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# Fuzzy Approach for Data Association in Image Tracking*

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**Abstract**

A fuzzy system has been developed to ponder update decisions both for the trajectories and shapes estimated for targets. It is embedded in an A-SMGCS Surveillance function for airport surface, based on video data processing, in charge of the automatic detection, identification and tracking of all interesting targets (aircraft and relevant ground vehicles). The tracking system captures a sequence of images, preprocesses them to extract the moving regions (blobs), and associates the blobs to tracks to estimate the number of targets in the scenario and their parameters. The system was initially built with a set of rules derived from performance analysis, and then a procedure based on neuro-fuzzy techniques was applied to automatically obtain rules from examples. A validation of learned system shows its capability to produce appropriate decisions. Results obtained with real data in representative ground operations show the system capabilities to solve complex scenarios and improve tracking accuracy.

## 1. Introduction

In airport area, Advanced Surface Movement, Guidance and Control Systems (A-SMGCS) (FAA 1993) are conceived as new procedures and technologies to support ground traffic management, increasing both safety and efficiency of traffic flow in complex, high-density airport ground scenarios. One of the core functions within A-SMGCS is Surveillance, in charge of the automatic detection and tracking of all relevant targets located in the airport movement area (runways, taxiways and apron areas). In this work we will focus on tracking aspects when the data to be processed are provided by cameras. Cameras can be configured as a set of local installations

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providing high-resolution images of dense airport areas, such as inner taxiways and apron, allowing tracking as the only data source or complementing other sensors such as surface radar.

The general architecture and main blocks integrated in the Video Surveillance System were described in (Besada 2001). Basically, the system follows a distributed structure, with a local processor operating on the image sequences provided by each camera. Each processor calculates target trajectories (local tracks) in the projected camera plane, performing two steps. First, moving targets are detected against their local background to generate detected pixels, connected then to form image regions referred to as blobs, defined with their spatial borders (a rectangular box), centroid location and area. In the second step, the tracker must distinguish all targets in the scene and track their motion, applying association and filtering processes to blobs extracted from the processed images. One of the key points of the whole tracking system to cope with dense multi-target scenarios will be the data association logic (Blackman 1999). This subsystem decides which target generated each sensor observation. In this case of processing video output in dense airport areas, each frame to process presents a set of blob-to-track multi-assignment problems to be solved, where several (or none) blobs may be assigned to the same track and simultaneously several tracks could overlap and share common blobs. The design of association logic must take into account the characteristics and quality of sensor data. In this case, data are the blobs resulting from detection and segmentation phases applied on image sequences of airport surface scenes. Figure 1 shows an example where a single target (aircraft) originates four blobs, to be grouped by the association logic before updating its track. Generally, blobs from each target must be distinguished from other targets or backgrounds elements in the image.

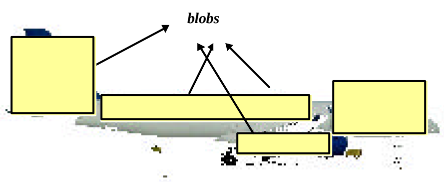


Figure 1. Blob-to-Track Association Problem

There are not detailed models or analytical expressions to design this process, similar to Bayesian approaches for probabilistic association (Ding 1999), but an analysis of continuity performance with different strategies, depending on numeric heuristics describing the situations, provide robust rules to take appropriate association decisions (García 2002). Rules have been obtained by analysis of performance under different conditions, characterized with these heuristics values. Rules represent the most proper actions to take under a set of particular extreme conditions to guarantee track continuity. Fuzzy reasoning techniques have been adopted to reproduce the system behavior under these conditions and besides generate the proper output for intermediate situations. A fuzzy system (Zadeh 1973) (Mendel 1995) is proposed to evaluate the confidence given to the information contained both in the gated blobs and predicted tracks, based on a set of numeric heuristics describing the characteristic of these multiple-blob-multiple-track association scenarios. Besides, an automatic procedure (neuro-fuzzy technique) has been applied in order to extract rules directly from examples (expert decisions in extreme conditions). The behavior of these extracted rules is similar than the fuzzy system developed.

