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Robust Multi-Bernoulli Sensor Selection for Multi-Target Tracking in Sensor Networks

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Abstract—This paper addresses the sensor selection problem for tracking multiple dynamic targets within a sensor network. Since the bandwidth and energy of the sensor network are constrained, it would not be feasible to directly use the entire information of sensor nodes for detection and tracking of the targets and hence the need for sensor selection. Our sensor selection solution is formulated using the multi-Bernoulli random finite set framework. The proposed method selects a minimum subset of sensors which are most likely to provide reliable measurements. The overall scheme is a robust method that works in challenging scenarios where no prior information are available on clutter intensity or sensor detection profile. Simulation results demonstrate successful sensor selection in a challenging case where five targets move in a close vicinity to each other. Comparative results show the superior performance of our method in terms of accuracy of estimating the number of targets and their states.

Index Terms—multi-Bernoulli filter, PHD filter, random set theory, finite set statistics, sensor selection.

I. INTRODUCTION

ESTIMATION and tracking of multi-target states, using a network of sensors with communication constraints is a challenging problem. The main challenge stems from the fact that while highly reliable measurements are required by multi-target tracking solutions, due to bandwidth and energy constraints of the sensor network, the system may need to select an optimal subset of sensors to communicate with, from which it is most likely to receive high quality target-related observations. This problem is termed sensor selection [1].

Most sensor selection solutions predict the quality of measurements provided by sensor nodes before initiating the communication with those sensors. The results of those predictions are then used to compute an objective function for selecting the desirable sensor(s) that is expected to provide the most informative measurements. A common approach is to quantify the information embedded in the existing observations and use that as a reward [2], [3]. One possible choice for this reward function is the statistical mean of Rényi divergence between predicted and updated distributions [3], [4].

Information theoretic methods are mostly formulated in partially observed Markov decision process (POMDP) framework using a myopic approach. A set of candidate sensors generate synthetic measurements that are used to update the multi-target state distribution and compute the reward associated with each candidate. The most informative candidate is then selected based on its reward [3], [4].

In this paper, we propose a new sensor selection solution for multi-target tracking, which similar to [3], [5] is formulated using the Finite Set Statistics (FISST) framework. Our contributions are two-fold. Firstly, our method does not need any prior information about the distribution of clutter measurements or the uncertainty in the sensor field of view. Secondly, with multi-Bernoulli assumptions for the random set state distribution, and within the adaptive multi-Bernoulli filtering scheme of [7], we have been able to define a novel cost function that is directly relevant both to error of state estimation and to error of estimation of the number of existing targets (cardinality of the multi-target set state). Simulation results for a challenging multi-target tracking scenario showed that our sensor selection method can successfully select the sensors with most informative measurements and its estimation errors were less than competitive methods.

II. SENSOR SELECTION PROBLEM

Consider a POMDP defined as the tuple

\[ \Psi = \{ X_k, S, \pi_k|k-1(X_k|X_{k-1}), g_k(z|x), \vartheta(X_{k-1}, s, X_k) \} \]

where \( k \) denotes the time step, \( X_k \) is a finite set of target states, \( S \) denotes a finite set of sensor nodes for selection, \( \pi_k|k-1(X_k|X_{k-1}) \) represents the multi-target dynamics modeled as multi-target state transition density, \( g_k(z|x) \) is a single-target measurement model, and \( \vartheta(X_{k-1}, s, X_k) \) is an objective function that returns a reward or cost for transition from the multi-object state \( X_{k-1} \) to the state \( X_k \), given that the sensor node \( s \in S \) is selected.

The aim of sensor selection is to find the candidate sensor node \( \hat{s} \) that optimizes the statistical mean of the objective function (cost or reward),

\[ \hat{s}_k = \arg\min_{s \in S} \max_{s \in S} \{ \mathbb{E}_{X_{k-1}, X_k} \left[ \vartheta(X_{k-1}, s, X_k) \right] \}. \quad (1) \]

This work presents a new sensor selection based on a novel objective function formulated in the adaptive multi-Bernoulli filtering framework of [7]. A brief overview of this filtering scheme is presented in section II-A.

A. Adaptive multi-Bernoulli filtering

Unlike the PHD-based filters which are moment approximations [12], the multi-Bernoulli filters are density approximations and are characterized by the probability of existence of a possible element and the probability density function of the state of that element \( \left\{ \left( r^{(i)}, p^{(i)} \right) \right\}_{i=1}^{M} \) [8], [9].

