SPECTRAL MULTISCALE COVERAGE WITH THE FEATURE AIDED CPHD TRACKER

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ABSTRACT

A closed loop approach for surveillance was developed leveraging the Spectral Multiscale Coverage (SMC) algorithm for sensor management coupled with the Cardinalized Probability Hypothesis Density (CPHD) multitarget tracker. Additionally, the CPHD was formulated such that it is able to ingest features, if available. Simulations with fixed and mobile sensors (the latter, tasked by the SMC) providing data to the tracker underlined the benefits of sensor fusion with respect to standard metrics of performance.

Index Terms— SMC, CPHD, multitarget tracking, sensor fusion, surveillance

1. INTRODUCTION

The traditional domain of sensor management for multitarget tracking has been the aerospace and defense industries that heavily rely on sensors such as radar and sonar for guidance, navigation, air traffic control, etc. Driven in part by the extended use of autonomous vehicles and robotics, newer applications have opened up in fields as diverse as oceanography, traffic monitoring, biomedical research and so on. Hero and Cochran [1] provides an excellent and compact overview of the theory, state of the art methods and application fields of sensor management.

Within the framework of Bayesian multitarget tracking using Random Finite Sets [2], the theoretical foundation of using the CPHD filter for sensor management was laid in [3] with follow up examples of proposed objective functions in [4, 5]. Further advances were recently summarized in [6].

In this work, we are interested in scenarios where the resources available consist of a high altitude ("fixed") sensor and low altitude mobile sensors because such a setup creates the opportunity for both multitarget tracking and data fusion in the context of complementary sensing modalities.

The fixed sensor has a wide field of view but low resolution, has more perception errors such as false alarms, missed detections and geolocation errors but can provide tracks for many targets over long periods of time (although tracks tend to be highly fragmented), as seen in Figure 6.

On the other hand, the mobile sensors with constrained dynamics have limited but high resolution field of view, detect reliable features, have a lower rate of perception errors but can only cover a small number of targets for short periods of time. The role of the low altitude sensors is that they can be tasked with a sensor management algorithm such as SMC[7] to reduce target uncertainty and enable stitching of tracklets obtained from high altitude sensor data. Figure 5 shows the interaction between sensor management and target tracking, with the mobile sensors measurements used in the update of the PHD surface which is further used for controlling the mobile sensors trajectories.

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how measurements from both the fixed and mobile sensors are used in the update step of the CPHD tracker and the resulting PHD surface is used in the dynamic SMC control algorithm that produces the mobile sensors control inputs specifying the tasking of these sensors in the next scan.

In the following, we briefly sketch the optimization setup of the SMC (Section 2), the CPHD filter (Section 3) and its new capability of tracking target features (Section 4). We then test the SMC-CPHD integration and performance on a moderate difficulty simulated scenario that involves both mobile and fixed sensors (Section 5) and conclude in Section 6.

2. SPECTRAL MULTISCALE COVERAGE

Cooperative active sensing uses mobility of a team of sensor/agents to enhance target search and tracking performance [11, 12, 13, 14, 15, 16, 8]. Such cooperative control problems are formulated as an optimization problem where the decision variables are the sensor actions (e.g. the location where to move next) and the objective function is often based on information-theoretic measures capturing sensing quality as a function of uncertainty target state and available sensor actions (e.g. Renyi divergence [13]).

Alternatively, SMC control employs a coverage metric [7] motivated by ergodic dynamical systems theory that measures sensing quality as a discrepancy in terms of amount of time spent by sensors in a region and the probability of finding target. Taking into account sensor motion dynamic constraints, optimal control techniques are used to derive feedback control laws with the objective of driving the sensors to locations which lead to the highest rate of decay of this coverage metric. Thus, sensors spend time proportional to probability of finding targets in different regions, making it difficult for a target to evade detection.

The SMC framework also provides a systematic way to incorporate and update prior information (e.g., likely location of targets) in the coverage metric. In particular, decision and estimation theoretic techniques can be used to automatically incorporate time evolving uncertainties in sensor coverage gaps and target locations in the coverage metric, and thereby adapt the SMC control. This idea has been used to develop SMC based robust and efficient search and tracking algorithms. SMC based adaptive search for a single static target using multiple mobile sensors in presence of terrain and sensor uncertainties (including false alarms/missed detections) has been shown to outperform other state of art search methods by 25-50% in terms of median search times [15]. Extension for search of an unknown number of static targets appears in [16]. For mobile targets SMC based control has been shown to facilitate tracking/coverage of multiple targets per sensor for extended periods of time [8, 9].