# 2. Representation of Targets and Scenario Heuristics

Traditional association systems represent targets with a single position and error parameters. Using a Video Surveillance System, an explicit representation of target shape and dimensions seems more adequate to select the set of updating blobs for each track. Track-state vectors with position and cinematic estimates (2D location and velocity referred to the camera plane) are complemented with attributes defining a spatial representation of target extension and shape. So, the predicted target contour is used to gate blobs extracted in next frame. For the sake of simplicity, first a rectangular box has been used to represent the target, as indicated in figure 2. Around the predicted position, $(\hat{x}_p, \hat{y}_p)$, a rectangular box is defined, ($x_{min}$, $x_{max}$, $y_{min}$, $y_{max}$), with the estimated target dimensions $(\hat{l}_H, \hat{l}_V)$. Then, an outer gate, computed with parameters $\Delta_H$, $\Delta_V$, is used to finally gate the potential blobs updating the track estimates.

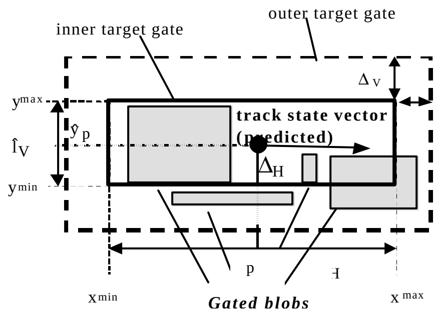


Figure 2. Target segmentation with estimated box

This outer gate allows the system track dynamic variations in target shape along the sequence, for targets not perfectly matching to predictions due to variations in projected shape (changes of orientation, distance, etc.), or maneuvers. Besides, it avoids the initialization of tracks around existing ones, potential source of instabilities. The process of shape update with new information should reach a trade-off between the conflicting requirements presented in previous section: it must re-connect the different blobs representing a single target to avoid track-splitting effects, grouping should be limited to avoid the connection of image regions originated by different objects and when different targets approach, it should avoid grouping their image regions, since their tracks can be wrongly updated. So, the shape must be dynamically updated with the information contained in blobs, but the changes must be smooth, avoiding instabilities in scenarios with closely spaced objects.

The final weight of gated blobs in the update phase should take into account the aspects mentioned before. Although there is not any closed expression doing that, similar to statistical residuals, some numeric heuristics, computed with simple geometrical analysis of blobs and predicted tracks, have shown to provide helpful indications to be considered. They can be used to assess the confidence given to each blob, after it is included into a certain group, an also to asses confidence in predicted track. They were detailed in (García 2002), and are summarized next:

**1.** Overlapping heuristic: this component can be seen as a "soft gating", computed as the fraction of blob area contained within track predicted region. Maximum value, 1, is given when blob is completely included within an inner track predicted gate, and minimum, 0, when blob is out of an outer track region (see figure 3). Both regions for each track allow adaptive grouping for targets not perfectly matching to predictions, due to variations in projected shape (changes of orientation, distance, etc.), or maneuvers.

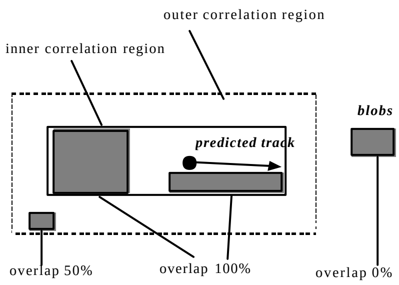


Figure 3. Overlapping degree heuristic

**2.** Group density and distance to track: this heuristic, ρ, $(\rho = \sum_i \mathrm{Area}_i / (l_x l_y))$ evaluates the ratio between areas of detected regions and non-detected areas (holes) in the finally reconnected pseudo-blob (see figure 4). So, in the case that the blobs grouped are very scattered, a low value of ρ will indicate that they probably have been originated by different targets.

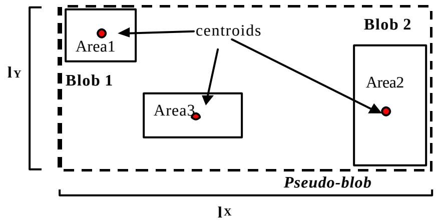


Figure 4. Group density after blob re-connection

**3.** Conflict with other tracks heuristic: this component evaluates the likelihood of blob being in conflict with other tracks. This problem appears when target trajectories are so close that track gates get overlapped and share the blob, as depicted in figure 5. To do that, a criterion based in the distance to track is used to finally compute this heuristic, whose values fall from 1, when distance is zero, to $\rho$, for the most separated blobs, so that they would be practically discarded when density is low. Evaluation of blob conflict degree is completely equivalent to the first heuristic, overlapping, but computed with the other existing tracks. In the case that more than one track are in conflict, the maximum overlapping degree is selected.

