Distributed Multi-Sensor Multi-Target Tracking with a Low-Cost Wireless Sensor Network: An Application to Intruder Detection

María Victoria Moreno [a], Miguel Ángel Zamora [a], Carolina Piñana-Diaz [a],
Rafael Toledo-Moreo [a b] IEEE Member, and Antonio F. G. Skarmeta [a]
Computer Science Faculty, 30071 Murcia, Spain [a]
School of Telecommunication Engineering, 30202 Cartagena, Murcia, Spain [b]
{mvmoreno, mzamora, carolina.pinana, toledo, skarmeta}@um.es

Abstract: In the context of wireless communication systems many applications oriented to parameter monitoring are developed, such as automatic tracking systems. In this paper, an automatic tracking system based on a network of presence and range sensors, is presented. The main goal is to offer a low cost alternative to increase security staff effectiveness and to avoid problems of scattered alarms management. For this purpose, information from different sources is fusioned to provide as output the trajectories of detected objects. Simulation results, with measurements of different sensors, show the suitability of the proposed distributed multisensor-multitarget fusion system to the specified requirements.

1 Introduction

In the last decade there has been a significant amount of progress in developing security systems based on wireless sensor networks. One of the most important functions of these systems is to determine the position of a moving target by solving the tracking problem. There is a growing interest in tracking systems applied to areas such as security [BH01], automatic control [BS90], robotics [FBT99], mobile networks and computation [RG02] and microelectronic system based applications [Tak02].

In this paper an automatic localization system based on tracking of target positions is proposed. Our system is composed of a reduced set of low cost sensors and a surveillance camera that can monitor the area indicated by the system output. The objective is to optimize resources reducing negative effects of cost, power and management of sensors. Another very important point is to control a given geographic area without affecting the system performance. In order to meet these requirements sensors need to be distributed to optimize global coverage and detection process must be capable of anticipate next states. In the literature we can find many works that solve localization and tracking problems using wireless sensor networks [DVB08] [KLM08]. However, the accuracy limitations of low cost sensor are not solved, and in most of the cases these solutions cannot be exploited in real scenarios where low cost and adaptive estimation mechanisms are required.

The structure of this paper is as follows. Section 2 describes the proposed scheme in order

erschienen im Tagungsband der INFORMATIK 2011
Lecture Notes in Informatics, Band P192
ISBN 978-3-88579-286-4

to process the information and maximize accuracy. The association mechanism for sensor data fusion is detailed in section 3. Simulation results are presented in section 4. Finally, conclusions and future works are drawn in section 5.

2 Problem Formulation

Let us consider a scenario where sensors are capable of detecting the presence of a target. Under the assumption that the overlap between the different areas covered by the sensors is minimum or null, distribution of sensors in the network needs to be chosen with the aim of covering the region of interest and optimizing the number of sensors. The output of the system will correspond to the time evolution of the measured parameters. These output data will be represented in a Geographic Information System (GIS) [Bur98] based on an accessible web application. Given that the application is accessible via internet, it should be possible monitoring the scene in the distance. Fig. 1 shows a distributed architecture scheme for the proposed tracking system.

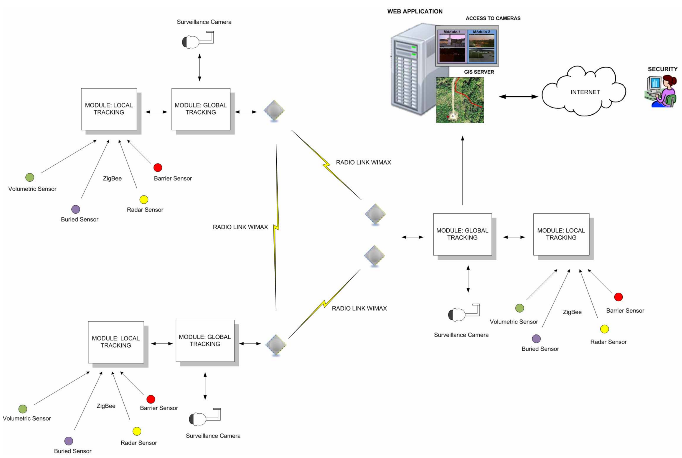


Figure 1: Fusion architecture at global level.

