Multi-target detection and estimation with the use of massive independent, identical sensors

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ABSTRACT

This paper investigates the problem of using a large number of independent, identical sensors jointly for multi-object detection and estimation (MODE), namely massive sensor MODE. This is significantly different to the general target tracking using few sensors. The massive sensor data allows very accurate estimation in theory (but may instead go conversely in fact) but will also cause a heavy computational burden for the traditional filter-based tracker. Instead, we propose a clustering method to fuse massive sensor data in the same state space, which is shown to be able to filter clutter and to estimate states of the targets without the use of any traditional filter. This non-Bayesian solution as referred to massive sensor observation-only (O2) inference needs neither to assume the target/clutter model nor to know the system noises. Therefore it can handle challenging scenarios with few prior information and do so very fast computationally. Simulations with the use of massive homogeneous (independent identical distributed) sensors have demonstrated the validity and superiority of the proposed approach.

Keywords: Target detection, multiple target tracking, sensor fusion, non-Bayesian method

1. INTRODUCTION

Multi-object detection and estimation (MODE), also referred to as multi-target/object tracking, involves the joint estimation of the number of multiple objects and their states in the presence of clutter. The realistic MODE scenario can be described as follows: an unknown and time-varying number of objects evolve in terms of spontaneous appearance, disappearance (including merging and splitting) and random movement (of possible high maneuver) both in the state space and in the time, affected by an unknown and time-varying level of clutter and noise. Both the objects and the clutter can be detected or missed by the sensors with an unknown probability.

The general MODE solution, whether for a single object or multiple objects, is to establish a hidden Markov model (HMM) where the system being modeled is assumed to be a Markov process with hidden state. A Bayes filter or approximately, such as the Kalman filter, Gaussian sum filter, particle filter and their extensions, can be employed for recursive estimation over time. The Bayes filtering of the prediction-correction format has been well demonstrated in the field for decades. However, a variety of models (and parameters) are involved with the targets (including appearance/disappearance/ deformation and target evolving dynamics), sensors (e.g. miss-detection), clutter and noises (e.g. state process noise, clutter density, observation noise) etc. in the filtering framework. In real life, these models and parameters are often time varying and unknown, which poses critical challenges for any filter. The performance of a filter depends greatly on the coinciding degree between the real system and the models assumed, see e.g. [1-5]. However, it is not easy to identify these models and parameters in practice but 'approximate' assumption has to be conducted.

It has been well acknowledged that all filters suffer from modelling errors [6-8]. The importance of the model to the Bayes filter cannot be overstated. Consequently, model assessment [9], performance assessment [10], outlier treatment [11], adaptive and robust technologies [12-15] for time-varying models have been developed. In the presence of a high maneuver (the motion model of targets is unknown and highly time varying), the filter can easily fail even in the case of a single target. To maximally reduce the mismatching between the model used and the real one, considerable efforts have been devoted into maneuvering target tracking for which the model and the states of targets need to be estimated jointly. An efficient solution in this aspect is using multiple models to represent the motion of targets and adaptively interact between them, such as interacting multiple model (IMM) [16] and so on [4, 5]. The parameter can be treated as a

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component of the state [13] or separately estimated based on the underlying observation [14]. Nevertheless, it is still very challenging to deal with the general MODE scene of very high maneuvering where both the system noises and the models are possibly highly time varying and completely unknown.

Even when the models are established correctly and there is no system disturbance, the correspondence between the observations and the targets in the clutter environment is ambiguous and prevents the direct use of a filter. The way in which this correspondence (referred to as data association) is identified distinguishes two main groups of existing solutions. First, the traditional solutions decompose the MODE problem into multiple sub-problems of single object detection and estimation (SODE) based on data association [1, 8]. In this framework, the data association as well as the detection of the targets (determining the number of real targets over time; an issue that does not occur in SODE) is the key to determining the filtering result. Secondly, state-of-the-art solutions include incorporating finite set statistics-based point process modeling [17] to the (approximate) Bayesian filtering framework. Significantly differently, our approach is sensor-oriented and is free of Bayes filtering.

Furthermore, with the rapid development of sensors, massive sensors are becoming available in practice that can provide us a greater breadth of observation information regardless of the individual sensor failure. While this will increase the capability of the system for better observability, it can also cause heavy computational burden for the filters. The topic of multi-sensor data fusion has been intensively investigated [18]. According to our knowledge, most existing MODE solutions only use/deal with a few sensors (e.g. lesser than 10 sensors), except in the case of tracking based on sensor network [19-20] where different combinations of sensors are used at different areas (but few have overlapping view field). These implementations that may perform well in well-defined environments are still far from reaching the advanced MODE realization. This paper is particularly concerned with the challenging albeit favorable use of a large number of independent identical sensors in the unknown and time-varying environment.

