An Adaptive Neuro-Fuzzy-based Multisensor Data Fusion applied to real-time UAV autonomous navigation

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Abstract. *The world trend in employing UAVs and drones is remarkable. The main reasons are that they may cost fractions of manned aircraft and avoid the exposure of human lives to risks. However, they depend on positioning systems that may be fallible. Therefore, it is necessary to ensure that these systems are as accurate as possible, aiming at safe navigation. In pursuit of this end, conventional Data Fusion techniques can be employed. Nonetheless, its high computational cost may be prohibitive due to the low payload of some UAVs. This paper proposes a Data Fusion application based on Computational Intelligence – Adaptive-Network-Based Fuzzy Inference System (ANFIS) – which is able to improve the accuracy of such position estimation systems.*

1. Introduction

Air and Space Power is an essential instrument to the collection of intelligence information. Such an instrument includes, for example, assessing public calamities, natural or induced, as well as integration and logistics for various sectors of the country, constituting a real deterrent [BRASIL. Ministério da Defesa. Comando da Aeronáutica. Planejamento. 2014]. In this sense, its dominance is desirable for all the Nations of the World, including Brazil [Agência Força Aérea 2017a; Centro de Comunicação Social da Aeronáutica 2018].

Several applications have been possible for the aerospace assets in countries such as Brazil, among which we can mention the monitoring of areas of government interest. Aircraft with onboard remote sensing equipment, such as cameras, sensors and radars, have been responsible for the detailed tracking of intelligence data and help in detecting threats and protecting the territory [Agência Força Aérea 2017b].

However, for many applications, the use of manned aircraft is not feasible or desirable since onboard human lives may be exposed to risk scenarios, which in many cases could be avoided. Furthermore, an alternative to the use of manned aircraft is the use of Unmanned Aerial Vehicles (UAVs) [Cook 2007; Davis et al. 2014], which are more difficult to be detected by conventional sensors and, in addition, some models cost only a fraction of a common aircraft. Also, according to [Cook 2007], the UAVs, which historically were thought of as merely complementary to manned aircraft, have proven to be an excellent power asymmetry tool.

The use of these systems plays an important role in surveillance, reconnaissance, target prediction and even combat missions by operating in a wider range of conditions and scenarios [Cook 2007; Davis et al. 2014; Glade 2000; Liggins et al. 2009]. Under the scope of civilian use of aerospace robotics, applications include rescue and disaster assessment, topographic surveys, mapping of areas of interest, precision agriculture, surveillance and access control, remote sensing for geological and climatic research and various utilities [Al-Kaff et al. 2018; Lacerda et al. 2018, 2017; Liggins et al. 2009]. Two UAVs in operation in Brazil are the RQ-450 and the RQ-900, presented in Figure 1. Such UAVs operate primarily in actions of Aerial Reconnaissance, Area Surveillance, Advanced Air Control and Airborne Communications, in singular, joint or interagency operations [Agência Força Aérea 2017b].

(a) RQ-450. **(b) RQ-900.**

Figure 1. Brazilian Airforce UAVs. Sources: [Agência Força Aérea 2016] e [Agência Força Aérea 2014].

Though, it is known that UAVs require a structured navigation control protocol, such as via Radio Frequency or via satellite, which makes it vulnerable to interference such as jamming or spoofing [Davis et al. 2014]. One solution to this is the use of autonomous navigation, but even the use of Global Navigation Satellite Systems (GNSS) or an Inertial Navigation System (INS) - systems widely covered in the literature - are not immune to faults or interference [Da Silva 2016]. In this sense, the use of Data Fusion to enable a more secure and robust navigation has proven to be a good alternative to exclusive reliance on the usual navigation systems, since it is essential to ensure the operational reliability, accuracy and robustness of their navigation, for ignoring the attitude and trajectory of an aircraft can put it on a collision course [Al-Kaff et al. 2018].

Given this need, the technology of Data Fusion is an alternative in the search for increased navigational safety, and is still one of the most critical technologies for a country [Cardoso 2003]. Therefore, given the reality of the current applications of aerospace robotics, the importance of promoting research and development in the area of Data Fusion is unequivocal [Al-Kaff et al. 2018; BRASIL. Ministério da Defesa. Comando da Aeronáutica. Planejamento. 2014; Liggins et al. 2009].