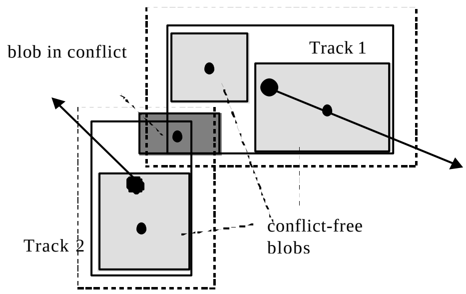


Figure 5. Blob in assignment conflict with two tracks

**4.** Proximity to image borders heuristic: Finally, image borders are the areas where tracks are usually initialized, and so they are transient areas where tracks are not stabilized yet. This number evaluates if the blob is close to any of the four image borders.

These heuristics provide useful information to be considered when assessing the confidence that may be given to each blob before track update. Additionally, the predicted track may be also characterized with some heuristics, indicating the confidence given to the fact that this track represents motion of a real target, detecting when it is deviated from real trajectory. They are the following: (1) number of missed updates, it is the number of consecutive frames where no blob was included into track inner gate, (2) track detected area, conversely to blob overlapping heuristic, it is the proportion of area, within predicted inner gate, filled with blobs detected in current frame, and, (3) proximity to image borders, this value is equivalent to the one computed for blobs.

## 3. Fuzzy System for Updating Multi-Target Shapes

The heuristics defined above will be the input to certain unknown functions computing confidence levels both for blobs and predicted tracks. A rules system based on fuzzy logic has been developed in order to approximate these functions with a symbolic representation of knowledge. The first step to build this system should be the selection of adequate descriptions of heuristics and rules relating them with the outputs: confidence levels for blobs and predictions. The inputs (heuristic values) are translated into linguistic variables. Using this concepts, for heuristic $h_i$, a linguistic variable $Lh_i$ is introduced, together with its set of values $\{lh_{i1}, lh_{i2}, ..., lh_{im_i}\}$, whose cardinality is $m_i$. Each term $lh_{ij}$ in the set labels a fuzzy set with membership function $\mu_{lh_{ij}}(h_i)$. A fuzzy relational algorithm (FRA) stores the rules to obtain the confidence levels, CONF, both for blobs and tracks involved in each decision. It is composed of a finite set of fuzzy conditional statements, making use of Mamdani implication, of the form IF $\{Lh_i$ is $lh_{ij}\}$ THEN {LCONF is $l\alpha_k\}$, being LCONF a linguistic variable representing blobs or track confidence levels, with a set of possible values $\{l\alpha_1, \ldots, l\alpha_n\}$. Finally, $\alpha$ is the defuzzification of LCONF, with a modified version of the Center of Gravity procedure.

Target estimated shape will vary smoothly, accordingly to confidence levels of gated blobs. The estimated position (measured centroid to update track vector) will depend both on these blobs confidence levels,? $\alpha_{bi}$, and on predicted track confidence, $\alpha_p$, which is lowered when tracks deviate from real trajectories and get no blobs. Estimated dimensions of box are the most constrained features, remaining “locked” while the blobs confidence levels are not high enough to guarantee stability, while estimated position (the box borders) is a trade-off between confidence levels of blobs and tracks.

With the rectangular simplification considered in this approach, only two shape parameters are estimated: length, width $(\hat{l}_H, \hat{l}_V)$. If we consider horizontal coordinate, the two gated blobs with the minimum and maximum extremes for coordinate x, $(x_{bmin}, x_{bmax})$ are taken into account. Denoting their associated confidence levels, computed by fuzzy system, as $\alpha_{1H}$, $\alpha_{2H}$, the minimum and maximum values are obtained: $\alpha_{minH}=\min[\alpha_{1H}, \alpha_{2H}]$; $\alpha_{maxH}=\max[\alpha_{1H}, \alpha_{2H}]$

First, the target horizontal length is updated considering the minimum blob confidence value:

$$\alpha_{minH}: \quad \hat{l}_H[k] = \alpha_{minH}(x_{bmax} - x_{bmin}) + (1-\alpha_{minH})\hat{l}_H[k-1] \tag{1}$$