The present approach does not need to make any assumption about the target (regarding to appearance, disappearance and dynamics), clutter density and system noises, as it is free of the use of any traditional filter. Therefore, it is insensitive to the target/clutter model and is extremely fast computationally. This however is based on the favorable case of massive sensors. The present solution can also be very accurate if the sensors are of high quality or if the number of sensors is large. Although multiple sensors have been investigated intensively within the target-tracking content with the use of filters [18-20], it is for the first time exploited, jointly in a large number, for MODE without the use of any filter. More comprehensive information is available in our preprint [21].

The paper is organized as follows. Sections 2 and 3 present the brief idea of the observation-only (O2 or O_2) inference and massive sensor O2 inference respectively. Simulation comparison with the state of the art multi-target tracking solution is given in Section 4 before we conclude in Section 5.

2. O2 INFERENCE: CONVERTINTG OBSERVATIONS INTO THE STATE SPACE

Loosely speaking, the greater the assumption, the more unreliable the tracker. In contrast, a tracker that makes fewer model assumptions will be better able to achieve the desired results in practice. Therefore, we develop a sensor-oriented solution that infers the estimate directly from the observations received by massive independent homogeneous sensors with no assumption on the target/clutter model and system noises. In this paper, we illustrate the O2 inference with regard to particular sensors commonly used for target tracking.

O2 inference

As sensors perform periodic scans, the observation function $h_t(\cdot)$ is generally formulated in discrete-time as

$$z_t = h_t(x_t, v_t) \tag{1}$$

where t indicates the discrete time-instant (positive integer), x_t denotes the state, z_t denotes the observation namely sensor data, v_t denotes the observation noise.

It is necessary to point out that a more general situation would include an unknown observation function. This (unknown sensory case) however is rare in the target tracking content and is omitted here. The observation function is arguably an indispensable requirement for the utilization of the observations in any estimator and has to be identified before target-state estimation. We do not include this case for avoiding distraction from the key contribution of the paper.

A straightforward way to estimate the state is to infer directly from its observation, regardless of the unobserved state model and clutter, namely the O2/O_2 inference. It can be conceptually written as follows (as long as it is invertible):

$$\hat{x}_t = h_t^{-1}(z_t, v_t) \tag{2}$$

where h_t^{-1} is the inverse function of h_t in real variable space.

This simply maps/converts the observations into the state space, with a deterministic accuracy that is consistent to the quality of the sensors. However, the inversing will often introduce biases (i.e. the expectation of the estimate is not equal to the true state) if $h_t(\cdot)$ is nonlinear; the higher the nonlinearity, the larger the bias/error. Simply, a nonlinear conversion of a Gaussian distribution is no more Gaussian and therefore the situation can be very complicated. This has been recognized when converting polar/spherical measurements to Cartesian coordinates for the use of filters, see e.g. [22, 23]. To a degree, the converting bias/error can be removed explicitly for simple inversing function and noises (such as Gaussian noises). However, when the noise v_t is unknown, a natural solution is setting it to be zero. Then, Eq. (2) reduces to

$$\hat{x}_t = h_t^{-1}(y_t, \mathbf{0}) \tag{3}$$

If the observation noise is known, we propose to use a sampling method to remove the inversing bias/error as follows. The idea is sampling a group of (random or deterministic) samples from the noise distribution $v_t^{(i)} \sim p(v_t), i = 1,2, \dots I$ and use them as noises separately in the inversing calculation of (2) as

$$\hat{x}_t^{(i)} = h_t^{-1}\left(y_t, v_t^{(i)}\right), i = 1,2, \dots I \tag{4}$$

Then, we have the unbiased (debiased) estimate as the mean of these sample-estimates as

$$\hat{x}_t = \frac{1}{I}\sum_{i=1}^{I} \hat{x}_t^{(i)} \tag{5}$$

Obviously, the sampling is unbiased and will avoid the bias caused by the nonlinear inversing, regardless the type of noises and the observation function. This is much simpler and more efficient than the analytical approximate methods given in [22, 23] and the references therein.

