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A finite point process approach to multi-target localization using transient measurements

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ABSTRACT

A finite point process approach to multi-target localization from a transient signal is presented. After modeling the measurements as a Poisson point process, we propose a twofold scheme that includes an expectation maximization algorithm to estimate the target locations for a given number of targets and an information theoretic algorithm to select the number of targets. The proposed localization scheme does not require explicitly solving the data association problem and can account for clutter noise as well as missed detections. Although point process theory has been widely utilized for sequential tracking of multiple moving targets, the application of point process theory for multi-target localization from transient measurements has received very little attention. The optimal subpattern assignment metric is used to assess the performance and accuracy of the proposed localization algorithm. Implementation of the proposed algorithm on synthetic data yields desirable results. The proposed algorithm is then applied to the multi-shooter localization problem using acoustic gunfire detection systems.

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1. Introduction

This paper considers the problem of multi-target localization using transient signals from a single-sensor as well as multi-sensor point of view. Here it is assumed that target identification is not possible, and therefore, no association between measurements and targets are available. Furthermore, the number of targets in the surveillance region is unknown. Additionally, due to the limited range of the sensors, missed detections can occur and the presence of clutter can induce false alarms. An example of such a scenario is shooter localization using a network of acoustic gunfire detection systems (GDSs) [1]. The individual GDSs composed of a passive array of microphones are able to localize[1] a gunfire event by measuring the direction and times of arrival for both the acoustic wave generated by the muzzle blast and the shockwave generated by the supersonic bullet [2–5]. Due to echo, reverberation, and the dissipative nature of the acoustic signal, missed detections and false alarms are prevalent in acoustic source localization. Furthermore, due to the transient nature of the event, sequential observations are not available and recursive Bayesian tracking schemes cannot be employed.

The multi-sensor fusion approach in [1] was designed for the case of a single shooter. The multi-target case is much more difficult for multi-sensor fusion because measurements from different sensors generated by the same target must be associated before a fusion approach similar to [1] can be applied. This is essentially an S-dimensional (S-D) assignment problem, which is known to be NP-hard for $S > 2$ [6]. Numerous multi-target tracking techniques tackle the associated problem. Conventional multi-target tracking (MTT) approaches like Multiple Hypothesis Tracking (MHT) [7,8] or the Joint Probability Data Association (JPDA) filter [9,10], which address the data-association problem, either are too computationally demanding or cannot be applied to the transient event localization problem since these approaches require persistent measurement signals and a fixed number of targets. In MHT, all possible combinations of tracks and data associations are exhaustively evaluated; therefore, it is an impractical scheme since the number of mappings between data and targets will grow exponentially with the number of targets [11,12]. Though more efficient than MHT, JPDA methods are not optimal since the detection is performed separately from tracking and cannot initiate tracks at low signal-to-clutter ratios [13]. A multi-target extension of the simultaneous localization and mapping (SLAM) problem for streaming data is presented in [14]. The multi-target simultaneous localization and mapping (MSLAM) scheme is based on the parallel

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[1] Localize means obtaining both the range and bearing from the array center to the target.

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partition particle filter and it outperforms the well-known FastSLAM [15] when there are multiple targets in the surveillance area. An extension of MHT, known as the multi-hypothesis localization (MHL), for mobile robot localization is given in [16]. MHL uses a multi-hypothesis Kalman filter along with a probabilistic formulation of hypothesis correctness to generate and track Gaussian hypotheses. However, almost all of the MTT techniques are recursive algorithms that require persistent observations and are futile in dealing with transient signals.

A finite point process approach known as the probability hypothesis density (PHD) filter [17], allows a more tractable implementation of multi-target tracking approaches since it only propagates the first-order moment of the multi-target density. Moreover, the PHD filter [18] is able to handle a time-varying number of targets, missed detections, and false alarms. Since the implementation of an exact PHD filter is intractable, a sequential Monte Carlo (SMC) or particle filtering approach [19] and the Gaussian sum filtering scheme [20] have been devised to approximate the PHD filter. Convergence properties for the particle PHD filter and Gaussian mixture PHD filter are presented in [21] and [22], respectively. A RaoBlackwellized implementation of the PHD-SLAM filter proposed in [23] has shown to outperform FastSLAM in mapping and localization. An SMC implementation of a finite set statistical filter for the localization of an unknown number of speakers in a multipath environment using time difference of arrival (TDOA) measurements is given in [19,24–26]. Similar to traditional MTT algorithms, the PHD filter is a recursive Bayesian approach, which also requires persistent observations for track update. A finite point process approach to maximum likelihood based multi-target localization of an unknown number of targets from transient signals has not been considered yet.