Thus, the main objective of this paper is to evaluate a Data Fusion application, based on Computational Intelligence, to the fusion and integration of data of several embedded sensors of the UAVs. This aims to improve the quality of the estimation of the positioning of UAVs provided to its control loop, which includes Decision-Making, and present solutions in feasible time to the problem of navigation in real-time. It should be noted that the control loop modeling is not in the scope of this paper.

Such Fusion, which can provide more secure and reliable navigation for aerospace systems since it reduces the inaccuracy of current methods of positioning estimation, is held by a Computational Intelligence technique, namely Adaptive-Network-Based Fuzzy Inference System (ANFIS). The used technique aims to increase the accuracy of the positioning estimation of the UAV held by the Global Positioning System (GPS), considering the Root-Mean-Square Error (RMSE) between the position taken as real and the estimated one.

2. Data Fusion

For navigation UAVs, the systems most widely used are the GNSS, the best known being the GPS [Al-Kaff et al. 2018; Da Silva 2016]. Nonetheless, several studies show that these systems may present flaws and inconsistencies, both from natural factors such as the South Atlantic Magnetic Anomaly (SAMA) and human factors such as jamming, spoofing and malicious blockages and interference [Braga et al. 2015; Conte and Doherty 2008; Da Silva 2016; Faria et al. 2016; Silva Filho 2016].

Another widely used system in the literature is the INS. The problems involving its use is that the low cost INS can accumulate drift error that, if not corrected, could result in a wide divergence between the estimated position and the real position of the UAV [Al-Kaff et al. 2018; Da Silva 2016; Silva Filho 2016]. Thus, the use of Data Fusion for the positioning estimation has proven to be a feasible option to the dependence on one or the other system alone [Luo et al. 2013; Oh 2010; Stamatescu et al. 2015].

Along with technological development, the number of available sensors and data has been increasing. In general, it is seen that there is a need to use a large amount of data to obtain more accurate estimates. In this context, Data Fusion techniques can be used to merge into information the data originated from various sensors [Silva Filho 2016].

Data Fusion acts through the detection, association, correlation, estimation and combination of data of different sensors [Cardoso 2003; Castanedo 2013], which may be invaluable for the collection of useful information aiming at the analysis of the various scenarios for Decision-Making. Regarding UAVs, the greater the exposure to an unfamiliar and unstructured scenario, the greater the risk in its operation due to eventual obstacles that may arise in its trajectory [Davis et al. 2014].

Among the several advantages of using Data Fusion from several sensors, instead of a single sensor, can be cited: improved estimates of information about the target, such as position and speed, when several identical sensors are used in combination in an optimized way, acquiring statistical advantages by increasing the number of observations of the same event; improvement of the observation process using relative data between multiple sensors, which opens up new possibilities for combining and extracting information; greater observability, since a sensor can capture data that another cannot, either by divergences in their physical nature, position or refresh rate, for example, reducing errors and complementing information [Castanedo 2013; Liggins et al. 2009].

However, the joint use of several sensors can imply large volumes of data, sometimes noisy, with different characteristics, unconjugated sampling rates or even nature and physical principles that are de-correlated with each other. Therefore, Data Fusion's conventional techniques may not provide solutions in feasible time to the navigation problem, given, in general, its high computational cost [Castanedo 2013], and also considering the need for real-time processing in the case of an ongoing flight.

Hence, a Data Fusion application is proposed in order to make possible its application in real-time flight applied to the navigation problem, given the nature of the used Computational Intelligence algorithm.

3. Adaptive-Network-Based Fuzzy Inference System

In this paper, the Adaptive-Network-Based Fuzzy Inference System (ANFIS) Computational Intelligence technique was used. This technique is an Adaptive Network – a class of feed-forward Neural Networks with supervised learning capability – that emulates the behavior of a Fuzzy Inference System (FIS) [Jang 1993].

In the case of a flight log containing real data captured from embedded sensors, such as the one used in this work, there is a large amount of data available for extracting information, a task that is not trivial. Consequently, techniques that use methods that combine knowledge areas such as machine learning, pattern recognition and information retrieval can be employed towards a better analysis of the data [Nerurkar et al. 2018].

