MULTI-TARGET, MULTI-SENSOR TRACKING BASED ON QUALITY-OF-INFORMATION AND FORMAL BAYESIAN FRAMEWORKS

Juo-Yu Lee, Kung Yao
Department of Electrical Engineering
University of California, Los Angeles,
California, USA
Emails: juoyul@ee.ucla.edu, kyao@ea.ucla.edu

***Abstract-** We consider a multi-target tracking problem that aims to simultaneously determine the number and state of mobile targets in the field. Conventional paradigms tend to report only the existence and state of targets according to centralized detection and data fusion. On the contrary, we investigate a multi-target, multi-sensor scenario in which (a) both the number and the state of the targets are unknown a priori; and (b) the detection with respect to targets is employed in a distributed manner. Toward this end, we exploit random set theory, a statistical tool based on Bayesian framework, for establishing generalized likelihood and Markov density functions to yield an iterative filtering procedure. We conduct a study regarding how the design of distributed detection has impact on the result of system level information fusion. The sources of analyzed data include (a) simulation-based sensor readings through bi-directional sensing/communication; and (b) practical images taken by multiple cameras through uni-directional sensing/communication. The formulation of Bayesian filtering suggests that a design of a tracking system be adaptive to change of detection performance.*

Index terms: Sensor networks, multi-target tracking, detection, random set theory.

I. INTRODUCTION

The development in sensor technology has increasingly led to the emergence of wireless sensor networks as a new family of system with wide variety of applications. With the ability of sensors to observe, process, and transmit data, they are well suited to perform event detection, which has been investigated extensively [7].

In this paper, we consider the applications of multi-target tracking. Our focus is on simultaneously estimating the number and the state (e.g. orientation) of mobile targets, within a 2-D plane. The targets act as signal sources, whose existence or non-existence is defined as an *event*. Imagine a number of sensor nodes are deployed into an environment to collect measurement data, i.e. signal and identity, broadcast by moving targets from underlying surroundings. The measured data can be processed at sensor level, and then forwarded to a fusion site where a system level decision is made. One of the central issues is that the dynamic render analysis difficult and lead to ad-hoc techniques to fulfil various system requirements. The lack of analytic framework hinders the fusion site from fully addressing general problems including miss detection, link failure and other disturbances.

To model disturbances such as miss detection, measurement noise, we employ random set theory (RST) that generalizes random variables to set domain. RST allows us to treat various sensing conditions, including miss detection and clutters, as random sets that has set density [4]. The approach resembles the way by which one operates on random variables. Specifically, one may utilize a statistical framework developed on RST, known as finite set statistics (FISST), to define a set function that depicts the mapping from set domain to real numbers [6]. Several statistics remain legitimate in FISST such as maximum a posteriori (MAP) estimator, maximum likelihood (ML) estimator. What needs one's caution is that, although expectation of a set function exists in FISST, expectation of a random set is ill-defined in set theory.

As a joint approach to estimation, detection and data fusion, RST thus provides performance that depends on several systematic parameters. The probability of detection (P_d) and probability of false alarm (P_f) are among important ones that have been studied broadly in the realm of sensor networks [1], [2], [3], [5]. Previous literature in RST-based data fusion usually implicitly adopts the concept that P_d and P_f are constant or known a priori through elusive means. Such assumption, though simplifying evaluation of data fusion algorithms, becomes questionable since the detection of mobile targets with respect to static sensors, as well as P_d and P_f, are time-varying. Non-constant P_d and P_f invites the following question: how the design of detection schemes has impact on system level data fusion? Hence, the study and choice of detection rules in sensor networks constitutes the second theme of this paper.

The authors of [1] have investigated centralized and distributed detection schemes in sensor networks. The centralized strategy achieves the best detection accuracy overall, while consuming much more energy for data transmission than the other. On the contrary, the distributed scheme asymptotically approaches optimal detection accuracy with the increase of the number of sensors and the amount of measured data at each sensor. In [5], the author presented an evaluation of P_d and P_f, termed as quality-of-information (QoI), in the application of sensor network deployment. A QoI-centered analysis demonstrates the detection performance of finite-sized sensor networks.

In this paper, the underlying detection scheme is similar to that in [5], which accommodates general network topology. Up at the system level, the fusion site attains aggregated QoI, i.e. P_d and P_f, and enables its data fusion algorithms.

The remainder of the paper is organized as follows: In Section II we review RST and the QoI-based distributed detection. Section III outlines the formalism of RST-centered iterative algorithm. Section IV evaluates the system-wide tracking result based on the performance of employed detection strategies. We choose target orientation as the state of our interest and to be estimated. Such case may find its crucial application in the design of human-computer interface [8]. Finally, the paper is concluded in Section V.