So, the estimated target length will be modified only in the case that both blobs have enough confidence. Then, the estimated target bounds (location of box) are updated from the blob with the highest confidence, $\alpha_{maxH}$, considering also the value for track confidence, $\alpha_p$. It is required that $\alpha_p$ reaches a minimum threshold, $T_p$, to weight the track prediction with the blob having highest confidence. In other case, track prediction is discarded, and box is positioned aligned with the best blob, in order to avoid track lost when deviation between predictions and detected regions increases. For instance, if left-hand side blob defining vale $x_{bmin}$ had the highest confidence, the estimated target bounds would be updated as follows:

- $\alpha_p > T_p$:

$$\hat{x}_{min}[k] = \alpha_{maxH} x_{bmin} + (1-\alpha_{maxH})\left(\hat{x}_{min}[k-1] + \hat{v}_x[k-1]T\right) \qquad \hat{x}_{max}[k] = \hat{x}_{min}[k] + \hat{l}_H[k]$$

- $\alpha_p < T_p$:

$$\hat{x}_{min}[k] = x_{bmin}$$
$$\hat{x}_{max}[k] = \hat{x}_{min}[k] + \hat{l}_H[k] \tag{2}$$

being $(\hat{x}_{min}[k-1], \hat{x}_{max}[k-1])$ the horizontal bounds in last update, $\hat{v}_x[k-1]$ is the horizontal velocity estimated by tracking filter, $\hat{l}_H[k]$ is the value computed in (1), and T the time elapsed. $T_p$ is the threshold on track confidence. Similar considerations are made for the other possible case (right-hand blob) and for the vertical dimension update.

A recursive filter of Kalman type is used to update then estimated centroid positions and velocities for each track, from the sequence of assigned values (pseudo-measurements computed from all gated blobs and predicted tracks by previous expressions).

## 4. Rule Extraction using Neuro-Fuzzy Techniques

As an alternative to the development of the set of rules in the system, manually fixed from experimentation, a neuro-fuzzy system was implemented to search appropriate rules from representative examples. The techniques based on neural networks are named neuro-fuzzy systems and they are usually represented as a multilayer feedforward neural network (Tschichold 1995). Two approaches of neuro-fuzzy systems exist. The first one uses differentiable operators in the fuzzy system to apply gradient descent procedures, these systems generate fuzzy systems that are not easy to interpret. The ANFIS model by Jang (Jang 1993) implements a Sugeno-like fuzzy system (Sugeno 1985) in a network structure, and applies a mixture of backpropagation and least-mean-square procedure to train the system. The GARIC model (Berenji 1992) uses a special "soft minimum" function which is differentiable. The second approach uses max-min operators and the learning procedure is heuristic, these systems are easy to interpret as the neuro-fuzzy systems developed by Nauck and Kruse (NEFCLAS (Nauck 1995a) and NEFCON (Nauck 1995b)). In this work, the fuzzy system for association uses Mamdami implication because the fuzzy system interpolates a generic function (the association function) that has not analytical expression. Then we apply the Nauck/Kruse neuro-fuzzy approach because they use directly this type of implication and the method is development for this type of fuzzy systems.

The scenarios were selected considering representative situations such as target splitting and merging in segmentation, occlusions and overlapping, in order to get a robust system able to attain acceptable behavior in the general case. The three possible outputs considered for blob confidence regarding track parameters update were {discard, low, high}. So, for each detected blob located around the target bounds (predicted by the tracking system), the three possible decisions were: accept the blob and update the estimated track parameters (high), if the blob information is reliable and only referred to the represented target; discard the blob (discard), if it clearly comes from a different source; or partially update the track (low), when the blob has information about target but it is corrupted by effects such as occlusion or overlapping. Three different scenarios have been selected. In the first scenario, three aircraft were moving in parallel taxiways, in an area covered by a camera with low depression angle, so their images get overlapped when they cross. The confidence level of blobs in such situations must be lowered to avoid degradation of estimated shape and kinematics of targets. In scenario 2, three vehicles were moving on a road, approaching until their images get overlapped, while at the same time one of them performs a deceleration maneuver. The third scenario contains multiple blob reconnections. An aircraft is moving behind stopped vehicles and aircraft. These vehicles occlude it and other vehicles move in close parallel roads. Multiple blobs representing different parts of aircraft and its shadow appear. These blobs must be grouped to update the aircraft track, avoiding splitting effects. Besides, images from other vehicles must be kept separated guaranteeing track continuity for all targets.

