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Online Estimation of Unknown Parameters in Multisensor-Multitarget Tracking: a Belief Propagation Approach

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***Abstract*— We propose a Bayesian multisensor-multitarget tracking framework, which adapts to randomly changing conditions by continually estimating unknown model parameters along with the target states. The time-evolution of the model parameters is described by a Markov chain and the parameters are incorporated in a factor graph that represents the statistical structure of the tracking problem. We then use the belief propagation (BP) message passing scheme to calculate the marginal posterior distributions of the targets and the model parameters in an efficient way that exploits conditional statistical independencies. As a concrete example, we develop an adaptive BP-based multisensor-multitarget tracking algorithm for maneuvering targets with multiple dynamic models and sensors with unknown and time-varying detection probabilities. The performance of the proposed algorithm is finally evaluated in a simulated scenario.**

***Index Terms*—Multitarget tracking, online self-tuning algorithm, adaptive processing, probabilistic data association, belief propagation, message passing, factor graph.**

I. Introduction

Multisensor-multitarget tracking is a challenging task, which aims at estimating the time-varying states—such as positions and velocities—of multiple moving objects (targets) [1]. This problem is crucial in many applications, which span from air traffic control, remote sensing, robotics, oceanography, to maritime surveillance. Measurements from multiple sensors, provided by various remote sensing devices, such as radar, sonar, and cameras are exploited in order to obtain satisfactory performance in conditions of low signal-to-noise ratio (SNR).

In the majority of real scenarios, the number of targets and the association between measurements and targets are unknown. Moreover, the sensor measurements are affected by noise, missed detections, and false alarms. These phenomena are usually modeled in a statistical fashion, and most tracking algorithms assume that the relevant model parameters are known in advance. However, in practice, these parameters are in fact unknown and time-varying [2]–[8], such as probabilities of observing (detecting) a target at the sensors, clutter intensity profile and target motion parameters (maneuvering targets).

The work in this paper extends [9] and presents a multisensor-multitarget tracking algorithm which is able to adapt to randomly changing conditions by sequentially estimating multiple unknown and time-varying model parameters, which are related either to the dynamics of the targets, such as interacting multiple models (IMM) parameters [10]–[13], or to the measurement model, such as detection probabilities and clutter intensity profiles. These parameters are modeled as discrete random variables, which take values on specific finite sets and whose time-evolutions are modeled by discrete Markov chains. This statistical modeling allows to incorporate the unknown parameters in the factor graph representing the statistical structure of the multisensor-multitarget tracking problem. The belief-propagation (BP) message passing scheme is then employed on the resulting factor graph in order to calculate the marginal posterior densities of both the target states and the model parameters at each time step. These marginal posterior densities are finally used for detection of the targets and estimation of the target states and the model parameters. The proposed adaptive multisensor-multitarget tracking algorithm extends also previous work [14] in the sense that arbitrary model parameters are considered. As a concrete example, we consider a maneuvering target scenario in which the IMM parameters for the individual targets are adapted in addition to the detection probabilities of the sensors.

This paper is organized as follows. In Section II, we describe the system model and the related statistical formulation. In Section III, we develop the proposed method. Finally, the performance of the proposed adaptive algorithm is evaluated in a simulated scenario in Section IV.

II. System Model and Statistical Formulation

In this section, we describe the system model and statistical formulation underlying the proposed algorithm.

A. Target States and Measurements

Following [9], we account for the fact that the number of targets is unknown by considering K *potential targets* (PTs) $k \in \mathcal{K} \triangleq \{1, \ldots, K\}$. Thus, K is the maximum possible number of actual targets[1]. The existence of PT k at time $n \in \{0, 1, \ldots\}$ is indicated by the binary indicator $r_{n,k} \in \{0, 1\}$, i.e., PT k exists at time n if $r_{n,k} = 1$. The state $\mathbf{x}_{n,k}$ of PT k at time n consists of the PT's position and possibly further

[1]A scalable multisensor-multitarget algorithm based on the BP method where the number of PTs is time-varying has been presented in [15].

parameters. For mathematical convenience, a state $\mathbf{x}_{n,k}$ is also defined (formally) for a nonexistent PT k.