The ANFIS algorithm, developed by Jang in 1993, uses a hybrid learning scheme and can construct an input-output type mapping based on human knowledge, represented by if-then rules and associated pairs of inputs and outputs. In this way, it is able to learn to map highly nonlinear functions [Jang 1993; Kamarian et al. 2014]. Briefly, this algorithm can be seen as a flexible mathematical structure that can address the approximation of a large class of complex nonlinear systems with a desirable level of accuracy [Kamarian et al. 2014], without, however, losing the mathematical rigor [Zadeh 1965].

Concerning the Fuzzy logic, it should be emphasized that there is no standard methodology for transforming human knowledge or experience into a rule base for an FIS and that there is a need to make adjustments to the established membership functions to both improving performance and minimizing systems' errors [Jang 1993]. Hence, finding appropriate rules and applying appropriate adjustment methods are key issues [Zamani Sabzi et al. 2016], and the adequate representation of these rules is crucial.

Given this reality, the form of treatment of if-then rules proposed by Takagi and Sugeno (T-S) is particularly interesting since it employs parameters of mathematical functions in place of the classic linguistic expressions [Zamani Sabzi et al. 2016] and has fuzzy sets involved only in the part of the premises [Jang 1993]. Here is an example of T-S type fuzzy reasoning:

$$Rule\ 1: \boldsymbol{IF}\ x\ is\ A_1\ \boldsymbol{AND}\ y\ is\ B_1, \boldsymbol{THEN}\ f_1 = p_1 x + q_1 y + r_1$$

$$Rule\ 2: \boldsymbol{IF}\ x\ is\ A_2\ \boldsymbol{AND}\ y\ is\ B_2, \boldsymbol{THEN}\ f_2 = p_2 x + q_2 y + r_2$$

being x and y the inputs, A_i and B_i fuzzy sets, f_i the outputs of same Universe of Discourse as the input variables and p_i, q_i and r_i calculated parameters during the learning.

In this approach, the consequent part is described by non-fuzzy equations of fuzzy input variables (antecedents) [Jang 1993], which allows its application in several machine learning algorithms, among which is the ANFIS algorithm.

By using a hybrid scheme of Fuzzy Logic and Adaptive Networks, an ANFIS Network harnesses advantages of these two large areas of Computational Intelligence [Amr and Qin 2017]. While Fuzzy Logic is able to handle uncertainty in inputs and outputs, Adaptive Networks can address the uncertainty of the model and thus, when employed synergistically, can be applied to a wide variety of complex problems [Tsoukalas and Uhrig 1997]. Figure 2 illustrates the complementarity of these two paradigms.

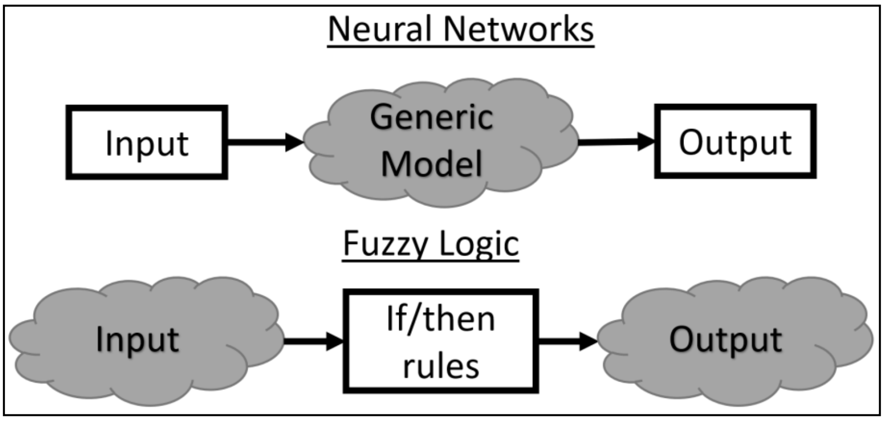


Figure 2. Neural Networks and Fuzzy Logic and how they deal with uncertainty (clouds)

The complementarity depicted in Figure 2 is achieved by means of an Adaptive Network structure, according to Figure 3 [Al-Hmouz et al. 2012; Jang 1993]:

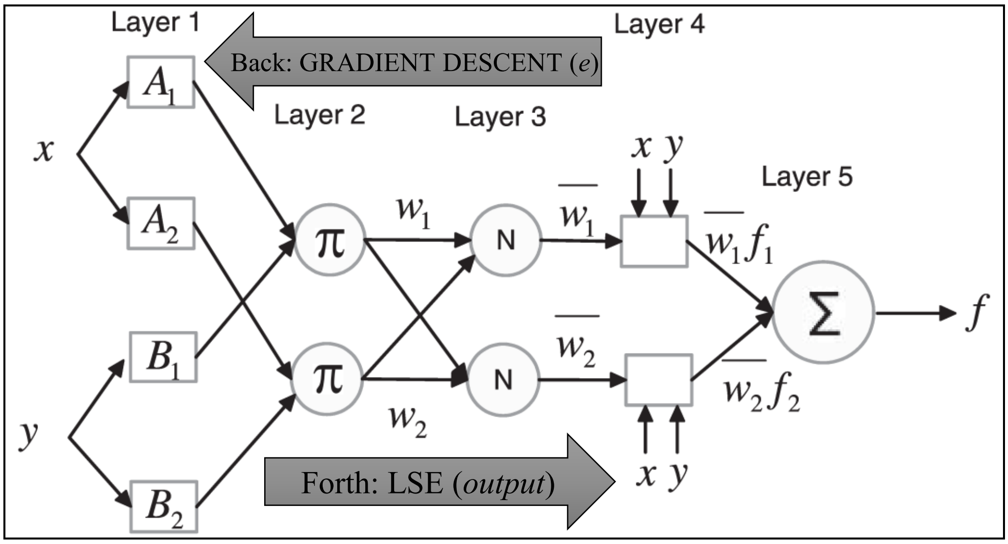


Figure 3. Structural model of an ANFIS Network. The arrows indicate the direction of the hybrid learning scheme. Source: Adapted from [Al-Hmouz et al. 2012]

Each layer of the structure has the following constitution:

Layer 1: Fuzzy sets that determine the degree of membership of inputs x and y: $\mu_{A_i}(x)$ and $\mu_{B_i}(y)$.

Layer 2: T-norm operator, such as the product $w_i = \mu_{A_i}(x) \cdot \mu_{B_i}(y)$, these being the membership functions of each fuzzy variable as a function of the inputs.

Layer 3: Normalization of activations, according to:

$$\overline{w_i} = \frac{w_i}{w_1 + w_2} \quad (1)$$

Layer 4: Defuzzification according to consequent's parameters p_i, q_i and r_i.

Layer 5: Output as a function of the sum of activation of all the rules (composition):

$$f = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad (2)$$

Once the structure of the Adaptive Network was detailed, the steps of the ANFIS algorithm applied to the context of this work are as follows:

1. Load the *training* and *validation* data and determine the input parameters and number of epochs;

2. Generate initial membership functions (antecedents);

3. Perform the training of the ANFIS System by means of a hybrid optimization of the FIS model (Figure 3) until a predetermined stop criterion is reached (maximum error, for example):

    a. Antecedents: Fixed in the forward pass (forth) of the algorithm and optimized in the backward pass (back) by the Gradient Descent method, based on the outputs of the model; and

    b. Consequents: Optimized on the forward pass (forth) by the Least Square Optimization (LSE), based on error rates (e), and fixed at the backward pass (back)

4. Validate training results - trained ANFIS systems - according to *validation* data; and

5. Verify the efficiency of the trained model by measuring the degree of accuracy of the model in predicting the output, given certain inputs, through RMSE.

The use of the ANFIS Networks proposed in this work is performed with real data obtained during flight as explained below. Several configurations were tested for four dimensions, namely: number of inputs (sensors used); number of membership functions for each input; amount of training epochs; and data division for training. The results are discussed below.

4. Execution of the flight and preparation of the data

The flight was performed in an area centered at the coordinates 58° 29′ 41.58″ N and 15° 6′ 9.048″ E. The UAV used is based on the commercial model "Yamaha Rmax UAV", equipped with avionics developed at the Department of Computer & Information Science - Linkoping University [Conte and Doherty 2009].

In Figure 4 the flight path of the UAV is presented, recorded with a Real-Time Kinetic (GPS-RTK) GPS, with sub-meter accuracy, in three dimensions: Latitude, Longitude and Altitude. The scale to the right of the graph reflects the Altitude values, in order to make it easier to understand the graph.