II. RANDOM SET THEORY

In this section we review RST [4]. A finite random set is a mapping $\mathbf{X}: \Omega \rightarrow F(S)$ from the sample space Ω to the collection of closed sets of the space S, with $|\mathbf{X}(w)| < \infty$ for all w in Ω. Here the space S of finite random sets is assumed to be the hybrid space $S = V \times U$, the direct product of the multi-dimensional Euclidean space V and a finite discrete space U. In our example, we choose $R \bmod (2\pi)$ as the first component V to model target orientation, and the positive integer set as the second component U to represent sensor ID.

The very fundamental of RST is the concept of belief function of a random set $\mathbf{X}$. This is defined as $\beta_{\mathbf{X}}(O) \equiv P(\mathbf{X} \subset O)$, where O is a subset of ordinary multi-target state space, $O \subset S$. The density of the belief function is defined as its set derivative, in a generalized Radon-Nikodym sense [4]. Set derivatives can be computed and result in the relevant properties of standard density functions of probability theory [6].

Let Z denote a random set describing the collective observations received at the fusion site from all sensors. Suppose that the maximum number of sensors is M. The random set Z belongs to the following macro-set:

$$\{\phi, \{z\}, \{z_1, z_2\}, \ldots, \{z_1, z_2, \ldots, z_M\}\} \tag{1}$$

To systematically compute the set density function, the first step is to partition the random set down into a finite union of smaller random sets, where each smaller random set has a maximum cardinality of one. Thus Z is partitioned as follows [4]:

$$Z = Z_1 \cup Z_2 ... \cup Z_M \tag{2}$$

where $|Z_i| \leq 1$, $i = 1, 2, \ldots, M$. Z_i represents the report received by the fusion site from sensor i, where Z_i belongs to $\{\emptyset, \{z_i\}\}$, and has the form (*orientation*, *id*).

Let O (S) denote the collection of closed subsets of S. The set density function f: O (S) → $[0,\infty)$ at a point Z in S is defined as [4]

$$f(z) = \frac{\partial \beta}{\partial Z}(S)\Big|_{S=\phi} = \frac{\partial \beta}{\partial z_1 ... \partial z_k}(S)\Big|_{S=\phi} \tag{3}$$

where Z is a k-element set.

The set integral of f over the closed subset $S \subset \mathbf{S}$ is given by [4]

$$\int_S f(Z)\partial z = f(\{\phi\}) + \sum_{k=1}^{\infty} \frac{1}{k!} \int_{S^k} f(\{z_1, ..., z_k\}) dz_1 ... dz_k \tag{4}$$

where $f(\{z_1, \ldots, z_k\}) = 0$ if $z_1, \ldots, z_k$ are not distinct (and hence the set has less than k elements). Since we are dealing with *finite* random sets, the summation above contains only a finite number of terms.

Let Θ be a random set that denotes target state information. Similarly Θ has the form $\{\emptyset, \{\theta\}\}$. For example, to compute the likelihood function with respect to sensor i and θ, the state information of some target, one first constructs the following belief function:

$$\begin{aligned} &\beta_i\ (S \mid \Theta) = 1 - P_d + P_d P(z \in S \,\|\, S| = 1, \theta) \\ &P_d = P(|S| = 1 \mid \theta) \end{aligned} \tag{5}$$

Then one can derive the density function as:

$$f_i(Z_i \mid \theta) = \begin{cases} 1 - p_d, Z_i = \phi \\ p_d f_i(z), Z_i = \{z\} \end{cases} \tag{6}$$

$$f_i(z) = \frac{dP(z \in S \,\|\, S| = 1, \theta)}{dz} \tag{7}$$

We assume the fusion site knows the associate between observation and sensor ID, and sensors originate the observation independently. Then the global density function available at the fusion site is:

$$f\ (Z) = f_1(Z_1)\, f_2(Z_2)...f_M(Z_M) \tag{8}$$

III. DECISION MAKING FOR DETECTION

In this section we discuss the detection schemes as similarly proposed in [2], [5]. Equation (5) reveals that the probability of detection (P_d) depends on the state of targets. In this subsection, we assume a general, though simple, topology as suggested by [5] and a model that allows each sensor node to independently observe, process and transmit data. Measurements are independently and identically distributed (*i.i.d.*), conditioned on a certain hypothesis H, at each single node and inter-sensor level; each sensor node sends data to the fusion site via a single hop. Notice that sensors address detection of targets based on the underlying signal-to-noise ratio (SNR). Later we will explain how sensors compute orientation according bearing (angle) information.