2.1 Sensor Information Processing

Sensor information processing is of key importance to achieve a high efficiency of the system because limitations from the nature of different sensors and their accuracy values are taken into account at this level. The objective of a tracking system for target detection is the store and classification of the information from the sensors according to their characteristics in a data structure known as *track*. Each track can be characterized according to its parameters such as velocity, type of target or estimation of its next state position.

The sensor network proposed in this paper is formed by presence and range sensors. Surveillance cameras used provide perimetral and indoor protection. Our goal is that these cameras confirm visually the tracks that have been outputted by our data fusion mechanism. Presence sensors provide alarm information at a given instant of time thus it is

erschienen im Tagungsband der INFORMATIK 2011
Lecture Notes in Informatics, Band P192
ISBN 978-3-88579-286-4
weitere Artikel online:
http://informatik2011.de/519.html

not possible to estimate directly the position of the target in a later time. However, this information may be used to check data from range sensors. The key of our system is the utilization of all the individual information from the network to describe the global behavior of the system.

Data fusion can be classified in many ways. A very usual method is based on the level where the fusion process is performed. The fusion process in our system is carried out at the decision level since some of the sensors of the system can provide its own tracks. Another classification of fusion techniques consists of the differentiation between algorithmic and not algorithmic methods. In this paper, a combination of *Fuzzy Clustering Means (FCM)* and *Nearest Neighbor (NN)* techniques is used to achieve fast computation in real time and fuse data of different characteristics. Before the association stage, input data refinement is required. The different stages of this processing scheme are: time alignment, space alignment, target extraction, target classification, filtering and association.

3 Recursive Association Mechanism

Stage 1. Fusion of the previous information: the first stage of the proposed mechanism is to try associate current tracks with generated tracks in the previous stage of evaluation. To evaluate this association we focus on ID sensors and ID targets of current and previous tracks, the goal is to find similarities between these IDs. Then tracks which match and have been previously associated will be fused.

Stage 2. Fuzzy Clustering Means algorithm for fusion data: after the association process, correlation between tracks is calculated. For this purpose, a NxN association matrix is initialized including correlation information between tracks, where N denotes the number of tracks. FCM equations will be used in order to calculate track correlation [Azi07], [ATC99]. Estimation methods are of crucial importance for the time alignment of tracks and the study of correlation. In this work a *Particle Filter (PF)* has been implemented. The PF employed in this work is slightly different from its most common implementation [Van01]. The main difference is the correction stage of the filter since particle weights will be modified according to their distances to the real measurement, as the following equation shows:

$$w(\vec{x}_t) = w(\vec{x}_{t-1}) \cdot \frac{p(\vec{y}_t \mid \vec{x}_t) \cdot p(\vec{x}_t \mid \vec{x}_{t-1})}{q(\vec{x}_t \mid \vec{x}_{t-1}, \vec{y}_t)} \tag{1}$$

Where $w(\vec{x}_t)$ represents the weights of the set of particles at instant t, $p(\vec{y}_t \mid \vec{x}_t)$ and $p(\vec{x}_t \mid \vec{x}_{t-1})$ denote respectively the probabilistic behaviour of the output model and the state model of the system, and $q(\vec{x}_t \mid \vec{x}_{t-1}, \vec{y}_t)$ is the approximation of the belief function. In addition to (1), information from discrete sensors, which give information of alarm in a concrete area in a given instant of time, is also used. The main advantage of this constraint is the faster convergence of the filter, hence there is some extra information to benefit those particles which fall inside this area. For this purpose, it should be added to the update stage the following condition:

$$\{\text{If: } y_t \in \Omega_t^j \Rightarrow w(x_t^i) = 0 \, \forall \, x_t^i \notin \Omega_t^j\} \tag{2}$$