For each one of the frames available in the scenarios, the blobs and tracks were used to compute the heuristics, while the label describing the confidence category of blob was manually assigned from direct observation. In order to analyze the quality of the classification scheme and its capability to predict the right decisions, the total set of data was split in subsets for validation. The three scenarios were divided into ten groups, depending on the characteristics of each sequence (segments without conflicts, segments with occlusions, with bad segmentations, etc.). The training and evaluation process was performed with different scenarios to obtain the rate of instances correctly predicted, as depicted in table 1. Two type of fuzzy sets were selected to represent the concepts: triangular and bell-shaped, whose performances are indicated in the top and bottom, respectively, of each cell. From the results, the learning capability is better when bell-shaped functions are applied. The main diagonal is blank since the test was always performed over data different from training. Final column has the mean performance with each training set applied to the rest of available data. The worst results were obtained when data from simple segments without problems were used for training. For instance, intervals (22-43) and (53-88) from scenario 1 contained only separated targets, while segments (44-52) and (61-67) conflict situations. The rules generated with the second type obtained better results than those generated with the first one.

Table 1. Accuracy of rules generated with different subsets of data

| **Test** | **S1** | **S1** | **S1** | **S1** | **S2** | **S2** | **S3** | **S3** | **S3** | **S3** | **All** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Training** | **(22-43)** | **(44-52)** | **(53-88)** | **(61-67)** | **(72-137)** | **(115-120)** | **(40-63)** | **(64-85)** | **(86-111)** | **(112-136)** | **All** |
| | - | 36,7 | 89,5 | 33,3 | 91,6 | 28,0 | 88,2 | 48,4 | 46,2 | 73,8 | 61,9 |
| **S1(22-43)** | - | 43,3 | 94,7 | 53,3 | 99,0 | 44,0 | 94,1 | 60,5 | 65,1 | 100,0 | 76,0 |
| | 100,0 | - | 94,7 | 63,3 | 92,6 | 56,0 | 88,2 | 68,6 | 63,9 | 73,8 | 76,2 |
| **S1(44-52)** | 93,5 | - | 81,6 | 63,3 | 74,7 | 64,0 | 79,4 | 67,7 | 60,3 | 70,2 | 70,2 |
| | 100,0 | 83,3 | - | 73,3 | 92,6 | 68,0 | 91,2 | 76,6 | 69,2 | 76,2 | 78,8 |
| **S1(53-88)** | 100,0 | 86,7 | - | 86,7 | 100,0 | 84,0 | 94,1 | 96,8 | 94,7 | 100,0 | 95,7 |
| | 100,0 | 83,3 | 94,7 | - | 94,7 | 56,0 | 91,2 | 74,2 | 70,4 | 77,4 | 80,7 |
| **S1(61-67)** | 96,8 | 90,0 | 96,1 | - | 84,2 | 80,0 | 82,4 | 67,7 | 74,6 | 96,4 | 81,2 |
| | 100,0 | 43,3 | 89,5 | 33,3 | - | 28,0 | 88,2 | 50,0 | 50,3 | 94,1 | 63,9 |
| **S2(72-137)** | 100,0 | 43,3 | 94,7 | 53,3 | - | 44,0 | 94,1 | 60,5 | 65,1 | 100,0 | 73,7 |
| | 100,0 | 83,3 | 94,7 | 63,3 | 94,7 | - | 91,2 | 85,8 | 73,4 | 75,0 | 83,4 |
| **S2(115-120)** | 100,0 | 86,7 | 96,1 | 76,7 | 92,6 | - | 91,2 | 95,1 | 89,4 | 73,8 | 89,6 |
| | 100,0 | 43,3 | 94,7 | 43,3 | 93,7 | 28,0 | - | 53,2 | 53,3 | 77,4 | 67,2 |
| **S3(40-63)** | 100,0 | 43,3 | 94,7 | 53,3 | 99,0 | 44,0 | - | 60,5 | 65,1 | 100,0 | 76,2 |
| | 100,0 | 83,3 | 100,0 | 73,3 | 92,6 | 60,0 | 91,2 | - | 75,7 | 77,4 | 83,8 |
| **S3(64-85)** | 100,0 | 86,7 | 100,0 | 86,7 | 96,8 | 84,0 | 94,1 | - | 91,7 | 85,7 | 92,5 |
| | 100,0 | 83,3 | 94,7 | 63,3 | 94,7 | 72,0 | 91,2 | 84,7 | - | 75,0 | 85,8 |
| **S3(86-111)** | 100,0 | 86,7 | 100,0 | 86,7 | 99,0 | 76,0 | 94,1 | 96,0 | - | 100,0 | 95,9 |
| | 100,0 | 43,3 | 94,7 | 43,3 | 93,7 | 28,0 | 94,1 | 55,7 | 56,8 | - | 68,7 |
| **S3(112-136)** | 100,0 | 43,3 | 94,7 | 53,3 | 99,0 | 44,0 | 94,1 | 60,5 | 65,1 | - | 73,9 |
| | 100,0 | - | - | 63,3 | 94,7 | 68,0 | 91,2 | - | 75,2 | 75,0 | 80,8 |
| **Repres.1** | 100,0 | - | - | 76,7 | 100,0 | 84,0 | 97,1 | - | 94,1 | 97,6 | 94,9 |
| | - | 100,0 | 94,7 | - | 94,7 | 72,0 | 91,2 | 87,1 | - | 76,9 | 88,4 |
| **Repres.2** | - | 86,7 | 100,0 | - | 96,8 | 84,0 | 97,1 | 97,6 | - | 83,3 | 93,8 |
| | - | - | - | - | - | - | - | - | - | - | **84,1** |
| **All** | - | - | - | - | - | - | - | - | - | - | **93,3** |
| **N.Instances** | 31 | 30 | 76 | 30 | 95 | 25 | 34 | 124 | 169 | 85 | 699 |