There are S sensors $s \in \mathcal{S} \triangleq \{1,\ldots,S\}$ which provide "thresholded" measurements out of a detection process. At time n, sensor s produces $M_n^{(s)}$ measurements $\mathbf{z}_{n,m}^{(s)}$, $m \in \mathcal{M}_n^{(s)} \triangleq \{1,\ldots,M_n^{(s)}\}$. We define $\mathbf{z}_n^{(s)} \triangleq \big[\mathbf{z}_{n,1}^{(s)\mathrm{T}} \cdots \mathbf{z}_{n,M_n^{(s)}}^{(s)\mathrm{T}}\big]^{\mathrm{T}}$, $\mathbf{z}_n \triangleq \big[\mathbf{z}_n^{(1)\mathrm{T}} \cdots \mathbf{z}_n^{(S)\mathrm{T}}\big]^{\mathrm{T}}$, and $\mathbf{z} \triangleq [\mathbf{z}_1^{\mathrm{T}} \cdots \mathbf{z}_n^{\mathrm{T}}]^{\mathrm{T}}$ as well as $\mathbf{m}_n \triangleq \big[M_n^{(1)} \cdots M_n^{(S)}\big]^{\mathrm{T}}$ and $\mathbf{m} \triangleq [\mathbf{m}_1^{\mathrm{T}} \cdots \mathbf{m}_n^{\mathrm{T}}]^{\mathrm{T}}$. There is a data association (measurement origin) uncertainty: it is not known which measurement $\mathbf{z}_{n,m}^{(s)}$ originated from which PT k, and it is possible that $\mathbf{z}_{n,m}^{(s)}$ did not originate from any PT (false alarm, clutter) or that a PT did not lead to any measurement at sensor s (missed detection) [1], [16]. We assume that an existing PT can generate at most one measurement at sensor s, and a measurement at sensor s can be generated by at most one existing PT [1], [16]. The measurement-PT associations at sensor s and time n can then be described by the random vector $\mathbf{a}_n^{(s)} = \big[a_{n,1}^{(s)} \cdots a_{n,K}^{(s)}\big]^{\mathrm{T}}$ with entries

$$a_{n,k}^{(s)} \triangleq \begin{cases} m \in \mathcal{M}_n^{(s)}, & \text{if at time } n, \text{ PT } k \text{ generates measurement } m \text{ at sensor } s \\ 0, & \text{if at time } n, \text{ PT } k \text{ is not detected by sensor } s. \end{cases}$$

Following [9], [17], we will use alongside with the "PT-oriented" association vector $\mathbf{a}_n^{(s)}$ the "measurement-oriented" association vector $\mathbf{b}_n^{(s)} = \big[b_{n,1}^{(s)} \cdots b_{n,M_n^{(s)}}^{(s)}\big]^{\mathrm{T}}$, whose entries are defined as

$$b_{n,m}^{(s)} \triangleq \begin{cases} k \in \mathcal{K}, & \text{if at time } n, \text{ measurement } m \text{ at sensor } s \text{ is generated by PT } k \\ 0, & \text{if at time } n, \text{ measurement } m \text{ at sensor } s \text{ is not generated by a PT.} \end{cases}$$

We also define $\mathbf{a}_n \triangleq \big[\mathbf{a}_n^{(1)\mathrm{T}} \cdots \mathbf{a}_n^{(S)\mathrm{T}}\big]^{\mathrm{T}}$ and $\mathbf{a} \triangleq [\mathbf{a}_1^{\mathrm{T}} \cdots \mathbf{a}_n^{\mathrm{T}}]^{\mathrm{T}}$ and $\mathbf{b}_n \triangleq \big[\mathbf{b}_n^{(1)\mathrm{T}} \cdots \mathbf{b}_n^{(S)\mathrm{T}}\big]^{\mathrm{T}}$ and $\mathbf{b} \triangleq \big[\mathbf{b}_1^{\mathrm{T}} \cdots \mathbf{b}_n^{\mathrm{T}}\big]^{\mathrm{T}}$. Note that $\mathbf{b}$ is redundant since it can be derived from $\mathbf{a}$ and vice versa. An existing PT k is detected by sensor s (in the sense that the PT generates a measurement $\mathbf{z}_{n,m}^{(s)}$ at sensor s) with an unknown probability $q_{n,k}^{(s)}$. We define $\mathbf{q}_n^{(s)} \triangleq \big[q_{n,1}^{(s)} \cdots q_{n,K}^{(s)}\big]^{\mathrm{T}}$, $\mathbf{q}_n \triangleq \big[\mathbf{q}_n^{(1)\mathrm{T}} \cdots \mathbf{q}_n^{(S)\mathrm{T}}\big]^{\mathrm{T}}$, and $\mathbf{q} \triangleq [\mathbf{q}_1^{\mathrm{T}} \cdots \mathbf{q}_n^{\mathrm{T}}]^{\mathrm{T}}$. The number of false alarms at sensor s is modeled by a Poisson probability mass function (pmf) with mean value $\mu^{(s)}$, and the distribution of each false alarm measurement at sensor s is described by the probability density function (pdf) $f_{\mathrm{FA}}\big(\mathbf{z}_{n,m}^{(s)}\big)$.