It is worth noting that the observation function may be irreversible, preventing the direct inversing calculation; further discussion is given in [21]. Instead of a comprehensive discussion on this fundamental mathematical problem, this paper focuses on the observation functions used in the target tracking content only. Because of this, the inversing issue is limited to a few typical models for which observation inversing is relatively simple.

The O2 inference using range-bearing sensor

Range-bearing sensor (e.g. active radar): the observation is a noisy range and bearing vector, given by

$$z_t = \begin{bmatrix} r_t \\ \theta_t \end{bmatrix} = \begin{bmatrix} \sqrt{\left(p_{x,t} - S_{x,t}\right)^2 + \left(p_{y,t} - S_{y,t}\right)^2} \\ \arctan\left(\frac{p_{x,t} - S_{x,t}}{p_{y,t} - S_{y,t}}\right) \end{bmatrix} + v_t \tag{6}$$

where $[p_{x,t}, p_{y,t}]$ and $[S_{x,t}, S_{y,t}]$ are the $x - y$ position of the target and the sensor in the Cartesian coordinate system respectively, and v_t is the observation noise.

To implement the O2 inference, one estimate can be inferred by inversing Eq. (2) after taking off v_t, leaving

$$\begin{bmatrix} p_{x,t} \\ p_{y,t} \end{bmatrix} = +/- \begin{bmatrix} \tan(\theta_t)\sqrt{\frac{r_t^2}{1+\theta_t^2}} \\ \sqrt{\frac{r_t^2}{1+\theta_t^2}} \end{bmatrix} + \begin{bmatrix} S_{x,t} \\ S_{y,t} \end{bmatrix} \tag{7}$$

As shown, inversing the arctan function involves a sign problem. Often, the state is bounded in a positive/negative state space (since the coordinate system is built by the user with respect to the sensors used, thus allowing the user avoid this problem easily) as shown in our simulation, so the sign is known. Otherwise at least two active sensors distributed at different positions will be needed, and the sign of the estimate can be determined by the triangular relationship among the target and two sensors. One pulsed radar and one forward-looking infrared imaging sensor can work together to measure the range and bearing information separately, equivalent to one active radar.

We omit here more other types of sensors such as bearing-only sensor, camera and Doppler sensor, whose observation can be under-determined (one bearing-only sensor is not enough to determine the position of targets) or irreversible. Further discussion of this can be partly found in [21] and will appear in our future work. One active range-bearing sensor is adequate to conduct O2 inference, while at least two passive bearing-only sensors located at different positions are required to serve as *one adequate sensory unit* for estimating. We note that, the estimates obtained by nonlinear inversing as shown in (7) is biased, although generally the bias is insignificant when the target is far from the sensor and when massive sensors are used.

It is necessary to note that the O2 approach only estimates the dimensions of the state that have been observed, while the unobserved dimensions will be further inferred through the observed dimensions based on their physical relationship. Typically, the differentiation of the position is the velocity, and the differentiation of the velocity is the acceleration. If only the position of an object is observed (e.g. range and bearing observations), the O2 inference can only directly provide the position estimate; the same occurs when only the velocity is observed (e.g. Doppler observation). Note that it is the same story in filters where the unobserved dimensions of the state are also inferred from the observed dimensions.

3. MASSIVE SENSOR O2 INFERENCE

In addition to the use of massive independent identical sensors with known observation function, we consider the following very general assumptions (A.1-3):

(A.1) Each target generates observations independently of others and one target generates no more than one observation at each scan of each sensor (extended target is not involved);

(A.2) The clutter distribution is independent of the target and shall not concentrate locally more significantly than the observations of targets;

(A.3) The target detection probability given by sensors is not too low.

Clutter filtering based on unsupervised clustering

As addressed so far, the direct application of the O2 inference on the sensor data of massive sensors will generate a huge number of observations that include the undistinguished observations of real targets and false alarms because of the clutter. The key task required for MODE as compared with SODE to distinguish the real observations of each individual target from each other and from the false alarms, for which we will develop an unsupervised online clustering procedure. Since the observations of the same target given by different sensors will concentrate at the same area while false alarms will not, we have the following criterion to distinguish the observations of real targets from false alarms:

Criterion 1 *The observations are of high density in the area containing targets and of low density in other areas.*

Therefore, we can confirm target existence in the area of high density of observations. The observations from different sensors lying in the same high-density area are more likely from the same or close targets. For illustration purposes, an example is given in Fig.1 and 2. Fig.1 gives the observations (green 'x') reported in six independent identical active radars and Fig.2 gives all the observations reported from ten active radars in the same state space. Intuitively, the real observations can be distinguished from false alarms based on the spatial distribution of the data points. To deal with this, we are proposing here a clustering method based on unsupervised learning of the sensor data as follows (more detail of the multi-source data clustering is separately given in [24]).