The UAV avionics has captured 139 different types of real-time flight data, including data from embedded sensors such as compass, barometer, GPS, INS, Gyroscope, among others. For this work, the data listed in Table 1 were extracted.

Table 1. Data used in this work.

SENSOR	REFRESH RATE	DATA : NO. OF VARIABLES
Embedded GPS	10 Hz	Clock, Latitude (GPS-Lat) e Longitude (GPS-Lon) : 3
Embedded INS	66 Hz	Acceleration fields - X, Y and Z axis: 3
Embedded Gyroscope (GYRO)	200 Hz	Angular rates relative to Euler angles (Roll, Pitch and Yaw rates) : 3
GPS-RTK	50 Hz	Reference/truth Latitude and Longitude: 2

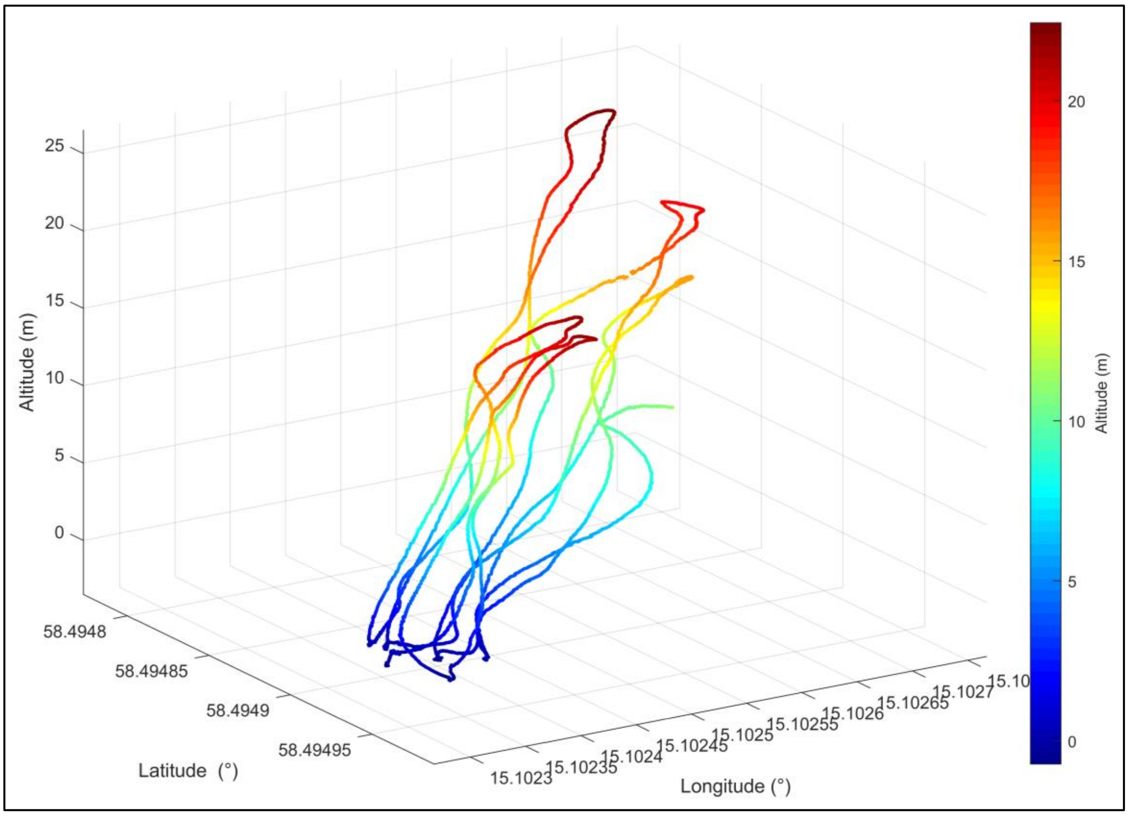


Figure 4. Trajectory of the flight performed by the WITAS Project UAV.

The data, arranged in 66483 lines (temporal samples) by 11 columns (measured variables), were organized as files, and those specified in Table 1 were accessed directly from these files. For all experiments the samples were randomly permutated.