While these previous works do account for noisy sensors with limited field-of-view, they do not consider the possibility of missed detection and false positive detections leading to errors in data association. To account for such errors and an unknown/variable number of targets, it is often necessary to use non-parametric target distributions, such as those offered by PHD filtering [17]. In this paper, we provide the extension to cooperative active tracking of an unknown number of multiple mobile targets.

In the case of identical target dynamics the PHD filter can be naturally coupled to SMC framework without any modification. Seamless integration is possible as the SMC needs a cumulative (i.e. it does not rely on the individual components) uncertainty field [9] which the CPHD effortlessly provides. Moreover, the dynamic coverage becomes independent of number of targets. Alternatively, when target dynamics are non-identical, the framework can still be used with the additional requirement of estimating the different types of targets. For such applications, interactive multi-modal version of PHD filtering will have to be employed [18].

3. CPHD TRACKER

Mahler introduced a new approach to multi-target tracking based on finite set statistics (FISST) [2], in which target states and measurements are modeled as random finite sets (RFS). The probability hypothesis density (PHD) is the intensity function of a Poisson RFS and represents the density of the expected number of targets per unit volume [19]. The PHD was to be propagated as a first moment approximation to the multi-target Bayesian posterior distribution instead of the full posterior distribution [2].

A disadvantage of the PHD, however, is that the Poisson assumption for the target number (cardinality) distribution often leads to large fluctuations in the target-number estimates, and thence to the “target death” problem [10]. The Cardinalized PHD (CPHD) filter [20] offers a nice cure to the problem.

Closed form CPHD prediction/update equations have been derived [19] for cases in which linear Gaussian assumptions for the target motion and observation models hold and probabilities of detection and survival are state independent.

At each time scan, mode means and covariances are propagated by an Extended Kalman Filter (EKF) while mode weights are calculated using the CPHD equations.

A multitarget tracker is composed of a filter followed by track management policies. In its original form the Gaussian Mixture CPHD (GMCPHD) filter is not able to provide scoreable tracks, so a track display/management scheme had to be devised [21, 22] in order to make the transition from filter into tracker. This is a set of policies dealing with track initiation, update and deletion, spawning, mode pruning and merging. Track management is separate from the operation of the filter.
4. FEATURE AIDED CPHD TRACKER

Target feature measurements, e.g. target class available from automatic target recognition systems, object color and texture available from video streams, etc. can be incorporated into multiple target tracking algorithms to improve the accuracy of the difficult data association step that is at the core of multitarget tracking [23].

4.1. Features Modeled as SNR

In previous work [24], the performance of a classifier was modeled as a confusion matrix, whose entries are target class likelihood functions that are used to modify the update equations of the multiple models CPHD (MMCPHD) filter [18]. The result was the classification aided CPHD (CACPHD) filter[24]. Specifically, in the CACPHD filter, the likelihood of a measurement accounts for both the kinematic and the feature (i.e. class) information provided by the measurement $f (z_s | x_i) \times f (\text{class of } z_s | \text{class of } x_i)$, where $z_s$ is the $s^{th}$ measurement, $x_i$ is the $i^{th}$ Gaussian mode on the PHD surface at the current scan and $f (\cdot)$ is a likelihood function, usually Gaussian. In the original CPHD filter, the likelihood of a measurement is simply $f (z_s | x_i)$, which contains only kinematic and no class information about the target. The above change propagates through the update equations for the PHD surface, affecting the weights of the modes on this surface.

4.2. Features Modeled in the State

In contrast, in the current work, target features are included in the state space. The advantage of this approach is that the resulting tracks have identifying features, such as color or texture, that can facilitate downstream analysis in the processing exploitation and dissemination toolchain. Note that incorporating long feature vectors in the state space will be at the cost of an increased run time. Figure 4 shows the setups of the two feature aided CPHD approaches.