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Vo et al. [7] have recently tackled the problem of multi-Bernoulli filtering for cases with unknown clutter intensity and detection probability profile. In their solution, the detection probability was augmented to the multi-target state, and propagated in time. A set of clutter generators was used to create hypothetical targets (with Poisson distribution) associated with clutter measurements. The transition and observation models for the clutter-associated targets were taken to be similar to actual targets. Two types of targets form a hybrid space $X = X^0 \cup X^1$ where the $0$ and $1$ superscripts denote the space of clutter-associated and actual targets, respectively. Their augmented multi-target state includes a state $a$ (denoting the probability of detection) and a multi-Bernoulli set state $X$.

The multi-Bernoulli random set of targets is the union of an ensemble of $M$ Bernoulli sets, each having a probability of existence, $r^{(i)}(u)$, and two single-object densities denoted by $p^{(i)}(u)(a,x)$ where $u = 1$ corresponds to objects that are actual targets, and $u = 0$ corresponds to clutters.

In this method, the prior multi-target distribution at time $k - 1$ is used by the prediction step at time $k$ that incorporates models of the dynamic and birth of targets and clutter generators. The multi-target distribution is then updated using current sensor measurements. In the following section, we explain how the above method can be modified to incorporate a sensor selection step.

III. ADAPTIVE MULTI-BERNULLI SENSOR SELECTION

Our sensor selection solution is based on adding a few steps between the prediction and update steps of the adaptive multi-Bernoulli filter described in Section II-A. In this method, when the predicted multi-Bernoulli state is computed, for each sensor node $s \in S$, the distribution of all states is updated. Since no measurement is yet available and we are not in the position of acquiring all measurements (hence the need for sensor selection), we use the MAP estimates of all measurements for the next update. This measurement estimate depends both on node location and on the predicted state [5].

For each sensor node, the updated multi-object distribution at time $k$ is denoted by \{ $(r^{(i)}(s), p^{(i)}(u)(s)) \}_{i=1}^{M_k}$ where each density $p^{(i)}(u)(s)$ is approximated by a set of particles \{ $(a^{(i)}(u)(s), x^{(i)}(u)(s)) \}_{i=1}^{L^{(i)(u)}}$ with weights \{ $w^{(i)}(u)(s)$ \}_{i=1}^{L^{(i)(u)}}$ for the sake of brevity, henceforward, $s$ is suppressed from the notation.

In our approach, sensor selection is conducted by minimizing a novel cost function that can be defined and computed for every sensor node. The proposed cost directly quantifies the statistical mean of an error term over all possible updated multi-object states. The error term is a linear combination of average uncertainties in cardinality estimates, target state estimates, and estimated clutter intensity. The EAP estimate of the number of targets is given by $E(|X|; s) = \sum_{i=1}^{M_k} r^{(i)(1)}$ and its uncertainty, quantified by its variance, is

$$\sigma^2_{|X|}(s) = \sum_{i=1}^{M_k} \left[ r^{(i)(1)} \left( 1 - r^{(i)(1)} \right) \right].$$

The second term is indicative of average error in estimating the targets states. Note that we may be only interested in minimizing the average error of some state components. For instance, in the case study presented in the next section, only the variance of location of targets is considered as important.

To quantify the uncertainty in single object state estimates, we first compute the average error of state estimates for each Bernoulli component, from the updated distribution:

$$\sigma^2_{x,i} = \sum_{j=1}^{L^{(i)(1)}} w_k^{(i,j)} (x_k^{(i,j)(1)} - \hat{x}_k^{(i,j)(1)})^2 \quad (3)$$

where $(\cdot)^2$ is performed component-wise over the components of interest. The total error can be normalized by dividing with the weighted average of the errors of single Bernoulli components, where the weights are the updated $r^{(i)(1)}$'s,

$$\sigma^2_{s} = \sum_{i=1}^{M_k} \frac{E_{k}^{(i)(1)} \sigma^2_{x,i}}{\sum_{i=1}^{M_k} E_{k}^{(i)(1)}} \quad (4)$$