5. Experiments and results

Two experiments were carried out, totaling more than 125 different tests with more than 1,000 evaluations of the objective function, namely the RMSE of the trained ANFIS Networks, in order to evaluate the effectiveness of the methods studied in this work. These experiments enabled a better understanding of the data set and of the ANFIS performance, as well as a satisfactory result regarding the improvement of the position estimation by embedded sensors.

For all experiments, the truth used for both training and evaluating results was the set of data obtained by the GPS-RTK sensor, given its notorious accuracy, either for Latitude or for Longitude. Therefore, in relation to GPS-RTK, it was measured that embedded GPS presents RMSE of approximately 21.10cm in Latitude and 30.81cm in Longitude.

In the experiments, tests were performed by varying the four dimensions mentioned above, in order to gather intuitions about the behavior of the ANFIS Network in each configuration. The fused sensors were also varied.

5.1. First experiment battery

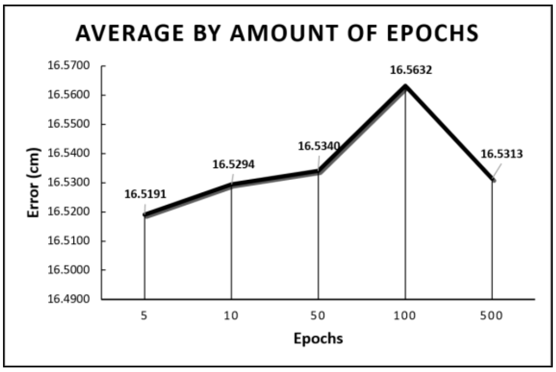
Twenty-five tests were performed by varying the four mentioned dimensions. Each trained FIS system had its performance evaluated based on the estimation for the entire dataset in sequence, to simulate its application in real-time, having as inputs the coordinates (Latitude or Longitude) and the data of the other sensors (INS and / or GYRO). In general, it was observed that the higher the percentage of data used for training, the better the overall performance of the network. The different tested data percentages were 10%, 30%, 50%, 60%, 70% and 80%.

5.2. Second experiment battery and final experiments

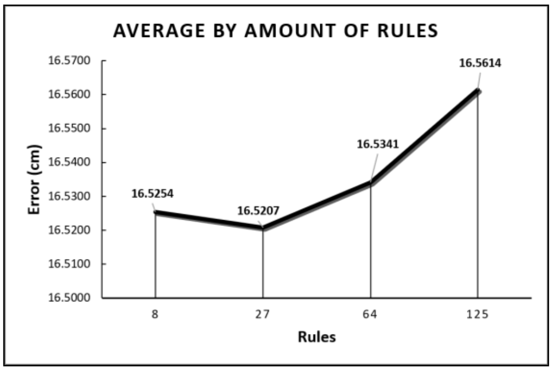
In this battery of 102 tests the fused sensors were GPS-Lat and INS, an association that presented relevant results in the previous battery. Both the number of rules (8, 27, 64, 125 rules) and the number of epochs (5, 10, 50, 100 and 500 epochs) were combined and tested. For each of the 20 combinations of rules and epochs, the generalization capability was evaluated by the average of 10 repetitions of the evaluation of 10,000 points randomly taken from the whole dataset. Unlike the previous battery, here the coordinates are not inputs, so the input variables of the FIS relate only to the other sensors, which are mapped to the difference between GPS-RTK and embedded GPS data.

The aforementioned strategy is interesting in the sense that performing the mapping for a difference enables direct application in regions of flight other than that used for training. This is due to the maximum and minimum values of each input variable being used to establish the FIS Universes of Discourse. Thus, to include the coordinate as input, besides increasing the computational cost, determines that the direct (i.e., no offset) operation of the FIS is restricted to the window of the coordinates used for training.

Confirming the hypothesis about the results obtained previously for this dataset, it was seen that increasing the number of training epochs in many cases proved to be ineffective in the generalization results, in relation to the RMSE mean. Also, increasing the number of rules indistinctly has led to a worsening of the results, except for the leap from 8 to 27 rules. Finally, the best results were achieved with a 5 epoch and 27 rules setting, as seen in Figure 5.



(a) Average by amount of epochs.



(b) Average by amount of rules.

Figure 5. Average error of 10 repetitions of the combinations of the Second Battery.

