Optimization of Multi-Target Tracking in a Multi-Agent Architecture with Multi-Sensor Data Fusion

Tahereh Koohi[1], Fatemeh K. Dehkordi[2], Ali Izadi-Pour[3], and Mehdi N. Fesharaki[4]
1- CE Department, Shahrood University, Shahrood, Iran
Email: tahere.koohi@gmail.com (Corresponding author)
2,3- Engineering Department, Ferdowsi University of Mashhad, Mashhad, Iran
Email: f.dehkurdy@gmail.com, ezadi.2007@gmail.com
4- CE Department, Science & Research Branch, Islamic Azad University (IAU), Tehran, Iran
Email: mehfesharaki@yahoo.com

Received: October 2014 Revised December 2014 Accepted January 2015

ABSTRACT:
This Article presents a Surveillance Multi-Agent System (S-MAS) architecture which focuses on the fusion of data from multi sensors for enhanced automotive safety and traffic efficiency. In S-MAS, tools will be introduced as autonomous agents for implementing a multi-sensor data fusion at architectural level: surveillance–sensor agents, a fusion agent, interface agents, record agents, planning agents, etc. They differ in their ability to carry out a specific surveillance task. A surveillance–sensor agent controls and manages individual sensors. In this work we focus on the fusion agent, addressing specific problems of on-line sensor alignment, registration, bias removal and data fusion. We show how the inclusion of this fusion agent guarantees that objects of interest are successfully tracked across the whole area.

KEYWORDS: Multi Agent Systems, Multi-Sensor Multi-Target Tracking, Random Set Sensor Data Fusion.

1. INTRODUCTION

With the increasing need for more security in airports [1], sea environments [2, 3], railways, underground [4-6], and other critical environments, the demand for surveillance system developments is growing rapidly [17]. Many of these systems require cognitive capabilities in vehicles and in the infrastructure as a key technological component to enhance safety and efficacy of them. For example, cognitive automobiles acquire data from their environment by video, radar, and lidar sensors. Based on an interpretation of this data, they build a mental model of the real world and are able to plan and conduct automated driving maneuvers or to assist humans in their driving task. As the potential roadmap of automotive sensors and functions depicted in Fig. 1 shows, the trend towards an increasing number of sensors and multi-sensor functions is not new to the automotive domain.

A surveillance system may suffer from biased estimation; an optimal estimator may lose its optimality when there are outliers or sensor anomalies. A way to overcome this shortcoming is the use of techniques that combine data from multiple sensors to achieve improved accuracies and more specific inferences than could be achieved by using a single sensor alone [18].

Multi-sensor platforms allow recognizing selected critical situations with a level of plausibility. In order to have a robust Recognized Operational Picture (ROP), one can generate a multi-sensor surveillance system with exploiting overlapped areas (redundancy) to get more accurate results and guarantee coherent monitoring in the global. So, in the contribution of this paper, we utilize multi-sensor data fusion to increase optimality of Multi-Target Tracking. We propose a systematic model for sensor fusion to help a vehicle *optimize* its underlying processes to achieve more efficient results. This model is discussed in detail below in Section 3.

In this paper, tracking of targets has been addressed in a random set based framework based on hard/soft fusion. To the best of our knowledge there has been no previous attempt to deploy Random Set Theory (RST) for fusion of soft/hard data, except Khaleghi et al.'s work [8]. In their proposed approach, the RST has been used to model fuzzy type-1 data as sets of infinite size in Kalman Evidential Filter (KEF) [9]. However the focus was on hard/soft data fusion application and not the novelty of approach; was deployed Mahler's KEF [9] to fuse hard/soft data. Further, in their employed scenario was not considered multi target tracking.