The best results were obtained with a representative set containing a sample of conflictive situations in scenarios 1 and 2 (row labeled as representative 2), with some overlaps, occlusions and splits. Finally, the table entry All represents the result obtained with a random sampling for training and validation complementary sets, applying cross validation, very similar to the best result.

## 5. Experiments

Some results about the effect on tracking accuracy are presented next. The system proposed with fuzzy association logic is compared with a hard-decisions system behaving as follows: update with all blobs included in the gate if group density is higher than 0.7, otherwise, remove the farthest blobs from the group, and, if two or more tracks share any conflictive blobs, predict them without update.

Accuracy is defined by means of the root mean squared error (RMS) in the estimator for each coordinate. This analysis has been performed on real data, without any reference trajectory available to compute the errors. To overcome this problem, a linear trajectory with uniform motion has been selected to reasonably estimate a Least Squares approximation from the track estimators as a reference to compute the errors. The trajectory estimated for the aircraft moving from right to left, indicated as track 18, has been used to compare both systems. The errors are normalized by the target dimensions, available in the blobs extracted from images, and so they are expressed as fractions of target size in each coordinate (%).

Two different scenarios are presented. In the first scenario there is an aircraft moving from right to left, with partial occlusions from a bus and an aircraft stopped in front. As a consequence, multiple blobs representing different parts of aircraft and its shadow appear, which are grouped to update the aircraft track (Id=18), without splitting effects. Figure 6 shows the estimated trajectories (X,Y coordinates against processed frames) with fuzzy association (circles) and previous system (triangles), and a LS approximated trajectory (dotted line). The normalized magnitude of error with respect to the straight line for X and Y coordinates are shown in figures 7 and 8, respectively, comparing fuzzy and previous systems, which are represented by solid and dashed lines. RMS values, averaged along the time duration of trajectory are indicated too. As it can be seen, an improvement of 35% in vertical accuracy appears with the new system, due to the fact that track is more stable, integrating the fuzzy combination of blobs to be grouped.