The variance of the clutter intensity estimate can be approximated by updated particles for generated clutter samples:

$$\sigma^2_{\lambda} = \sum_{i=1}^{M_k} \left[ r^{(i)(0)} \sum_{j=1}^{L^{(i)(0)}} \left( r^{(i,j)} - r^{(i)(0)} \right) \right] \quad (5)$$

where $r^{(i,j)} = w_k^{(i,j)(0)} a_k^{(i,j)(0)}$ [7]. The proposed objective function is defined as the following cost comprising a weighted sum of the three error terms:

$$\bar{\eta}(s) = \eta_{|X|} \sigma^2_{|X|}(s) + \eta_s \sigma^2_{s}(s) + \eta_{\lambda} \sigma^2_{\lambda}(s) \quad (6)$$

where the positive weights $\eta_{|X|}, \eta_s$, and $\eta_{\lambda}$ are user-defined importance weights for minimization of each of the variances and are positive values. To have a normalized weighted sum of the error terms in the cost, the weights are chosen to satisfy $\eta_{|X|} + \eta_s + \eta_{\lambda} = 1$. In low-to-medium clutter applications, the precision of the clutter intensity estimate is of less priority. Thus, in such applications, it is reasonable to put more emphasis on the weight of the variance of the number of targets and their states ($\eta_{|X|}$ and $\eta_s$). The sensor node is then chosen by minimizing the above cost function:

$$\tilde{s} = \arg\min_s \bar{\eta}(s). \quad (7)$$

IV. SIMULATION RESULTS

A challenging non-linear multi-target tracking scenario, similar to the one reported in [3], was employed to evaluate the performance of the proposed adaptive multi-Bernoulli sensor selection method. In this scenario, the sensor network was composed of sensor nodes laid out uniformly over a square of size $1000m \times 1000m$ divided into $50m \times 50m$ blocks. Each sensor regularly scans the surveillance area and returns a set of bearing and range measurements corresponding to detected targets, each in the form of $z_k = [\theta_k, R_k]^T$. A total of five targets appear in the scene and maneuver in the surveillance area. One of the challenging aspects of this scenario is that (due to energy and bandwidth constraints), the central processor is restricted to communicate and receive only one sensor measurement set for multi-target detection.
and tracking purposes. At each time step, \( k \), the set of sensor nodes, \( S \), that are examined for sensor selection, is comprised of the previously chosen node \( \hat{s}_{k-1} = [x_{s_{k-1}}, y_{s_{k-1}}]^T \), and its horizontal and vertical neighboring nodes up to two blocks. The initially selected sensor node starts from \( \hat{s}_0 = [0, 0]^T \).

**Measurement model:** The measurement data is synthetically generated according to the following distance-dependent detection probability:

\[
p_{D}(s, \tau) = \begin{cases} 
1, & \text{max}\{0, 1 - \beta(|y - s| - R_0)\} \\
\text{otherwise} \end{cases} \tag{8}
\]

where \( s = [x_s, y_s]^T \) and \( \tau = [x, y]^T \) denote the locations of the sensor node and target, respectively, \( ||\cdot|| \) denotes Euclidean distance in 2D space, and \( R_0 = 320 \, \text{m}, \beta = 25 \times 10^{-5} \, \text{m}^{-1} \).

Note that the \( p_{D}(s, \tau) \) is not assumed available and in our simulations it is only used to generate the synthetic measurements. Each synthetic point measurement \( z = [\theta, \mathcal{R}]^T \) in a scan (in case of detection) includes a bearing component \( \theta = \sqrt{(\tau - s) + \epsilon_\theta} \) and a range component \( \mathcal{R} = ||\tau - s|| + \epsilon_{\mathcal{R}} \), where \( \epsilon_\theta \) and \( \epsilon_{\mathcal{R}} \) denote samples of i.i.d. Gaussian measurement noise with zero mean. The angle measurement noise power is assumed to be constant at \( \sigma_\theta = \pi/180 \), but the noise power for range measurements linearly increases with range,

\[
\sigma_{\mathcal{R}} = \sigma_0 + \eta||\tau - s||^2 \quad \sigma_0 = 1\text{m}, \eta = 5 \times 10^{-5} \, \text{m}^{-1}. \tag{9}
\]

**Target states and their dynamic model:** At any time \( k \), each single target state is comprised of the unknown detection probability, location and velocity components in \( x \) and \( y \) directions, and detection type label \( u_k \in \{0, 1\} \), together denoted by \( [a_k, x_k, y_k, \dot{x}_k, \dot{y}_k, u_k]^T \). The targets are positioned relatively close to each other in the surveillance area and their initial locations and velocities are at \([800, 600, 1, 0]^T, [650, 500, 0.3, 0.6]^T, [620, 700, 0.25, -0.45]^T, [750, 800, 0, 0.6]^T, \) and \([700, 700, 0.2, 0.6]^T\), where the units of \( x \) and \( y \) are meters and \( \dot{x} \) and \( \dot{y} \) are m/s.