Consequently, based on the best parameters of the previous results, the last two experiments were performed, one for the Latitude coordinate (GPS-Lat sensor) and the other for the Longitude coordinate (GPS-Lon sensor). It considered the same data from other sensors, although now sorted sequentially for the entire data set, as in the first battery. Thus, the RMSE calculated for the ANFIS Network trained with GPS-Lat, INS and GYRO and GPS-Lon, INS and GYRO configurations were 17.609828cm and 24.894156cm respectively.

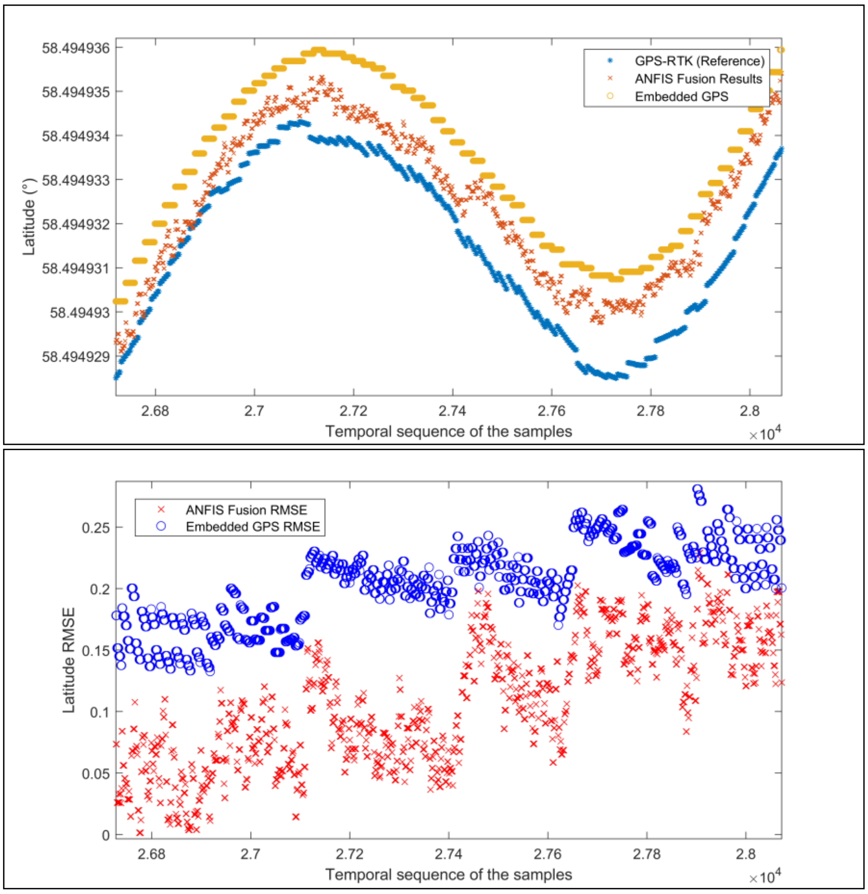
5.3. Final results of the fusion

Based on the estimates of Latitude and Longitude performed by FIS and trained by ANFIS Networks, a comparison can be made with the estimates made by the GPS system, through the evaluation of their respective RMSE, which is shown in Table 2. The trajectories estimated by the trained ANFIS Systems, the real trajectory provided by the GPS-RTK and the trajectory estimated by the embedded GPS are shown in Figs. 6a (Lat.) and 6b (Lon.), as well as the comparison error between ANFIS and GPS for the given coordinate. It is appropriate to mention that the figures include only short excerpts of such trajectories and that at other regions of the plot the GPS was eventually more precise than the trained ANFIS algorithm. The analysis of this fact is suggested as future work. Thus, it was observed that the overall performance of the ANFIS Systems exceeded by 32.57% the accuracy of the estimation performed by the GPS, considering the whole data set.