Algorithm 1 Clutter filtering based on clustering

1) Apply the O2 inference on all observations as addressed in Section 2, obtaining undistinguished data-points (including state-estimates of targets and false alarms) in the same space.

2) Calculate the distances between any two data-points from different sensors. Data-points from different sensors will be identified as connected if their distance is smaller than a threshold $d = l \times \sigma_v$ (where σ_v estimates the standard deviation of the observation noise in the state space, and we use a scaling parameter $l \in [1,4]$).

3) Since data-points in the same cluster can be from a single target or multiple close targets, a detection of the number of data-points in each cluster shall be applied to distinguish isolated targets from close-targets. Here, another

threshold p is needed to give the average number of data-points in a single cluster that contains one target. It shall be designed with respect to N e.g. $p = 0.8 \times N$ in our simulation. The static parameter 0.8 is scalable for fine adjustment.

-3.1) If a data-point has been connected with more than p but smaller than $2 \times p$ other data-points, the data-point and its connections will be identified from a single target, forming a sub-cluster to extract one estimate.

-3.2) If a data-point has been connected with more than $k \times p$ (but smaller than $(k+1) \times p$ where $k \geq 2$) other data-points, that data-point and its connections are identified from multiple targets. Then, these connected data-points will be partitioned into $k+1$ groups based on their proximities in the state space, each of which has approximately p but no more than N data-points that shall all come from different sensors; See Remark 2.

Remark 2. The state-estimates of close-distributed targets, inferred from the same sensor shall be clustered into different groups even they are closely distributed in the space, namely cannot link (CL) constraint on the estimates from the same sensor (see [24]). Therefore, there shall be only one estimate in each sub-cluster that is from the same sensor. The obtained sub-clusters will have approximately equivalent number of data-points. In our current application, there are few targets ($k \leq 3$) moving closely, therefore making the partitioning of the cluster relatively easy. Close-target is also a very challenging problem for the filter-based multi-target tracker [25].

Given that the independent identical estimates from real targets are distinguished from false alarms in the above clustering process, the next is to fuse these estimates for each individual target as one single final estimate. Based on the independent identical property of these sensors, the final position estimate of each target can just be given as the mean of the corresponding estimates. By clustering, the proposed massive sensor O2 inference for MODE without the use of any filter is able to handle miss-detection and clutter (false alarms). In addition, the O2 inference almost surely have a faster computational speed than any filter, which is highly preferable in practice [21]. However, we do not emphasize this in our simulation study but the filter and the O2 inference use the same amount of observation information.

In the present clustering method, we focus on the application of homogeneous independent sensors and their view fields cover all targets, regardless of complex issues such as sensor correlation, heterogeneity and inconsistency etc. Future work is desired to dealing with these practical, complicated issues.

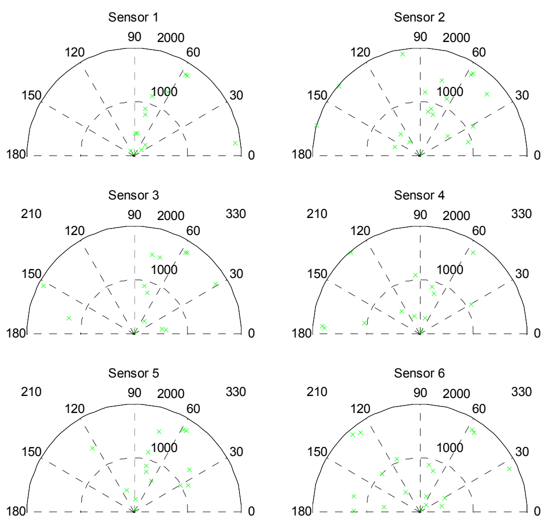

Fig. 1 Observations (green 'x') of six active radars

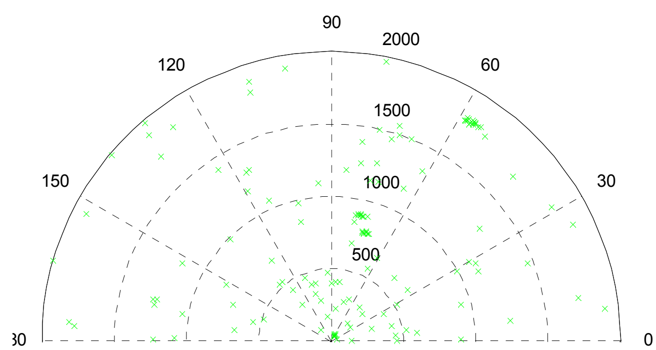

Fig.2 Observations (green 'x') of ten active radars, mapped in the same state space