Here we first focus on one single target. Since time synchronization is beyond the scope of this paper, we assume all local clocks of sensors have been aligned to that of the fusion site. Let d_k be the distance that a signal takes from the target (event) location to sensor k, $1 \le k \le M$. Based on simple free-space propagation model with negligible delay, the signal (power) seen by sensor k when target's transmitter is on, excluding measurement noise, is approximately:

$$s_k = \frac{PW_0 d_0^2}{d_k^2} \tag{9}$$

where PW_0 is the emitted power from the target measured by sensor k at distance d_0. Though Equation (9) represents a simple model, the simulator [9] that we work on has taken propagation into account.

The first main step is to base the analysis on hypothesis testing, i.e. considering binary hypotheses target presence, (hypothesis H_1) vs. target absence (hypothesis H_0). The traditional formulation of binary hypothesis testing for a single sensor system is as follows [5]:

$$\begin{aligned} H_1 &: r_i = s_i + n_i;\ i = 1, 2, \ldots; \\ H_0 &: r_i = \quad\ \ n_i;\ i = 1, 2, \ldots; \end{aligned} \tag{10}$$

Here s_i represents the value of the signal at the i-th sampling instance under hypothesis H_1, and n_i represents an additive noise component under both hypotheses. Moreover, r_i represents the i-th measurement that is contributed to the associated sensor. A decision is made based on the likelihood ratio test (LRT) with threshold $\eta = P_0/P_1$, received signal vector $\mathbf{r} = [r_1,\ldots, r_{|r|}]$, (source) signal vector $\mathbf{s} = [s_1,\ldots, s_{|s|}]$, noise signal vector $\mathbf{n} = [n_1,\ldots, n_{|n|}]$, covariance matrix $\mathbf{C} = E[\mathbf{n}^\mathbf{T}\ \mathbf{n}]$ and the sufficient statistics $l \equiv \mathbf{r}^\mathbf{T}\ \mathbf{C}^{-1}\ \mathbf{s}$. (Notice that the vector length |r| = |s| = |n|.) The probability of detection P_d and the probability of false alarm P_f can be derived [5], with Φ representing the cumulative distribution function of a $N(0,1)$ random variable.

$$P_d = 1 - \Phi\left(\frac{\ln(\eta)}{SNR} - \frac{SNR}{2}\right) \quad (11)$$

$$P_f = 1 - \Phi\left(\frac{\ln(\eta)}{SNR} + \frac{SNR}{2}\right) \quad (12)$$

In [10], the authors discuss a distributed detection scheme based on a hierarchical architecture. Each sensor first determines local QoI based LRT, and the fusion site makes global decision based on a counting policy. Stating alternatively, the fusion site asserts the detection of a target if at least τ out of M sensors claim so. Let S_q^M denote the subset all groups of sensors that have cardinality q, and x_q the subset in S_q^M. Assume at some time instance, the local QoI with respect to sensor k is $\{P_d, P_f\}$. Then the system-wide QoI $\{P_d(\tau; M), P_f(\tau; M)\}$ is given by:

$$P_d(\tau;M) = \sum_{q=\tau}^{M}\{\sum_{x_q \in S_q^M}[(\prod_{k\in x_q} P_d^k)(\prod_{k\notin x_q}(1-P_d^k))]\} \quad (13)$$

$$P_f(\tau;M) = \sum_{q=\tau}^{M}\{\sum_{x_q \in S_q^M}[(\prod_{k\in x_q} P_f^k)(\prod_{k\notin x_q}(1-P_f^k))]\} \quad (14)$$

IV. TARGET ORIENTATION MEASUREMENT

From the perspective of geometry, one may realize that the orientation can be determined unambiguously between two devices once their mutual specific topological configuration is identified. To see how one successfully determines the relative orientation, the basic configuration of our scheme consists of two devices that can mutually communicate with each other. Each device is also capable of dealing with (approximately) simultaneous, with respect to the sampling period, incoming multiple signals. As shown in Figure 1, sensor $\boldsymbol{sn}_i$ measures $\boldsymbol{u}_{ij}$, the relative bearing of target $\boldsymbol{tg}_j$. Similarly, target $\boldsymbol{tg}_j$ measures $\boldsymbol{u}_{ji}$, the relative bearing of sensor $\boldsymbol{sn}_i$. Devices $\boldsymbol{sn}_i$ and $\boldsymbol{tg}_j$ communicate and exchange their observation of neighboring nodes. Once both devices recognize mutual sensing relation has been established, they can individually calibrate the relative orientation. Let $\mathbf{R}_{ji}$ denote the *relative rotation* matrix that transforms a bearing in the coordinate system of $\boldsymbol{tg}_j$ into that of $\boldsymbol{sn}_i$.