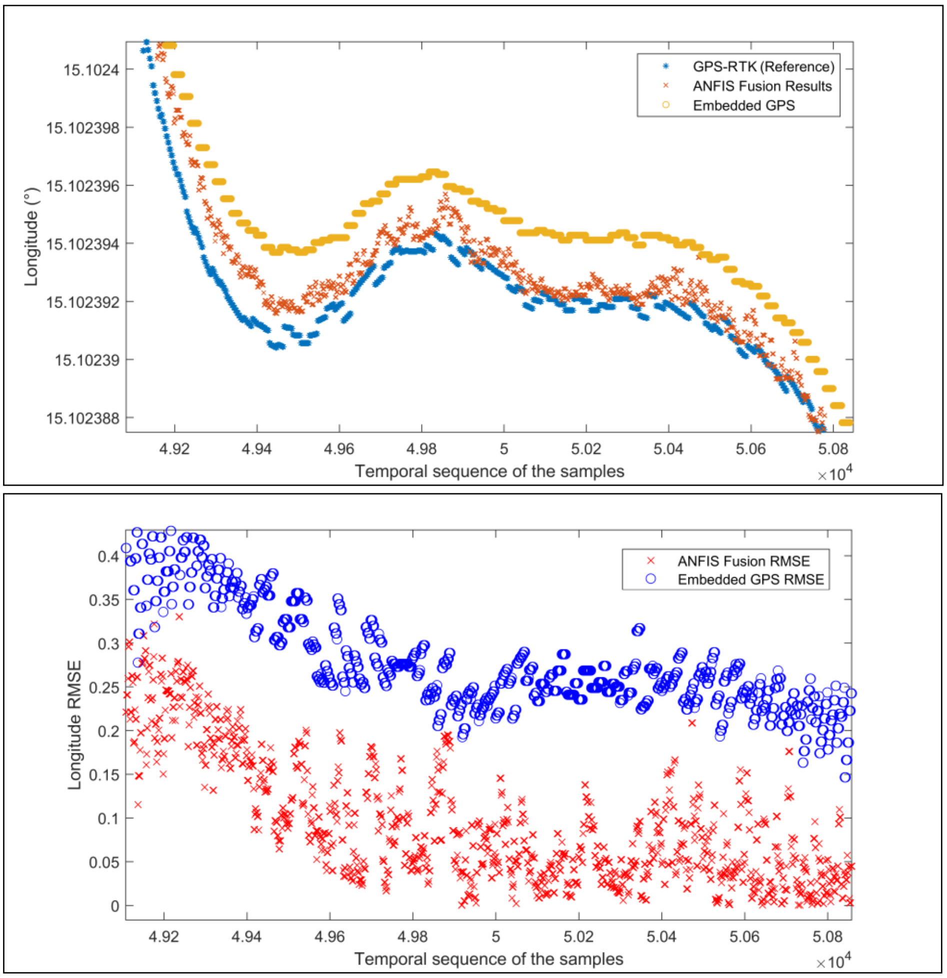
Table 2. Comparison of position estimation accuracy.

System	Lat error (cm)	Lon error (cm)	Inaccuracy (area in cm²)	Inaccuracy reduction (%)
GPS	21.099384	30.811140	650.0960893	-
ANFIS	17.609828	24.894156	438.3817907	32.57%

It was also found that, for a total of 10,000 estimates fusing three sensors, the average time for 10 tests was 7.5525s, or about 7.55 x 10^{-4} seconds per estimation (≅1,324Hz). This shows that indeed a FIS is of rapid processing, 6.62 times faster than the update rate of the fastest sensor (GYRO), what is invaluable for real-time navigations.



(a) Excerpt of UAV trajectory with error comparison – Latitude.



(b) Excerpt of UAV trajectory with error comparison – Longitude.

Figure 6. Trajectories estimated by the trained FIS from the last experiments.

6. Conclusions

As demonstrated in the results of the carried-out experiments, the methodology employed in this application of Data Fusion, using the ANFIS Computational Intelligence technique, is effective in increasing the situational awareness about the flight scenario in which the UAV is located. This fact is corroborated by a reduction of more than 210cm² in the area error, compared to the estimation of the position provided by the embedded GPS. The results obtained show that the use of multiple data sources has brought benefits to the navigation problem, bearing in mind the safety in the operation of the UAV, by offering less uncertainty to the Decision-Making System.

The main contribution of this work is the development of a Data Fusion application of low computational cost, which can make feasible its use in real-time. This feature makes it possible to use the developed application in low performance UAVs, which tend to lack computational power and payload.

Suggestions for future work include: a study of why the GPS was more precise than ANFIS in some particular regions of the graph; a study of the choice of the data used for training; use of clustering techniques in training data; stochastic optimization of parameters for the ANFIS technique; and the conduction of tests on new flights.

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