Where Ω_t^j represents the j alarm whose control area is Ω at instant t, and both y_t and $w(x_t^i)$ denote respectively the measured parameter and the weight of the set of particles i at the same instant of time. The commom particle filter uses the *Sequential Importance Sampling algorithm (SIS)* [Dou00]. In our filter implementation the *Multinomial Sample tecnique* is used because the SIS method has the drawback of the high probability of degradation of the filter, to avoid this problem the Multinomial Sample tecnique is a powerful approach for Multitracking problems [Van01]. In order to represent the motion model of the set of particles, a *Gauss-Markovian model* has been used whose equations are included in [SMH99]. The main advantage is the realistic motion pattern with a proper configuration of the equation parameters. It is important to note that some constraints, such as the possibility of zero velocity of the target, have been taken into account for its definition. With this motion model, particles maintain a certain speed and direction that are randomly changed. After it has been applied the FCM algorithm, the new association matrix elements, that show the correlation between tracks, can be: "there is no correlation" ($a_{ij} = -1$), "there is correlation" ($a_{ij} = \mu_{ij}$) and "unsolved" ($a_{ij} = NaN$). Unsolved cases correspond to when FCM has not been applicable because the previous track R_i finished before the current track R_j started, so the grade of membership may not be calculated. These additional situations will be solved in the next association stage.

Stage 3. Nearest Neighbor algorithm for fusion data: finally, the Nearest Neighbor algorithm [HL01] is recursively applied to the set of tracks to find a solution to the unsolved cases.

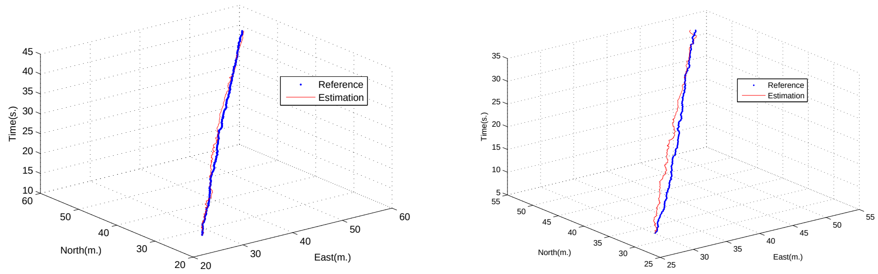
Track fusion will be performed in pairs, by grouping those tracks whose correlation value is higher. The resultant track of this association will be fused and the algorithm will recursively run until the association matrix indicates there are no correlated tracks. Let us remind the existing difference between sensors with different precision values. For this reason, information will be fused taking into account track data from the most accurate sensor.

4 Simulation Results

To validate our fusion mechanism some simulations have been performed. For this it has been used measurements of different sensors, which had been scattered in controled places. The following sensors have been used for the simulations: "volumetric sensor" (binary sensor), "buried sensor", precision values for this sensor include $15m$ for distance (σ_r), $5m/s$ for velocity (σ_v) and 10^o for detection angle (σ_θ), and "radar sensor", precision values for this sensor include $30m$ for distance (σ_r), $1m/s$ for velocity (σ_v) and 2^o for detection angle (σ_θ).

Below, a comparison between results using equations (2) and (1) respectively is given. The idea is to show that although binary sensors provide no information about the position and velocity of the detected objects, when the particle filter includes binary sensor information, the output of filter is more accurate than when such information is neglected. As it can be seen in Figure 2, solution (a) matches more accurately the reference trajectory than solution (b). This means a lower estimation error and a mayor effectiveness of the associa-

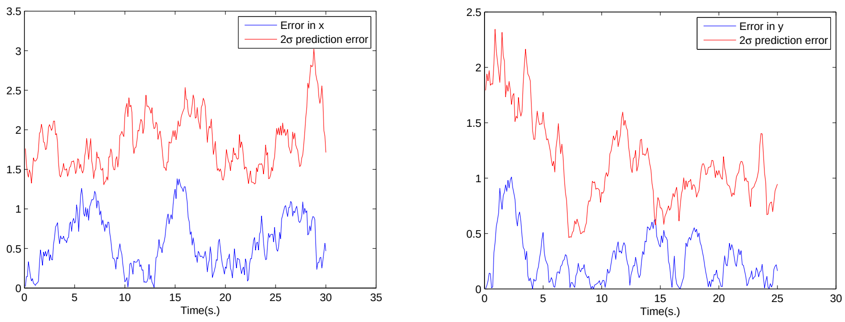
erschienen im Tagungsband der INFORMATIK 2011
Lecture Notes in Informatics, Band P192
ISBN 978-3-88579-286-4



(a) Estimation with binary sensor information. (b) Estimation without binary sensor information.