Recently has been proposed an approach based on RST, the MeMBer filter, which has showed advantageous properties over other filters such as particle filter, Kalman filter and (C)PHD filters [10]. MeMBer filter is an effective method which has properties such as high accuracy, cheap computation

and parallelizability. The Monte Carlo based MeMBer filter weights particle set based on a likelihood score and then propagates the weighted particle set according to a motion model. The use of the MeMBer filter allows the reliability of the sensors to be modeled easily. Hence, in this paper, has been extended MeMBer filter with a novel paradigm which especially increases the effect of map-updates in the field of view of multiple scanners. This approach is discussed in detail in Section 3. Furthermore, has been proposed an architecture which is logical framework of autonomous agents working in sensor network environments.
The rest of this paper is organized as follows: In section 2 we present the proposed surveillance multi-agent architecture. In section 3 we present the process of fusion algorithm. In section 4 we illustrate our experiments. In Section 5 we show the results. Finally, we conclude and bring the future work in section 6.

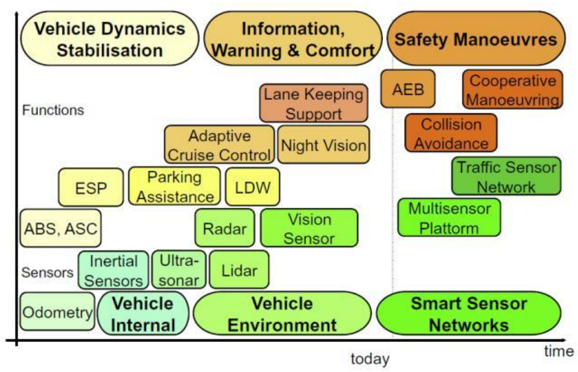

Fig. 1. Potential evolution of automotive sensors (green) and functions (orange) [7].

2. SURVEILLANCE MULTI-AGENT ARCHITECTURE

In this section, we give a brief description of the different types of autonomous agents [11], belonging to the multi-agent system (see Fig. 2):

- Surveillance-sensor agent: It tracks all the targets moving within its local FoV and sends data to the fusion agent. It is coordinated with other agents in order to improve surveillance quality. It can play different roles, each with different specific capabilities. The role may change at each time.
- Fusion agent: Fuses the data sent from the associated surveillance-sensor agents. It analyzes the situation in order to manage the resources and coordinate the surveillance-sensor agents. This agent has the global view of the environment being monitored by all the surveillance-sensor agents. It is in charge of creating the dynamic coalitions of surveillance-sensor agents using contextual information and the prediction of certain situations requiring a cooperative fusion process.
- Recorder agent: This type of agent has recording features only.
- Planning agent: It has a general view of the whole scene. It makes inferences on the targets and the situation.
- Interface agent: It provides a graphical user interface.

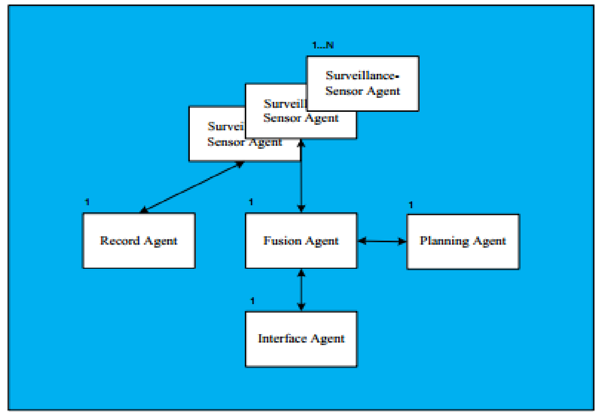

Fig. 2. Different types of agents in S-MAS

Fig. 3 depicts our proposed S-MAS architecture. It has two layers: (1) sensor layer, (2) fusion layer. In the sensor layer, each sensor is controlled by an autonomous agent. At this level, autonomous agents can cooperate with other agents (through dynamic coalitions) to use other agents' capabilities and carry out tasks that they are not able to achieve alone [12] or to improve upon such capabilities. In this paper, we develop a fusion layer in the S-MAS architecture. This layer includes a new fusion agent. This agent is in charge of fusing several sensor agents' data with the specific goal of achieving better performance or accuracy for specific surveillance tasks.