4. SIMULATIONS

We compare the multi-sensor O2 inference with the state-of-the-art SMC-PHD filter (i.e. the sequential Monte Carlo/particle filter implementation of the PHD filter). To extract the estimates from the joint PHD of multiple targets, additional multi-estimate extraction is further required. In our simulations we use the multi-expected a posterior (MEAP) estimator [25], which has been demonstrated to be reliable, accurate and computationally fast. As stated, the biggest challenge for the filter is modeling error. However, in our simulations we will only employ perfectly correct models for the filters to allow them to achieve the best possible performance. This is the most favorable situation for filters (otherwise if the filters use models that are different from the true model, their performances will be highly reduced). That is to say, the performance of the filter-based solutions is as good as possibly.

The ground truth of the trajectories of targets are plotted in Fig.3 where the color distinguishes different birth models and each trajectory starts at 'Δ' and ends at '□'. As shown, new targets appear from four different areas following Poisson RFS with different intensity $\gamma_t = \sum_{i=1}^{4} r_{t,i} N(\cdot; B_i, Q)$, where new target birth with initial states $B_1 = [-1500,0,250,0,0]$, $B_2 = [-250,0,1000,0,0]$, $B_3 = [250,0,750,0,0]$, $B_4 = [1000,0,1500,0,0]$, Q=diag$([50,50,50,50,6*\pi/180]^T)^2$ and probabilities $r_{t,1} = 0.02$, $r_{t,2} = 0.02$, $r_{t,3} = 0.03$,$r_{t,4} = 0.03$. The target state variable $x_t = [\tilde{x}_t, \omega_t]^T$ consists of the planar position and velocity $\tilde{x}_t = [p_{x,t}, \dot{p}_{x,t}, p_{y,t}, \dot{p}_{y,t}]$ and the turn rate ω_t. Each target either continues to exist at time k with survival probability $p_S = 0.99$ and to move to a new state with a nearly constant turn-rate (NCT) state transition model or disappear with probability 0.01. The NCT state transition model can be written as

$$\tilde{x}_t = F(w_{t-1})\tilde{x}_{t-1} + G w_t, w_t = w_t + \Delta\, u_{t-1} \tag{8}$$

where

$$F(w) = \begin{bmatrix} 1 & \frac{sinw\Delta}{w} & 0 & -\frac{1-cosw\Delta}{w} \\ 0 & cosw\Delta & 0 & -sinw\Delta \\ 0 & \frac{1-cosw\Delta}{w} & 1 & \frac{sinw\Delta}{w} \\ 0 & sinw\Delta & 0 & cosw\Delta \end{bmatrix}, G = \begin{bmatrix} \frac{\Delta^2}{2} & 0 \\ \Delta & 0 \\ 0 & \frac{\Delta^2}{2} \\ 0 & \Delta \end{bmatrix}$$

$w_{t-1} \sim N(\cdot; 0, \sigma_w^2 I), u_{t-1} \sim N(\cdot; 0, \sigma_u^2 I), \Delta = 1\text{s}, \sigma_w = 15 m/s^2$ and $\sigma_u = \pi/180$rad/s.

The homogeneous sensors are of the same observation function and are located at the same planner position [0, 0]; the range-bearing observation region is the half disc of radius 2000m. This corresponds to the scenario in which sensors are arranged in the same planner position but at different altitudes. This is not mandatory as one can place these sensors at different positions and they will have a different view field. The target detection probability is the same $p_{D,t}(x)$= $0.95\mathcal{N}([p_{x,t}, p_{y,t}]^T; 0, 6000^2 I_2)/\mathcal{N}(0; 0, 6000^2 I_2)$. The observation is a noisy range and bearing vector given as (6) for $[S_{x,t}, S_{y,t}]$=[0, 0], where $v_t \sim \mathcal{N}(\cdot; 0, R_t)$, with $R_t = \text{diag}([\sigma_r^2, \sigma_\theta^2]^T)$, $\sigma_r = 20$m, $\sigma_\theta = \pi/90$rad/s. Since the tracking scenario is in the area of $p_{y,t} > 0$, the sign of the state in *y*-dimension is always positive for the O2 inference (7), while in *x*-dimension it is the same with tan (θ_t). Therefore, this inverse function does not have a sign problem.