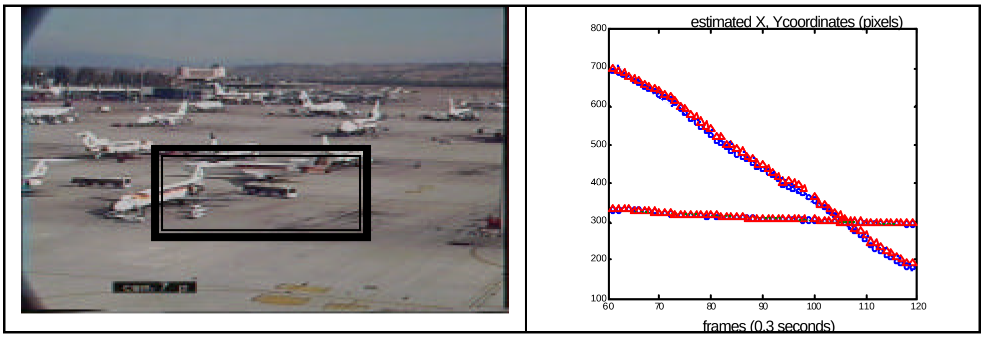


Figure 6. Estimated and approximated trajectories for track 18

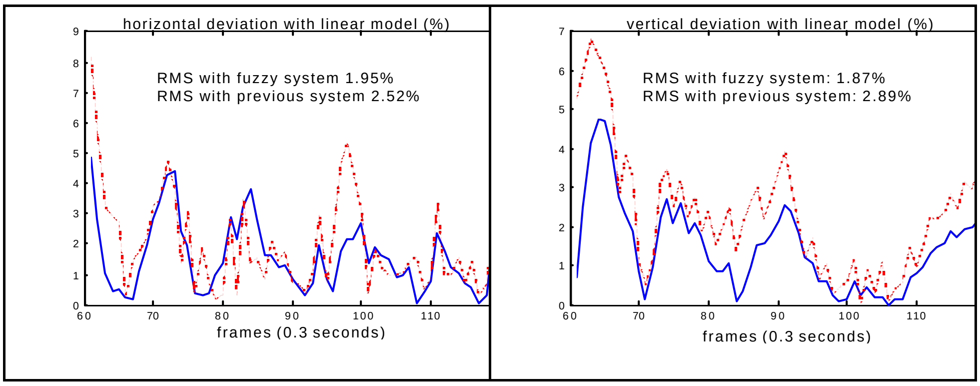


Figure 7. Horizontal and Vertical errors with respect to straight line

In the second scenario, two aircraft cross and their images get mixed with association conflicts for an interval of 25 frames (frames 90 to 113). In frame 95, where an aircraft is clearly occluded by other. Fuzzy system successfully avoids update with corrupted blobs due to conflict, (frame 101), but as soon as targets separate (from frame 105) tracks are gradually updated to follow the trajectory. The output of both systems is displayed in figure 8. The rigid system with extrapolation during conflicts clearly separate from real trajectory, due to maneuver during the conflict interval. This fact is illustrated in figure 9, depicting the horizontal and vertical residuals with both systems (fuzzy with solid line, and previous one with dashed). In this case with maneuver it is not applicable using a linear approximation of trajectory, and so the residual (difference between blobs centroids and track predictions) have been shown for evaluation.