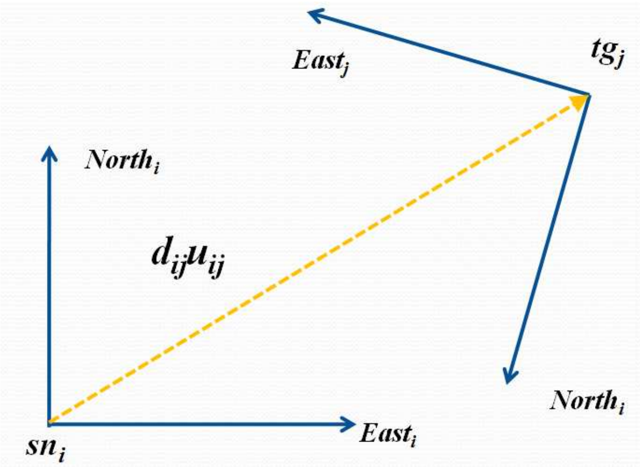

Figure 1. Two devices determine the relative orientation by mutually making relative bearing measurements. The relative range and bearing is also shown in the figure.

$$u_{ij} = -R_{ji} u_{ji} \tag{15}$$

Without loss of generality, R_{ji} has the following form:

$$R_{ji} = \begin{bmatrix} \gamma & \omega \\ -\omega & \gamma \end{bmatrix} \tag{16}$$

Consider the decomposition of $\boldsymbol{u}_{ji}$ $[\boldsymbol{u}_{ji,1}, \boldsymbol{u}_{ji,2}]^T$. Thus the sensor can solve $\mathbf{R}_{ji}$ by recognizing that **t**he transpose of the first row in $\mathbf{R}_{ji}$ satisfies Equation (17).

$$u_{ij} = \begin{bmatrix} u_{ji,1} & u_{ji,2} \\ u_{ji,2} & -u_{ji,1} \end{bmatrix} \begin{bmatrix} \gamma \\ \omega \end{bmatrix} \tag{17}$$

One can construct the proof as follows. The determinant of the coefficient matrix in Equation (17) is non-zeros since $\boldsymbol{u}_{ji}$ is a unit vector. The unit norm of [γ ω] is preserved in Equation (17), as can be seen from Equation (18).

$$1 = |u_{ij}|^2 = (\gamma^2 + \omega^2)|u_{ji}|^2 = (\gamma^2 + \omega^2) \tag{18}$$

The fact that $\mathbf{R}_{ji}$ is unitary follows immediately.

Once sensor $\boldsymbol{sn}_i$ has determined its orientation $\mathbf{R}_i$ in a global coordinate system, it can also compute the orientation $\boldsymbol{tg}_j$, $\mathbf{R}_j$, based on the following equation.

$$R_i = R_{ji}^T R_i \tag{19}$$

Then the orientation can be transformed from matrix to scalar (angle) information.

V. FUNCTION OF RANDOM SET CORRESPONDING TO TWO TARGETS

Here we consider two targets that are far enough apart that their randomness is independent of each other. The attained observation associated with two targets can be modeled as a randomly varying two point set of the form $\Psi = \{\mathbf{Z}_1, \mathbf{Z}_2\}$ where $\mathbf{Z}_1$, $\mathbf{Z}_2$ are random scalar variables. Miss detection is not considered here since both targets are assumed quite 'visible' to sensors. The belief function describing that Ψ will be contained within S, given some multi-target state random set Θ, is [4]:

$$\begin{aligned} &\beta_\Psi(S \mid \Theta) = \Pr(\Psi \subseteq S \mid \Theta) \\ &= \Pr(\{Z_1, Z_2\} \subseteq S \mid \Theta) = \Pr(\{Z_1 \in S, Z_2 \in S \mid \Theta) \\ &= \Pr(Z_1 \in S \mid \Theta) \Pr(Z_2 \in S \mid \Theta) \end{aligned} \tag{20}$$

The corresponding set density function is defined by

$$f_\Psi(Z \mid \Theta) \equiv \begin{cases} 0 & if \quad Z = \phi \\ 0 & if \quad Z = \{z\} \\ \begin{array}{l} f_{Z_1}(z_1) f_{Z_2}(z_2) \\ + f_{Z_1}(z_2) f_{Z_2}(z_1) \end{array} & if \quad Z = \{z_1, z_2\} \quad z_1 \neq z_2 \\ 0 & if \quad otherwise \end{cases} \tag{21}$$