In this simulation, different numbers of sensors from 1 to 200 will be used. Clutter is uniformly distributed over the region with an average rate of $r = 10$ points per scan. Fig.4 gives the range and bearing observations over time separately, which also gives the starting and ending time of targets. 1000 particles per expected target are used and the total number of particles is hard-limited to be not fewer than 600. The optimal sub-pattern assignment (OSPA) metric [26] is used to evaluate the multi-object estimation accuracy. For finite subsets $X = \{x_1, x_2, \dots, x_m\}$ and $Y = \{y_1, y_2, \dots, y_n\}$ where $m, n \in \mathbb{N}_0 = \{0,1,2, \dots\}$, the OSPA metric of order p between $X$and Y is defined as (if $m \leq n$)

$$\bar{d}_p^{(c)}(X,Y) = \left(\frac{1}{n}\left(\min_{q\in\Pi_n} \sum_{i=1}^{m} d^{(c)}\left(x_i, y_{q(i)}\right)^p + c^p(n-m)\right)\right)^{\frac{1}{p}} \tag{9}$$

where $d^{(c)}(x,y) = \min(c, d(x,y))$, the cut off value $c > 0$ and $d(x,y)$ is the Euler distance. $\bar{d}_p^{(c)}(X,Y) = \bar{d}_p^{(c)}(Y,X)ifm \geq n$ and $\bar{d}_p^{(c)}(X,Y) = 0$ if $m = n = 0$. The parameters used for the OSPA are $c = 100, p = 2$.

There are several ways to incorporate different sensors to work for the SMC-PHD tracker, differing from one another in terms of how to fuse the sensor data [2, 8, 27]. First, we apply a naive track-to-track (T2T) fusion that is to run the SMC-PHD filters separately for different sensors, and then fuse their estimates at the end. The overestimation of the number of targets of one filter with regard to the average of others will be simply eliminated. Secondly, we apply a single "super" sensor based SMC-PHD filter where the single sensor has a much lower observation noise $v_t \sim N(\cdot; 0, R_t')$, where $R_t' = \text{diag}([\sigma_r'^2, \sigma_\theta'^2]^T) = R_t/N$, i.e. $\sigma_r' = \frac{20}{\sqrt{10}}$m, $\sigma_\theta' = \frac{\pi}{90\sqrt{10}}$rad/s. This corresponds to an observation quality that is equivalent to the Kalman fusion of N sensors. This is referred to as observation fusion and tracking (OFT).

First, we set $N = 10$ for each of the three methods, i.e. ten sensors for the O2 inference and the T2T SMC-PHD filter. The estimates of six sensors for the same scenario has been given in Fig.1 for time $t = 40$ in one trial of simulation (clutter rate $r = 10$). Correspondingly, all the estimates from ten sensors and the true state positions are given in Fig.5. The average results of the estimates of the number of targets and the mean OSPA of different filters over 100 Monte Carlo runs are given in Fig.6. The average results over 100 steps×100 MC runs are summarized in Table 1 where the time refers to one iteration of the full filter. Although the multi-sensor O2 method does not employ any knowledge about the target/clutter, it can still estimate the number of targets with acceptable accuracy and has produced an even better estimation than the multi-sensor T2T SMC-PHD filter. To the best of our knowledge, MODE has been achieved for the first time in the clutter environment without any prior knowledge of the target/clutter model.

We iterate that such a proper assumption of the target and clutter model and relevant parameters required by the SMC-PHD filters that is consistently the same as the truth is not available in many real-life problems. Consequently, the filters will not give as good a result or even inapplicable results; however, the O2 inference will be the same since it does not rely on the target/clutter model at all. In contrast, if the observation noise is exactly known for the O2 inference, debiasing can be applied to further improve the estimation accuracy. Using correct prior knowledge of the system, the OFT SMC-PHD filter performs better than the T2T SMC-PHD filter, indicating that our multi-sensor T2T solution (a naive version) implemented is not optimal. In the following, we will only compare the OFT SMC-PHD filter (using MEAP) with the O2 inference under different N (i.e. a different number of sensors used in the multi-sensor O2 approach and correspondingly a different observation noise used in the OFT SMC-PHD filter).