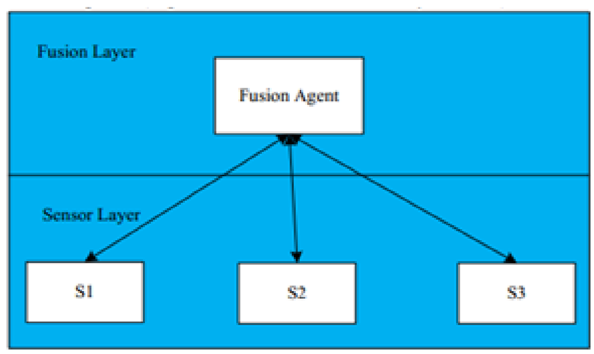

Fig. 3. The S-MAS logical layers. In the sensor layer, S1, S2 and S3 are examples of surveillance-sensor capabilities

In many surveillance systems, trajectory tracking is employed to identify individual objects and keep a temporary history of their evolution within the guarded areas. We show how our S-MAS architecture improves multi-target tracking by fusing data from several neighboring surveillance–sensor agents (e.g. camera agents in a visual sensor network), which are in a coalition. The main aim of the fusion agent is to solve tracking problems present with specific surveillance-sensor agents (e.g. false alarms, uncertainty in data).

3. DATA FUSION FOR MULTI-TARGET TRACKING ACROSS MULTIPLE SENSORS IN THE MEMBER FILTER

In this section we describe the fusion process for tracking multiple targets while the coalition is active. The coalition includes several surveillance-sensor agents and a fusion agent. Sensors (surveillance–sensor agents) are deployed with partially overlapped FoVs. This provides redundancy for smooth transitions across overlapped areas and continuity of targets across the whole area covered by the sensor network. The fusion process here is achieved in a MeMBer filter. The cyclic process of surrounded environment modeling is achieved with this filter in three phases of predict, match and update. In predict phase measurements of this filter are Random Finite sets. Hence, using the RST, in this section we explain the algorithm proposed in this work. The goal of tracking is to estimate the state of a dynamic system. The system might be comprised of a set of v subsystems, each of which has its own dynamics such that

$$X_t^1 = \{x_t^1, \ldots, x_t^n\}$$
$$\vdots \qquad (1)$$
$$X_t^v = \{x_t^1, \ldots, x_t^m\}$$

Where v is the number of sensors, and $n \neq m$.

The underlying idea of the MeMBer Filter implementation is similar to that employed in particle filter. The true vehicle state is estimated from a set of possible states (i.e. particles). The main difference with regard to particle filter is that the MeMBer filter does not evaluate the vector based likelihood of particles (in the conventional Bayesian sense), but their set based likelihood (in the RST sense). The algorithm is specifically conceived to simultaneously deal with multiple sensors. Hence, the set based likelihood of particles is evaluated using all the available sensors and finally fused.

We consider MeMBer filtering in a joint configuration proposal, as explained below. We can sample from the joint proposal distribution as

$$X_t^{(s)} \approx q(X_t) = \sum_r \pi_{t-1}^{(r)} P(X_t \mid X_{t-1}^{(r)}) \qquad (2)$$

And can weigh the samples according to the following expression:

$$\pi_t^{(s)} = P(M_t \mid X_t^{(s)}) \qquad (3)$$

Where M_t refers to a finite set representation of the scanned map.

4. EXPERIMENTS

The overlapped area exploited in this paper (illustrated in Fig. 4) is a scene in which scanners cover the path of moving vehicles. Both surveillance-sensor agents and a fusion agent establish a coalition in order to track the same object. In the shared area, the agents are simultaneously tracking the object, which is used by the fusion agent to align time-space coordinates and fuse their local tracks while the coalition is maintained. The overlapped regions are marked in Fig. 4. In this paper to show results we choose especially target separation metric (section 5).