Now we consider two well-separated targets but miss detection occurs with certain probability. They can be considered to be statistically independent with different probability of detection. The two targets are mathematically modeled as the union $\Psi = \Psi_1 \cup \Psi_2$ where Ψ_1, Ψ_2 are statistically independent and where

$$\begin{aligned}\Psi_1 &= \phi^{p_1} \cap \{Z_1\} \\ \Psi_2 &= \phi^{p_2} \cap \{Z_2\}\end{aligned} \tag{22}$$

The discrete random set $Ø^p$ is defined by

$$\Pr\ (\phi^p = S) \equiv \begin{cases} 1-p & if \quad S=\phi \\ p & if \quad S=[0,2\pi)\times U \\ 0 & if \quad otherwise \end{cases} \tag{23}$$

Then one can derive belief function describing, given some multi-target state random set Θ, is [4]:

$$\begin{aligned}&\beta_\Psi(S\mid\Theta) = \Pr(\Psi \subseteq S\mid\Theta)\\ &= \Pr(\Psi_1 \subseteq S, \Psi_2 \subseteq S\mid\Theta)\\ &= \Pr(\Psi_1 \subseteq S\mid\Theta)\cdot\Pr(\Psi_2 \subseteq S\mid\Theta)\\ &= (1-p_1+p_1\cdot p_{Z_1}(S\mid\Theta))(1-p_2+p_2\cdot p_{Z_2}(S\mid\Theta))\\ &= (1-p_1)(1-p_2)+p_1(1-p_2)p_{Z_1}(S\mid\Theta)\\ &+ p_2(1-p_1)p_{Z_2}(S\mid\Theta)+p_1p_2p_{Z_1}(S\mid\Theta)p_{Z_2}(S\mid\Theta)\end{aligned} \tag{24}$$

The corresponding density function is defined as

$$f_\Psi(Z\mid\Theta) \equiv \begin{cases} (1-p_1)(1-p_2) & if \quad Z=\phi \\ p_1(1-p_2)f_{Z_1}(z) + p_2(1-p_1)f_{Z_2}(z) & if \quad Z=\{z\} \\ p_1p_2(f_{Z_1}(z_1)f_{Z_2}(z_2) + f_{Z_1}(z_2)f_{Z_2}(z_1)) & if \quad Z=\{z_1,z_2\} \quad z_1 \neq z_2 \\ 0 & if \quad otherwise \end{cases} \tag{25}$$

To perform multi-sensor data fusion, one may apply equations similar to Equation (8), given that independence property holds.

Let μ_0 be the expected number of new targets, $b(\theta)$ their physical distribution, and p_s the probability such that a target with state Θ' survive into time step t+1. The corresponding true Markov density can be evaluated as [6]:

$$f_{t+1|t}(\Theta\mid\Theta') = e^{\mu_0} f_B(\Theta)\, f_{t+1|t}(\phi\mid\Theta')\sum_{\zeta}\prod_{i:\zeta(i)>0}\frac{p_s(\theta_i')\, f_{t+1|t}(\phi\mid\Theta')}{(1-p_s(\theta_i'))\mu_0 b(\theta_{\zeta(i)})} \tag{26}$$

$$f_B(\Theta) = e^{-\mu_0} \prod_{\theta \in \Theta} \mu_0 b(\theta) \tag{27}$$

$$f_{t+1|t}(\phi \mid \Theta') = e^{-\mu_0} \prod_{\theta' \in \Theta'} (1 - p_s(\theta')) \tag{28}$$

Here ζ depicts the association hypotheses between the previous state set Θ' and new state set Θ.

VI. RST-BASED BAYESIAN FILTERING

With the set up as shown in the last subsection, the target states can be updated via formal Bayesian filtering [6]: initialization, prediction and error correction, which may be viewed as generalization of Kalman filtering. Essentially, we argue that Kalman filter does not deal with ad-hoc situation such as missed-detection. In this case data is missing and cannot contribute to usefulness of information fusion. The RST-based filter is implemented by realizing particle approximation. Values around zero are rounded into the miss-detection case. By doing so, tiny and spurious peaks in density function can be removed.