Fig. 7 gives the observations and estimation when 200 sensors are used at time $t = 40$. Fig. 8 gives the mean OSPA results obtained by the O2 inference and the OFT SMC-PHD filter against different N. The results show that with an increase of N, the O2 will surely get more reliable and accurate results (up to a relatively stable level), but this is not guaranteed with the SMC-PHD filter. The SMC-PHD filter gets the best accuracy when approximately $N = 10$. An observation noise that is too large (small N) is not good for all methods while a very small observation noise corresponds to a sharp likelihood distribution and thereby may cause significant sample degeneracy or impoverishment [28] in particle filter (this is the problem of the particle filter; further results and discussion can be found in [21]); both cases will cause a reduction in the performance of the filter. This simply exhibits the advantage of the O2 method, which guarantees reliable performance that is consistent to the quality of sensors and insensitive to the prior knowledge. In contrast, traditional filter based trackers may not benefit from more or accurate sensors.

Overall, the result has demonstrated that the massive sensor O2 inference is qualified for independent MODE which enjoys statistically increasing estimation accuracy with an increasing number of sensors and can perform better even than the perfectly modelled filter when the number of sensors increases. More importantly, the massive sensor O2 inference can work efficiently in the challenging unknown and time-varying scenario with very few background knowledge for which the traditional filter-based tracker is inapplicable. These indicate that it may be not always preferable to employ a Bayesian filter for tracking but instead, in certain cases the non-Bayesian O2 approach with the use of proper data-learning technologies may be more promising.

Table 1. The performance of different estimators when r=10, N=10.

	SMC-PHD (OFT)	**SMC-PHD (T2T)**	**O2 Inference (10 sensors)**
OSPA	31.5482	40.3143	36.9991
Time (second)	1.8905	19.771	1.1224

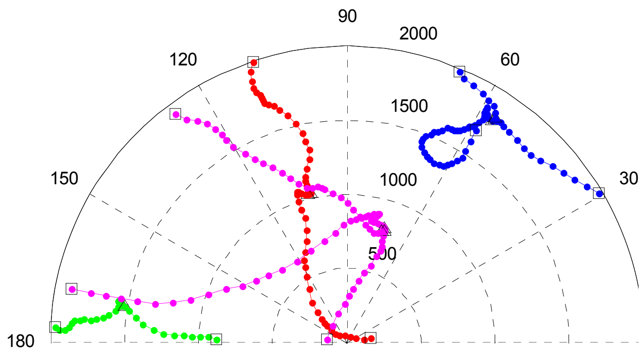

Fig. 3 Trajectories of targets born in four different areas

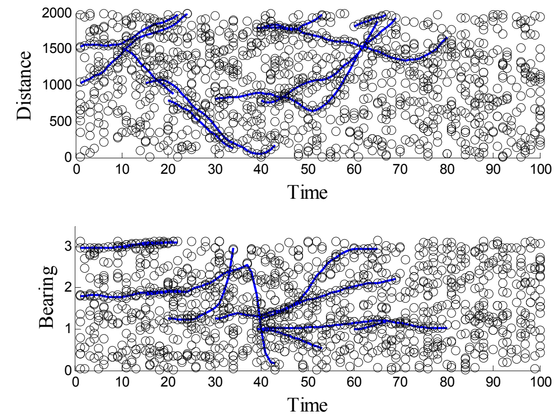

Fig. 4 Range-bearing observations (black ‘o’) and the true trajectories of targets (blue line) when r=10

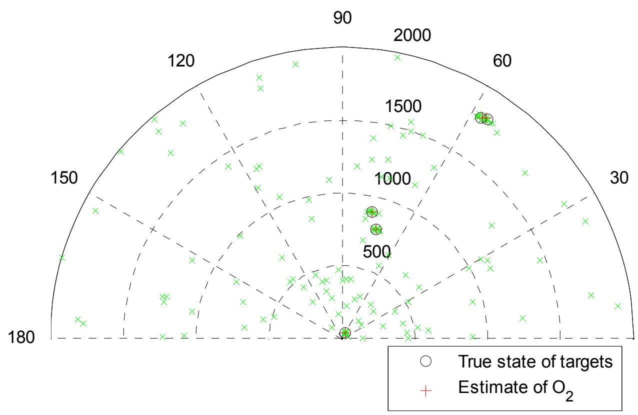

Fig.5 Observations (green ‘x’) of 10 sensors mapped in the same state space, true states (black ‘o’) and the O2 estimates (red ‘+’) at time $t = 40$ when r=10