5. RESULTS

5.1. Simulation

In a simulated practical scenario with moderate level of difficulty, six targets start relatively close to each other and later disperse. The fixed sensor was assigned a target probability of detection of 0.25, false alarm density of 10 and its measurement noise standard deviation was 1. The mobile sensors were assigned a target probability of detection of 0.9 (given the target is in their field of view), false alarm density of 0.1 and measurement noise standard deviation 0.1.

The simulated feature is a 24-dimension Gaussian i.i.d. vector with mean 4 and standard deviation 0.1 when generated by a target and a 24-dimension uniform i.i.d. vector between 0 and 6 when generated by clutter.

To quantify performance we use the metrics of performance (MOPs) agreed upon by the members of the Multistatic Tracking Working Group² (MSTWG). Thus, we report: track detection probability ($PD$), i.e., the ratio of the total duration of all true tracks and the total scenario duration; track fragmentation ($FRAG$); number of false tracks ($FT$); and root mean square error ($RMSE$) evaluated only where tracks exist. Further detail on these definitions can be found in [25].

5.2. Performance

Table 1 summarizes the selected MOPs calculated for the target dispersal scenario averaged over all targets. When using only the two mobile sensors, performance is unsatisfactory (see Figure 5) as they are only able to track two of the six targets due to their narrow field of view and dynamics constraints (i.e. they can not travel fast enough to assure coverage of all targets even if tasked perfectly). Their small target localization errors translate however into low RMS errors.

When using only the fixed sensor, the metrics are indicative of a difficult scenario (see Figure 6) as explained above. Having to deal with large measurement noise, the CPHD outputs tracks with considerably higher RMS error than in the case when only mobile sensors were used.

When fusing the sets of measurements coming from the fixed and mobile sensors (see Figure 7), track $PD$ is significantly higher due to support from effective SMC tasking and RMS error is lower than in the case of relying only the fixed sensor due to more precise measurements generated by the mobile sensors. Track $FRAG$ however increases due to the "oscillation" between the two sensing modalities.

Note that one of the assumptions in the CPHD filter is that only one measurement can come from one target at every one scan while in our simulation, there can be multiple measurements from one target in one particular scan coming from the three available sensors. As a way to circumvent implementing the complex multisensor PHD filter [26], we have applied a measurement gating procedure in which if two or more measurements are in close proximity of each other, only the measurement with the smallest covariance is passed to the tracker and the rest are discarded.

²The Multistatic Tracking Working Group is an international group of researchers with interest in multistatic sonar tracking. It began in 2004 and now exists as a panel within the International Society for Information Fusion.
When features are available in the measurements from both the fixed and mobile sensors, tracking results (see Figure 8) are much improved and the CPHD is able to follow all targets for about the whole duration of the scenario with smaller localization error than in the case of using both types of sensors but without the addition of features.

A strong feature was simulated in order to illustrate the benefits that arise when features are brought into the state space. The strength of the feature boosts the weights of the Gaussian modes that represent the targets and therefore tracks are not deleted as easily (then track $PD$ is high) later to be reinitialized (then track $FRAG$ is low) while measurements with close features to the ones being tracked by the Gaussian modes are preferred (then track $RMS$ is low).

6. CONCLUSIONS

In this work, we have integrated the SMC sensor management algorithm with the CPHD multitarget tracker. We have equipped the CPHD with the ability of ingesting and tracking features. Table 1 shows how sensor and information fusion (kinematics and features) improve metrics of performance.

Next, we plan to apply the feature aided CPHD tracker to the VIVID dataset provided by DARPA, which is a video surveillance dataset collected from UAVs. Color and texture histograms of the bounding boxes can serve as features.

The bottleneck of sensor management for multitarget tracking in practical systems is computational feasibility [1] as the inherent optimization problems have large parameter spaces and time constraints. Hence, future work will also address larger scale scenarios and semiautomatic tuning of the parameters in the CPHD tracker with human in the loop.

<table>
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<tr>
<th>Scenario</th>
<th>PD</th>
<th>FRAG</th>
<th>RMSE</th>
<th>FTs</th>
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<td>1.25</td>
<td>10.07</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 1. Average MOPS per Target Improve with Fusion.
7. REFERENCES