Again, the density function may be factorized as shown in Equation (8), given that independence property holds. One then can employ RST version of Bayesian filter given as

$$\begin{aligned} f_{t+1|t+1}(\Theta_{t+1} \mid Z^{(t+1)}) &= \frac{f(Z_{t+1} \mid \Theta_{t+1}) f_{t+1|t}(\Theta_{t+1} \mid Z^{(t)})}{\int f(Z_{t+1} \mid Y_{t+1}) f_{t+1|t}(Y_{t+1} \mid Z^{(t)}) dY_{t+1}} \\ f_{t+1|t}(\Theta_{t+1} \mid Z^{(t)}) &= \int f_{t+1|t}(\Theta_{t+1} \mid \Theta_t) f_{t|t}(\Theta_t \mid Z^{(t)}) d\Theta_t \end{aligned} \tag{29}$$

where $Z^{(t)} = \{Z_1, \ldots, Z_t\}$ is the collected report sequence.

VII. EVALUATIONS

In our simulation, we use a uniformly distributed 4 (i.e. M=4) sensors over 40 by 40 meters square ([-20, 20] × [-20, 20]). To model source signal transmission and decay, parameters in Equation (9) is set as d_0=1 and PW_0 = 160. The noise variance for each sensor in Equation (10) is $\sigma_n^2 = 0.5$.

The traces of the orientation with respect to two targets are shown in Figure 2. Target #1 starts from (15.8189 *m*, -39.7809 *m*) at *t*=1 second, rotates clockwise for 18 seconds, and then disappears. The position of target #1 varies according to a cut arc, and so does target #2. At *t*=11 seconds, target #2 starts from (-16.5418 *m*, -16.2695 *m*) and rotates clockwise for 19 seconds. If the target trigger its transmitter less frequently such that $\eta = P_0/P_1 = 2$ and $\tau = 4$ are chosen, the result is shown in Figure 3. An obvious amount of mismatches appear because of poor QoI. If η=2 and τ =2 are chosen (Figure 4), the tracking performance improves to some extent. In Figure 5, η=0.5 and τ =2 are used that yield some mismatches. In Figure 6, η=0.5 and τ =4 are used that improves the tracking performance. The following adaptive detection policy is suggested [11]: as $\eta = P_0/P_1$ increases above 1, a threshold τ satisfying $M/2 > \tau > 1$ may be chosen. On the contrary, the threshold τ satisfying $M/2 < \tau < M$ may be selected as η decreases below 1. As η and QoI vary, different density function (Equation (21) or (25)) may interchangeably describe appropriate model for underlying dynamic system and serve as a set of flexible filtering tools.

One should notice that, periodicity of angular variable demands that, in strict sense, one place multi-mode Gaussian distribution over bearing estimation [13]. According to such convention, a Gaussian-distributed angle Z ($-\pi \leq Z \leq \pi$) with mean μ_z and variance σ_z^2 satisfies ($-\pi \leq z_1 \leq \pi$, $-\pi \leq z_2 \leq \pi$)

$$\Pr(z_1 \leq Z \leq z_2) = \sum_{l=-\infty}^{l=\infty} \int_{z_1+2l\pi}^{z_2+2l\pi} N(z;\mu_z,\sigma_z^2)dz \tag{30}$$

In another experiments, to track the orientation of moving targets (humans), we first consider the empirical results reported in [12]. The statistics of (face) orientation detection with respect to the observed targets can be established based on retrieved data (images, Figure 7) from multiple cameras and the computer vision analysis outlined in [12]. In such case, the orientation of targets is determined through uni-directional sensing and communication, as opposed to the bi-directional procedure described in Section IV. In [12] the authors described a Kalman-filter based method to track the orientation of one moving person. On the contrary, we consider multiple moving humans monitored by a set of distributed and networked cameras, and data fusion based on RST that can address miss detection in Bayesian framework.

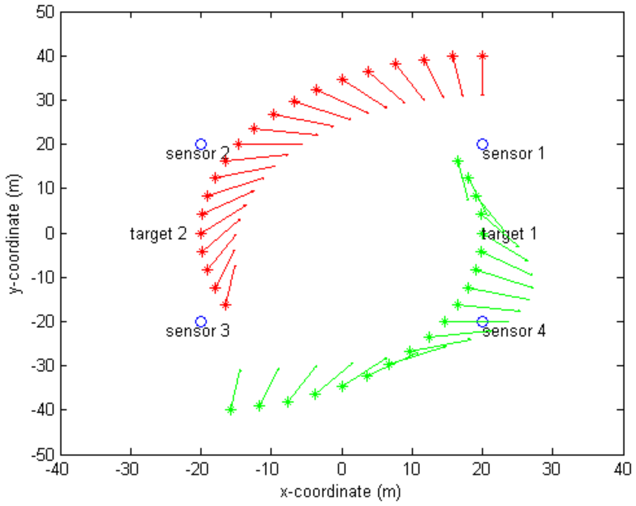

Figure 2. Trace of orientation.