Actual targets move according to the constant velocity model [10], in which the transition density of target location and speed is given by a Gaussian density with the same parameters as used in [3]. The transition density of the augmented state, \( a_k \), is assumed to be a beta distribution [7]. The survival probability for actual objects is fixed thorough a value of 0.98 for probability of detection, which contrasts to the ground-truth value of 0.10 and fluctuate around it with a relatively small standard deviation.

**Results:** The proposed adaptive multi-Bernoulli sensor selection method was used to compute the number and locations of all targets for a sequence of 35 steps. In each step, one node of the sensor network was selected to communicate with a central processor where the scan provided by that node was used to update the multi-target state and to extract estimates for the number of targets and their states. As it was mentioned earlier, the initially selected node was at the origin. The sensor selection method is expected to select the sensor nodes that are closer to existing targets, ending up with selecting the nodes located in the vicinity of the targets. The rationale behind this expectation is two-fold: Firstly, the noise power for range measurements increases with the distance—see equation (9). Secondly, the detection probability decreases for large distances—see (8). Thus, more accurate measurements are expected from closer sensors.

Figure 1 shows how our method selects sensor nodes that become closer to the five targets in the scene as the time evolves. It is important to note that sensor selection converges early at \( k = 15 \) and during the rest of the time, the selected node does not change within more than one block. The evolution of selected sensor nodes has also been demonstrated in a recorded video of the code run in MATLAB (attached as supplemental material).

As it is observed in Fig. 1 and in the supplemental video, the selected sensor node ends up in the center of the targets area where it has the least distance from the targets and hence, acquires most accurate range measurements. In order for this phenomenon to be clearly observable, in our simulations, the targets do not move apart substantially so their center point is quasi-stationary. However, if this was not the case, the selected node would be still tracking the center point of the five targets.

![Fig. 1: Sensor selection during 35 scans.](image)

![x: sensor nodes, ○: candidate nodes evaluated in one of the scans, ●: selected nodes, ★: initial target locations, ■: final target locations.](image)
sensor-target distance—see equation (8).

From Fig. 2(b), we observe that in terms of estimating the cardinality, the proposed selection method leads to better accuracy, as the averaged cardinality estimates over 200 MC runs of the scenario are closer to the ground-truth number of 5 targets. The superior performance of our method mainly lies in its adaptive nature. Indeed, in the absence of accurate knowledge of the measurement process, inaccurate assumptions for measurement process parameters would lead to inaccurate results and frequently missed targets. This is while without the need for such prior information, our method intrinsically adapts the multi-target filtering process to work best with the measurements received from the selected node.

To evaluate the estimation accuracy, we computed the OSPA miss-distances [11] with parameters \( p = 2 \) and \( c = 100 \). Fig 3 presents comparative results for the performance of our method against the state-of-the-art methods. The compared methods are the multi-Bernoulli [5] and CPHD-based [3] sensor selection methods both with fixed clutter intensity and detection probability profile.

For the CPHD filtering-based sensor selection method, the correct detection profile is given to the filter and clutter intensity is assumed to be equal to 2 (higher clutter intensities failed to converge). These results confirm that the proposed method significantly outperforms the state-of-the-art techniques in terms of estimation accuracy.

Another significant advantage of the proposed method is its computational cost which is substantially lower than the competing methods. The reason is that in contrast to sensor selection methods that are based on information theoretic objective functions, our method does not need to sample the space of measurement sets and to repeat the update computations for each sample [5]. This means significant savings in computation, as the creation and processing of numerous MC samples of measurement sets is no longer needed in our method. Furthermore, extracting cardinality and single-target state estimates from distributions is straightforward in a multi-Bernoulli scheme, compared to PHD and CPHD filtering-based methods where clustering is needed.

**V. Conclusion**

The problem of multi-target tracking in a large sensor network with bandwidth and energy constraints was studied. A novel solution was presented in which a new criterion (in the form of a cost function) was introduced to select a minimum subset of sensors which are most likely to provide the most informative measurements. The proposed solution is based on the robust multi-Bernoulli filter. The objective function is comprised of three terms, each quantifying uncertainties in the multi-Bernoulli filter estimates. Those terms are estimates of cardinality, object states and clutter intensity. The proposed sensor selection method is shown to work in challenging multi-target applications in which for the sensor nodes of the network, no prior information is available on their clutter intensity or their field-of-view parameters. Simulation results show that the proposed technique is able to select the sensors in locations where most accurate measurements can be acquired, leading to accurate estimates of the number of targets and their states and better detection of clutters compared to state-of-the-art techniques.

**References**