5. RESULTS

Our approach is optimal in the sense that yields the minimum achievable probability of error rate. In order to measure optimality, we have considered a particle weight evaluation [13], which is based on optimal sub-pattern assignment (OSPA) [14].

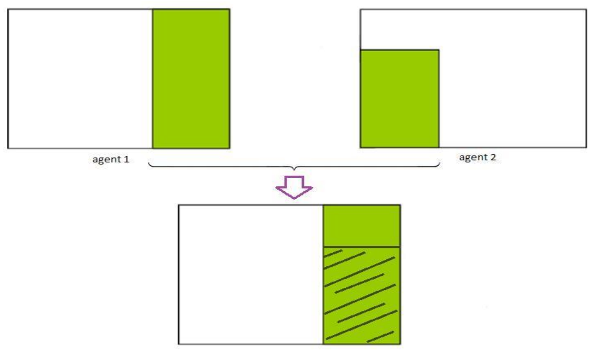

Fig. 4. Size and overlapping area of scanned maps with surveillance-sensor agents

It has been demonstrated to be most suitable metric in applying to finite-set-valued estimation error [15].

We have included soft data with $\alpha = 0.5$ probability. The confidence interval of soft/hard data fusion is 99.99988818%, obtained from 100 Monte Carlo iterations. To show the effect of fusion with the Multi-Sensor MeMBer filer the target separation metric has been obtained from this formula [16]:

$$\forall i,j \in targets, (i,j)=(j,i) \wedge i \neq j,$$

Target Separation Metric =

$$\frac{\sum \text{target pair separation metric}_{i,j}}{N_p} \times N_k \qquad (4)$$

Where N_p and N_k are the total number of target pairs and targets in the scenario respectively. The target-pair separation metric quantifies the ease with which a pair of targets can be distinguished from one another over the entire scenario run-time and is given by:

$$g(X_t) = \frac{\sum_{t \in samples} \text{Inter Target Score}_t^{(ij)}}{n}, \qquad (5)$$

Where n is the number of time instances.

$$\text{intertargetscore}_t^{(ij)} = \begin{cases} 0 & \text{if } \text{dist}_t^{(ij)} \geq r \\ 1 - \dfrac{dist_t^{(ij)}}{r} & \text{if } \text{dist}_t^{(ij)} < r \end{cases} \quad (6)$$

Where r is the inter-target distance threshold, and $\text{dist}_t^{(ij)}$ is the distance between target i and j at a given time t.

The results have been shown in Table 1 and present substantial improvement in tracking the targets.

Table 1. Target Separation Probability.

Target separation	With multi-sensor data fusion	Without multi-sensor data fusion
probability	0.89	0.79

The performance with increasing target separation probability increases. As can be seen in Table 1, the target separation probability has been increased when multi-sensor data fusion is added. The results show that the estimates with including multi-sensor data fusion in calculations are closer to the true value; so the estimations are less biased and more robust.

6. CONCLUSION AND FUTURE WORK

Multi-agent coordination enhances the continuous and accurate tracking of objects of interest within the area covered by a sensor network. In this paper we proposed a multi-agent architecture. This architecture enables global tracking in a sensor network. The main goal is to improve the knowledge inferred from the data captured by different surveillance-sensor agents, extending surveillance functionalities. In this paper, we detailed the specific process of data fusion in a fusion layer. The experiments showed the inclusion of this fusion agent guarantees that objects of interest are successfully tracked across the whole area. As ongoing work we are considering comparing the surveillance fusion process with other data fusion strategies.

7. ACKNOWLEDGMENT

The authors gratefully acknowledge the editor in Chief of Majlesi Journal of Telecommunication Devices Dr. Mohsen Ashourian.