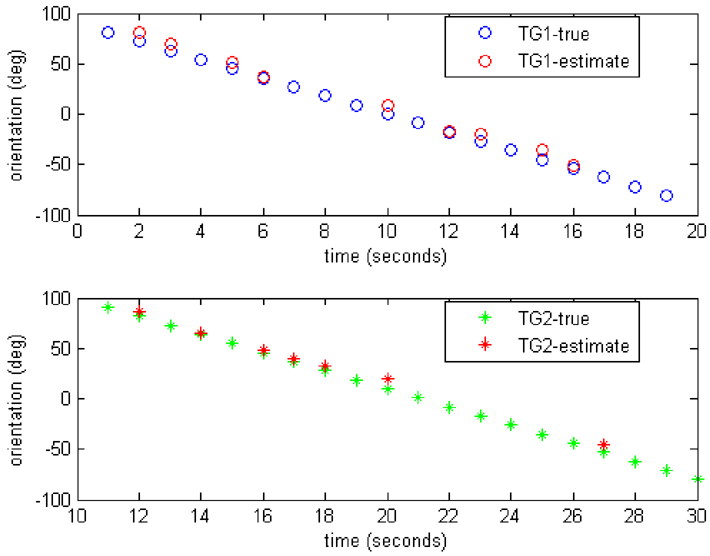

Figure 3. Tracking performance: $\eta = 2$, $\tau = 4$.

VIII. CONCLUSIONS

In this paper, we have studied the problem of multi-target tracking in a multi-sensor system. The underlying statistic tool to address data fusion problem is random set theory (RST) and its derived framework, known as finite set statistics (FISST). Instead of assuming that the system-wide probability of detection (P_d) and probability of false alarm (P_f), regarding mobile targets, are fixed and arbitrary determined through elusive means, we incorporate a QoI-based scheme [5] that is reflective of real time detection performance of deployed sensor systems. We discover that the fusion algorithm should respond to time-varying detection performance and be adaptive in order to choose different model. For example, when attained QoI is nearly ideal (P_d ->1, P_f ->0), density function in the form of Equation (21) may be applied. When attained QoI is poor, Equation (25) may be applied. To attain consistent result, more sensors in use are generally preferred in order to achieve better QoI. However, concerning power consumption, a smaller set of sensors can be chosen first. If the attained QoI is poor, more sensors may be included to provide higher QoI and better results of data fusion algorithm.

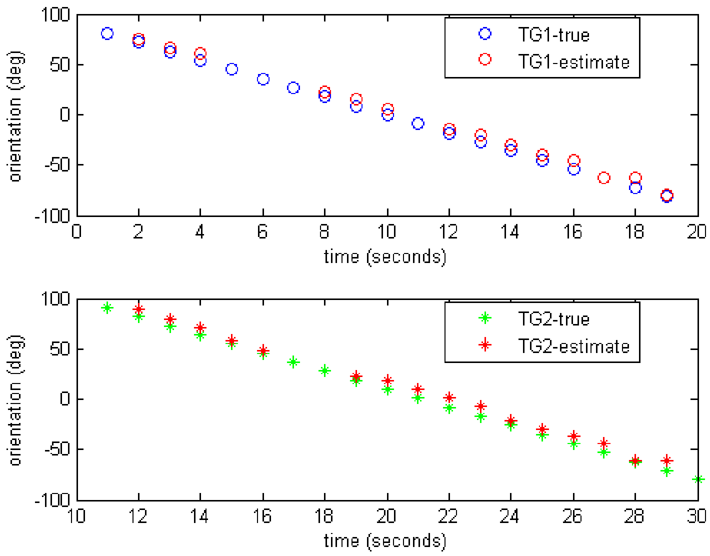

Figure 4. Tracking performance: η= 2, τ =2.

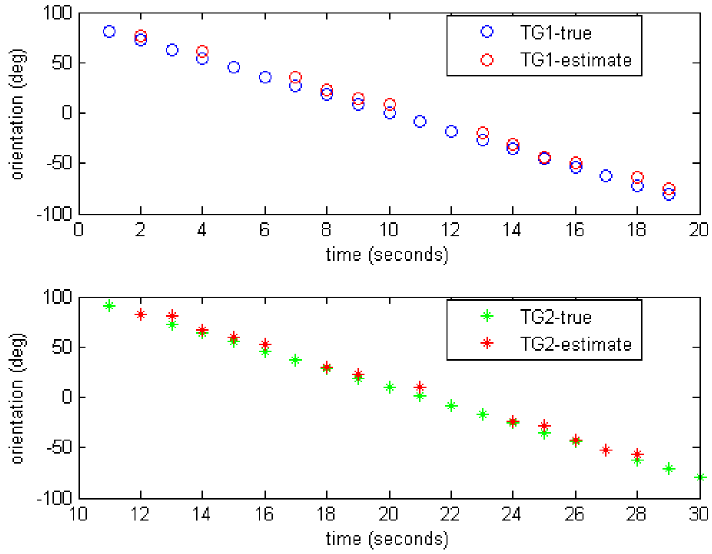

Figure 5. Tracking performance: $\eta = 0.5$, $\tau = 2$.