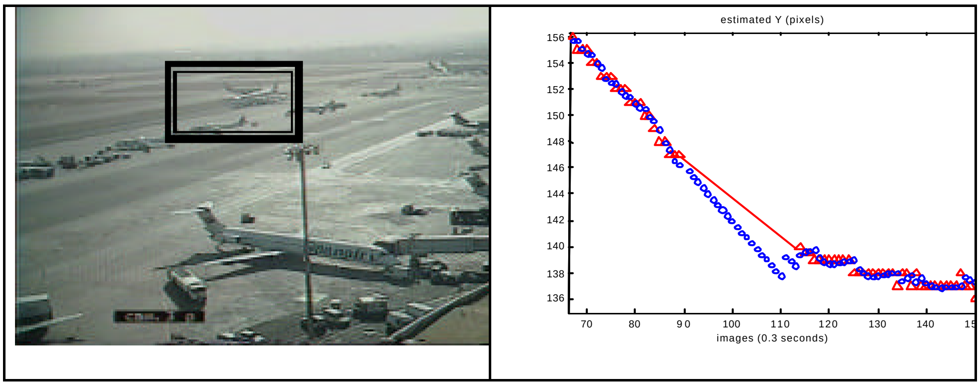


Figure 8. Estimated Y coordinate with both systems in scenario 2

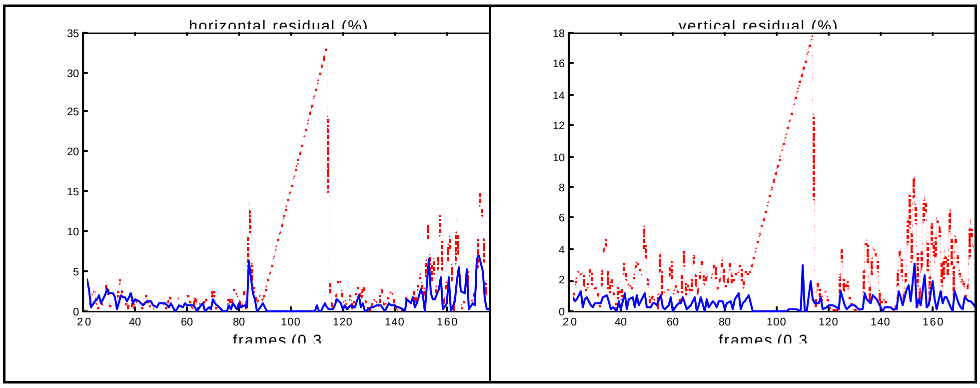


Figure 9. Residuals of both tracking systems in scenario 2

## 6. Conclusions

Fuzzy reasoning has been successfully applied to solve the core problem of data association for video tracking under complex, high-density conditions. Specific domain knowledge is represented as a set of rules to adapt association decisions as a function of several heuristics inferred from experimentation. System performance in representative scenarios and computation efficiency achieves a satisfactory trade-off.

## 7. References

(FAA 1993) U.S. Department of Transportation. FAA. *The Future Airport Surface Movement Safety, Guidance and Control Systems: A vision for Transition into the 21st Century*. Washington. November 1993.

(Besada 2001) J. A. Besada, J. Portillo, J. García, J. M. Molina. *Image-Based Automatic Surveillance for Airport Surface* FUSION 2001. Montreal, Canada. August 2001.

(Blackman 1999) S. Blackman, R. Popoli. *Design and Analysis of Modern Tracking Systems*. Artech House. 1999

(Ding 1999) Z. Ding, H.Leung, L. Hong. *Decoupling joint probabilistic data association algorithm for multiple target tracking*. IEE Proceedings- Radar, Sonar and Navigation, Vol 146, Nº5. pp 251-254. October 1999

(García 2002) J. García, J. A. Besada, J. M. Molina, J. Portillo. *Fuzzy data association for image-based tracking in dense scenarios.* IEEE International Conference on Fuzzy Systems. Honolulu, Hawaii. May 2002

(Zadeh 1973) L. A. Zadeh, *Outline of a New Approach to the Analysis of Complex Systems and Decision Processes*, Trans. on SMC, Vol. 3, Nº 1. January 1973

(Mendel 1995) J. M. Mendel. *Fuzzy Logic Systems for Engineering: A Tutorial*. Proceedings of the IEEE. Vol. 83. Nº3,. pp 345-377. March 1995

(Tschichold 1995) N. Tschichold-Gürman, *Generation and Improvement of Fuzzy Classifier with Incremental Learning using Fuzzy Rulenet.* Proc. ACM Sym on Applied Computing, Nashville, pp 466-470, 1995.

(Jang 1993) JSR Jang, *ANFIS: Adaptive-network-based Fuzzy Inference Systems.* IEEE Transactions on System, Man and Cybernetics 23, 665-685, 1993.

(Sugeno 1985) M. Sugeno, *An Introductory Survey of Fuzzy Control.* Information Science 36, 59-83, 1985.

(Berenji 1992) HR Berenji, P. Khedkar, *Learning and Tuning Fuzzy Logic Controllers through Reinforcements.* IEEE Transactions on Neural Networks 3, 724-740, 1992.

(Nauck 1995a) D. Nauck, R. Kruse, *NEFCLASS- a neuro-fuzzy approach for the Clasification of Data.* Proc. ACM Sym on Applied Computing, Nashville, pp 461-465, 1995.

(Nauck 1995b) D. Nauck, R. Kruse, R. Stellmach *New Learning Algorithms for the Nuero-Fuzzy Environment NEFCON-1*. Proc. Nuero-Fuzzy Systems'95, armstadt, 357-364, 1995.