Figure 2: Estimations with different Particle Filters.

tion process. Figure 3 represents obtained errors with the Gauss-Markovian motion. Our solution meets the specified requirements, since position error is around $2.5m$ while the covariance matrix of the less accurate sensor shows a position error of $30m$.



(a) x coordinate position error estimation. (b) y coordinate position error estimation.

Figure 3: Position error estimations

5 Conclusion and future work

In this paper, a fusion architecture for a tracking system based on commercial sensors has been proposed. The goal is to enhance security in a given geographic area. In order to meet the requirements, presence and range sensors are used. Our work is focused on the solution of some problems derived from the use of sensors of different characteristics. For this purpose, an association mechanism is presented and simulations with different type of sensors are carried out. Simulations results show consistency, and problems of using low accuracy sensors are solved.

In the near future, field tests will be performed in order to collect data from a set of commercial sensors located in critical areas of different real scenarios. This information will validate the system proposed in this paper. A real time software application is being

erschienen im Tagungsband der INFORMATIK 2011
Lecture Notes in Informatics, Band P192
ISBN 978-3-88579-286-4

developed for the purpose of applying this method to real scenes.

Acknowledgment

This work has been carried out in frames of the grants from the Fundación Séneca "Assistance Program Excellence Groups 04552/GERM/06", "15493/FPI/10" and the project from the "PELGRIN CIPS/AG/C2-069" partially funded by the European Commision.

References

[ATC99] A.M. Aziz, M. Tummala, and R. Cristi.: Fuzzy logic data correlation approach in multisensor-multitarget tracking systems. *Signal Processing*, 76(2):195–209, 1999.

[Azi07] A.M. Aziz.: Fuzzy track-to-track association and track fusion approach in distributed multisensor-multitarget multiple-attribute environment. *Signal Processing*, 87(6):1474–1492, 2007.

[BH01] G. Borriello and J. Hightower.: A survey and taxonomy of location systems for ubiquitous computing. *IEEE Computer*, 2001.

[Bur98] P.A. Burrough et.al.: *Principles of geographical information systems*, volume 333. Oxford university press New York, 1998.

[BS90] Y. Bar-Shalom.: Multitarget-multisensor tracking: advanced applications. 1990.

[Dou00] A. Doucet et.al.: The unscented particle filter. *Cambridge University Engineering Department, Cambridge*, 2000.

[DVB08] P.M. Djuric, M. Vemula, and M.F. Bugallo.: Target tracking by particle filtering in binary sensor networks. *Signal Processing, IEEE Transactions on*, 56(6):2229–2238, 2008.

[FBT99] D. Fox, W. Burgard, and S. Thrun.: Markov localization for mobile robots in dynamic environments. *Journal of Artificial Intelligence Research*, 11(3):391–427, 1999.

[HL01] D.L. Hall and J. Llinas.: *Handbook of multisensor data fusion*. CRC, 2001.

[KLM08] N. Katenka, E. Levina, and G. Michailidis.: Robust target localization from binary decisions in wireless sensor networks. *Technometrics*, 50(4):448–461, 2008.

[RG02] H. Reichl and V. Grosser.: Overview and development trends in the field of mems packaging. In *Micro Electro Mechanical Systems, 2001. MEMS 2001. The 14th IEEE International Conference on*, pages 1–5. IEEE, 2002.

[SMH99] M. Sanchez, P. Manzoni, and Z.J. Haas.: Determination of critical transmission range in ad-hoc networks. *Proceedings of Multiaccess Mobility and Teletraffic for Wireless Communication 1999*.

[Tak02] M. Takeda.: Applications of mems to industrial inspection. In *Micro Electro Mechanical Systems, 2001. MEMS 2001. The 14th IEEE International Conference on*, pages 182–191. IEEE, 2002.

[Van01] R. Van et.al.: The unscented particle filter. *Advances in Neural Information Processing Systems*, pages 584–590, 2001.