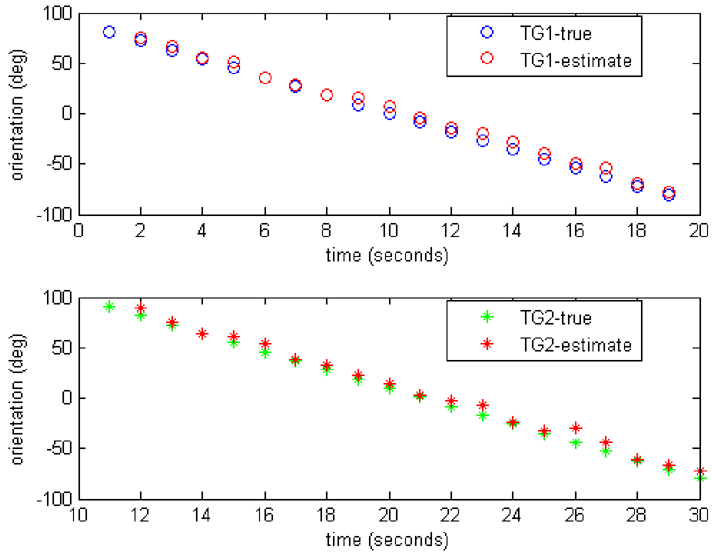

Figure 6. Tracking performance: $\eta = 0.5$, $\tau = 4$.

Figure 7. Target (human face) orientation may be analized based on the images retrieved via a distributed sensor (camera) network.

REFERENCES

[1] L. Liu, A. Ephremides, "*Energy-Driven Detection Scheme with Guaranteed Accuracy*", IPSN 2006.

[2] C. Bisdikian, "*On sensor sampling and quality of information: A starting point*", Proc. IEEE PerSeNS Workshop, White Plains,NY,USA, March 19, 2007.

[3] Y. Sung, S. Misra, L. Tong, A. Ephremides, "*Cooperative routing for distributed detection in large sensor networks*", IEEE Journal on Selected Areas in Communications 25(2), 2007.

[4] I. R. Goodman, R. Mahler, H.T. Nguyen, "*Mathematics of Data Fusion*", Kluwer Academic publication, 1997.

[5] C. Bisdikian, "*Quality of information trade-offs in the detection of transient phenomena*", In SPIE Unattended Ground, Sea, and Air Sensor Technologies And Applications IX Conference, Orlando, FL, USA, April 9-13 2007.

[6] R. Mahler, "Statistical *Multisource-Multitarget Information Fusion*", ARTECH HOUSE publication, 2007.

[7] J. -F. Chamberland and V. V. Veeravalli, "*Decentralized Detection in Sensor Networks,*" *IEEE Trans. on Signal Processing*, 51(2): 407-416, February 2003.

[8] C.Chang, H. Aghajan, "*Linear Dynamic Data Fusion Techniques for Face Orientation Estimation in Smart Camera Networks*", ICDSC 2007

[9] Simon, G.; Volgyesi, P.; Maroti, M.; Ledeczi, A, "*Simulation-based optimization of communication protocols for large-scale wireless sensor networks*", Aerospace Conference, 2003. Proceedings. 2003 IEEE

[10] Sadaf Zahedi, Chatschik Bisdikian, "*A framework for QoI-inspired analysis for sensor network deployment planning*," International Workshop on Performance Control in Wireless Sensor Networks, PWSN , October 2007.

[11] Jonathan Friedman, Zainul M Charbiwala, Thomas Schmid, Young H Cho, Mani B Srivastava, "*Angle-of-Arrival Assisted Radio Inteferometry (ARI) Target Localization*," Proceedings of MILCOM 2008

[12] C.Chang, H. Aghajan, "Linear Dynamic Data Fusion Techniques for Face Orientation Estimation in Smart Camera Networks", ICDSC 2007

[13] S. Funiak, C. Guestrin, M. Paskin, and R. Sukthankar. "*Distributed localization of networked cameras*", Proceedings of IPSN 2006.