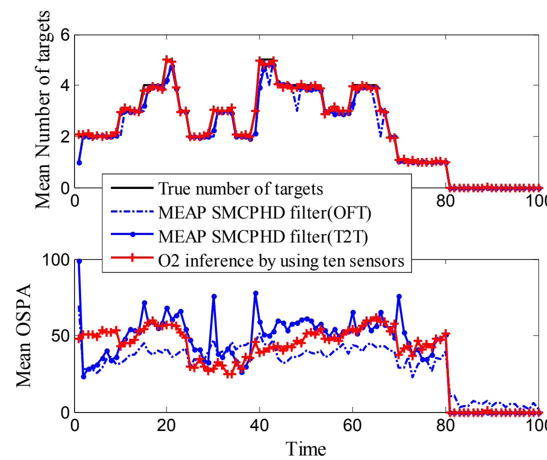

Fig. 6 Mean estimated number of targets and mean OSPA given by different estimators over 100 Monte Carlo trials

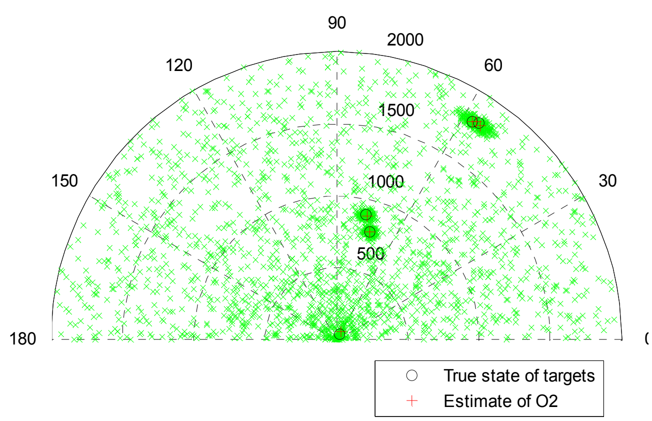

Fig.7 Observations (green ‘x’) of 200 sensors mapped in the same state space, true states (black ‘o’) and O2 estimates (red ‘+’) at time $t = 40$ when $r = 10$

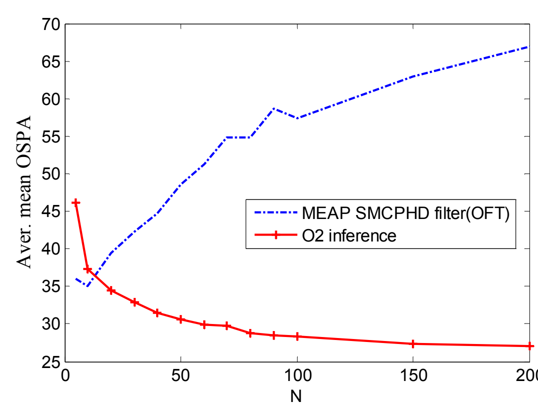

Fig. 8 Mean OSPA of 100 steps×100 MC runs of the O2 inference and the OFT SMC-PHD filter for different N.

5. CONCLUSION

This paper considers a particular class of MODE with two special challenges: 1) little/no prior information is given about the background; 2) massive (independent identical) sensors are available. It is shown that the use of massive sensors is actually favorable to circumvent the poor background/prior information, although this may go conversely in traditional filters. Based on an unsupervised clustering process, the present massive sensor O2 inference needs neither to assume the target/clutter model nor to know the system noises for MODE, while it is able to handle high maneuver targets, target splitting and merging, unknown and time varying system noises and clutter density, etc., and can do so computationally fast. It enjoys statistically increasing estimation accuracy with an increasing number of sensors and can perform better even than the perfectly modelled filter. Simulations based on massive independent homogeneous sensors have demonstrated the superiority of the present massive-sensor O2 inference. More importantly, the massive sensor O2 inference can work efficiently in the challenging unknown and time-varying scenario with very few background knowledge for which the traditional filter-based tracker is inapplicable. The present massive sensor O2 inference identifies a benchmark to evaluate the effectiveness of any other multi-target tracker.

The ability to deal with huge amounts of data raised with the use of massive sensors is an emerging trend for advanced target tracking, especially in challenging cases for which few prior knowledge is available. Our future work will consider complex sensor issues such as sensor register bias, sensor data correlation, heterogeneity, inconsistency and sensor network-communication etc.

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