REFERENCES

[1] M. E. Weber, M. L. Stone, **"Low altitude wind shear detection using airport surveillance radars"**, in: *Radar Conference, Record of the 1994 IEEE National*, pp. 52–57, 1994

[2] A. Pozzobon, G. Sciutto, V. Recagno, "**Security in ports: the user requirements for surveillance system"**, *Advanced Video-Based Surveillance Systems*, Kluwer Academic, 1998.

[3] P. Avis, **"Surveillance and Canadian maritime domestic security**", *Journal of Canadian Military*, Vol. 4, No. 1, pp. 9–15, 2003.

[4] B. P. L. Lo, J. Sun, S.A. Velastin, **"Fusing visual and audio information in a distributed intelligent surveillance system for public transport systems"**, *Acta Automatica Sinica*, Vol. 29, No. 3, pp. 393-407, 2003.

[5] C. Nwagboso, **"User focused surveillance systems integration for intelligent transport systems"**, *Advanced Video-Based Surveillance Systems*, Kluwer Academic, pp. 8–12, 1998

[6] N. Ronetti, C. Dambra, "**Railway station surveillance: the Italian case**", *Multimedia Video Based Surveillance Systems*, Kluwer Academic, pp. 13-20, 2000.

[7] Ch. Stiller, F. Puente-León, M. Kruse**, "Information fusion for automotive applications-An overview"**, *Information Fusion*, Vol. 12, pp. 244-252, 2011

[8] B. Khaleghi, A.Khamis and F. Karray**, "Random Finite Set Theoretic Based Soft/Hard Data Fusion with Application for Target Tracking"**, in *proceedings of IEEE International Conference on Multisensor Fusion and Integration for Intelligent Systems*, 2010.

[9] R.P.S. Mahler, **"Statistical Multisource Multitarget Information Fusion"**, Norwood, 2007

[10] B.-T. Vo, B.-N. Vo, Cantoni A., **"The cardinality balanced multi-target multi-Bernoulli filter and its implementations"**, *IEEE Transactions on Signal Processing*, Vol. 57, No. 2, pp. 409-423, 2009.

[11] F. Castanedo, J. Garcia, M.A. Patricio, J.M. Molina, **"Data fusion to improve trajectory tracking in a Cooperative Surveillance Multi-Agent Architecture**", in *Journal on Information Fusion*, Vol. 11, pp. 2243-255, 2010

[12] M.A. Patricio, J. Carbo, O. Perez, J. Garcia, J.M. Molina, "**Multi-agent framework in visual sensor networks"**, in *Journal on Advances in Signal Processing*, 2007.

[13] T. Koohi, A. Izadi-Pour and M.N. Fesharaki, "**MRF-based MeMBer Filtering for Multi-Sensor Multi-Target tracking in a biologically motivated Hard/Soft Fusion**", unpublished.

[14] D. Schuhmacher, B.-T. Vo, and B.-N. Vo, "**A consistent metric for performance evaluation of multi-object filters**", in *IEEE Trans. Signal Process*., Vol. 86, No. 8, pp. 3447-3457, 2008.

[15] J. Mullane, B.-N. Vo, M.D. Adams, and B.-T. Vo, "**Random Finite-Set Approach to Bayesian SLAM**", in *IEEE Transactions on Robotics*, Vol. 27, No. 2, 2011.

[16] G.-W. Ng, Tan, Ch.-H. Tan, Th.-P. Ng, Sh.-Yi. Siow, **"Assessment of Data Fusion Systems**", in *proceedings of 9th International Conference on Information Fusion*, Felorence Italy, 2006.

[17] T. Cho, Ch. Lee and S. Cho, "**Multi-Sensor Fusion with Interacting Multiple Model Filter for Improved Aircraft Position Accuracy"**, in *Journal of Sensors*, Vol. 13, pp. 4122-4137, 2013.

[18] Sh. Gao, Y. Zhong, and W. Li, "**Random Weighting method for multisensor Data Fusion**", in *Journal of IEEE Sensors*, Vol. 11. No. 9, 2011.