Traditionally, multi-target localization involves the maximum likelihood based approach, where the selected model yields the maximum likelihood of observing the given data across a possible number of targets and all possible target-data associations. As the number of sensors increases, the possible combination of target-data associations dramatically increases, and the problem often becomes intractable. Development of a multi-target detection and localization scheme based on a probabilistic framework known as modeling field theory (MFT) is presented in [27]. Though the computational complexity of a MFT-based approach scales linearly with the size of the problem, it involves an iterative scheme similar to the expectation maximization (EM) and an ad-hoc likelihood ratio test is needed to prune the number of targets. An iterative maximum likelihood optimization technique based on a modified deterministic annealing EM (MDAEM) algorithm for multi-target localization and velocity estimation using TDOAs is given in [28]. Since the MDAEM algorithm is executed for an assumed number of targets, [29] provides a systematic approach for determining which of the target models estimated by the MDAEM algorithm are related to the true targets. Both the MFT-based approach and the MDAEM algorithm require that the assumed number of targets is greater than or equal to the true number of targets. Also, the measurements are only assumed to contain clutter/false alarms and the problem of missed detection is not considered.

For the multi-target localization problem considered here, we utilize the frequentist counterpart to the Bayesian filtering approach, i.e., the maximum likelihood algorithm. The localization problem is formulated in two dimensions (2-D), where each sensor acquires several measurements and the proposed algorithm estimates the number of targets and their corresponding locations based on the erroneous measurements. The number of targets is certainly different from the number of measurements due to clutter and missed detections. The proposed solution draws inspiration from recent efforts in finite set statistics for multiple target tracking to localize multiple co-occurring transient events. The approach models the measurements for different sensors as conditionally independent[2] Poisson point processes[3] (PPPs) with a mixture density representing the intensity function that is parameterized by the target locations. For N targets, this leads to an EM algorithm that iterates between soft association and solving N parallel 2-D maximum searches. The main advantage of the proposed scheme is that it scales linearly with the size of the problem and avoids the curse of dimensionality associated with the traditional MHT-based multi-target localization scheme. For example, if there are N targets, L sensors, and m measurements per sensor, the computational complexity for the proposed scheme is on the order of $O(NLm)$ while the computational complexity for the traditional scheme, which consider hard associations, is on the order of $O(N^{Lm})$. Unlike the methods given in [27] and [28], the proposed approach accounts for probability of detection and missed detections along with clutter and false alarms.

The structure of this paper is as follows: the PPP model for the measurements is presented in Section 2, and Section 3 uses the model to formulate the new multi-sensor fusion approach for multi-target localization via the EM framework. A numerical simulation demonstrating the multi-sensor algorithm is presented in Section 4. Section 5 presents the results obtained from implementing the proposed algorithm on experimental data. Finally, Section 6 concludes the paper and discusses current research challenges.

2. PPP measurement model

The problem of target localization from transient signals consists of a sensor (or a group of sensors) estimating the target locations from observed transient events, e.g., shooter localization from gunfire events [1]. Due to the physical nature of the acoustic phenomenon associated with the gunfire event, the number of detections and corresponding location estimates vastly differ from the number of shooters. To this end, this section models the measurements from each sensor as a random sample of a PPP [31] that is conditioned on ground-truth target (e.g., shooter) locations. A PPP on state space $S = \mathbb{R}^d$ is defined as follows.[4]

Definition 1. A PPP Π on $\mathbb{R}^d$ with intensity measure Λ is a point process such that

- For every compact set $B \subset \mathbb{R}^d$, the number of points in $\Pi \cap B$ is a Poisson random variable with mean $\Lambda(B)$, i.e.,

$$\mathbb{P}(N(B) = k) = \frac{\exp\left(-\Lambda(B)\right)\Lambda^k(B)}{k!} = \mathrm{Pois}(k; \Lambda(B)) \qquad (1)$$

  where $N(B)$ denotes the cardinality of $\Pi \cap B$.
- Numbers of points of Π in each of disjoint sets $B_1, \ldots, B_n$ are independent for every $n \geq 2$, i.e., random variables $N(B_1), \ldots, N(B_n)$ are mutually independent.

If Λ admits a density λ, typically known as the *intensity function*, then we may write

$$\mathbb{P}(N(B) = k) = \mathrm{Pois}\left(k; \int_B \lambda(\mathbf{x})\, d\mathbf{x}\right), \qquad (2)$$

where $\mathbf{x} \in B \subset \mathbb{R}^d$. The intensity function represents the expected object density over the state space S. That is the expected number

[2] Throughout this paper, whenever measurement independence is assumed, it is conditioned on the truth.

[3] Here the term "processes" does not imply a dynamic, time varying quantity, rather point processes may consist of both time-independent and time-dependent random variables [30].

[4] Definition 1follows directly from definition 2.10 of [30]. Similar definitions of PPP can be found in page 11 of [32], definition 8.7 of [33] and page 41 of [34].