FACCT language that will allow the implementation of various distributed fuzzy control configurations using digital or analog fuzzy processors. In this way, the FACCT language will be able to be used in the development of fuzzy components with distributed intelligence on the structure of configurations with microprocessors or analog circuits.

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