B. Markov Chain Modeling of Unknown Parameters

In addition to the "primary" quantities tracked by the proposed multisensor-multitarget tracking algorithm—i.e., the target states $\mathbf{x}_{n,k}$, target existence indicators $r_{n,k}$, and association variables $a_{n,k}^{(s)}$—there are typically certain other parameters, that are also unknown and time-varying. These parameters might either characterize the dynamics of each single PT k, i.e. the driving noise variance in a nearly-constant velocity model, the turn rate in a coordinated turn model, IMM parameters, the birth intensity rate, or be strictly related to the measurements at each sensor s and the measurement model, i.e. the detection probabilities $q_{n,k}^{(s)}$ at each sensor s, the clutter intensity profile and the mean number of false alarms $\mu^{(s)}$. In order to obtain an adaptive tracking algorithm, that is able to cope with changing environmental conditions, we propose to track also unknown and time-varying parameters, within our BP-based sequential inference framework. To achieve this, each parameter is discretized for computational efficiency (unless it is already discrete-valued) and its time-evolution is modeled as a first-order Markov random process.

For concreteness, in our system model and tracking method, we will consider two specific types of tracked parameters, the IMM parameters, which are related to the dynamic motion of the targets and the detection probabilities, instead related to the modeling of the measurements. The detection probabilities, $q_{n,k}^{(s)}$, are assumed independent across k and s and to take their values from a finite set $\mathcal{Q} = \{\omega_1,\ldots,\omega_Q\}$, where $\omega_i \in (0,1]$. Furthermore, their temporal evolution conforms to the Markov chain model with a transition matrix $\mathbf{Q}^{(s)} \in (0,1]^{Q\times Q}$ that is time-invariant and equal for all PTs $k \in \mathcal{K}$ but generally sensor-dependent. Accordingly, the transition probability of $q_{n,k}^{(s)}$ is given by $p\big(q_{n,k}^{(s)} = \omega_j | q_{n-1,k}^{(s)} = \omega_i\big) = [\mathbf{Q}^{(s)}]_{i,j}$, for $\omega_i, \omega_j \in \mathcal{Q}$. Note that $\sum_{j=1}^{Q} [\mathbf{Q}^{(s)}]_{i,j} = 1$ for all $i \in \{1,\ldots,Q\}$. The initial distribution of $q_{n,k}^{(s)}$ is given by the pmf $p(q_{0,k}^{(s)})$. It follows that the prior pmf of $\mathbf{q}$ factorizes as

$$p(\mathbf{q}) = \prod_{s=1}^{S}\prod_{k=1}^{K} p\big(q_{0,k}^{(s)}\big) \prod_{n'=1}^{n} p\big(q_{n',k}^{(s)} | q_{n'-1,k}^{(s)}\big) \qquad (1)$$

The IMM parameters will be considered in the next subsection.

C. Target Dynamics

We follow the IMM approach [10]–[13], i.e., each PT can switch among different dynamic models ("modes") at any time n. Therefore, the temporal evolution of the state of a PT k that exists at times $n-1$ and n (i.e., for which $r_{n-1,k} = r_{n,k} = 1$) is modeled as

$$\mathbf{x}_{n,k} = \mathbf{f}_{\ell_{n,k}}(\mathbf{x}_{n-1,k}, \mathbf{u}_{n,k}). \qquad (2)$$

Here, $\mathbf{f}_{\ell_{n,k}}(\cdot,\cdot)$ is the state-transition function of PT k that is in force at time n, and which is selected from a set $\big\{\mathbf{f}_j(\cdot,\cdot)\big\}_{j=1}^{J}$ of J different state-transition functions by the IMM parameter $\ell_{n,k} \in \mathcal{J} \triangleq \{1,\ldots,J\}$. Furthermore, as it is usually assumed [1], [10], $\mathbf{u}_{n,k}$ represents a driving process independent and identically distributed (iid) across n and k. We note that $\mathbf{f}_j(\cdot,\cdot)$ and the statistics of $\mathbf{u}_{n,k}$ determine the *state-transition pdf* $f_j(\mathbf{x}_{n,k}|\mathbf{x}_{n-1,k})$.

The IMM parameters $\ell_{n,k}$ are modeled as random variables that are independent across k and evolve temporally according to the Markov chain model with transition matrix $\mathbf{L} \in [0,1]^{J\times J}$ that is time-invariant and equal for all PTs $k \in \mathcal{K}$. Thus, the transition pmf of $\ell_{n,k}$, $p(\ell_{n,k} = j | \ell_{n-1,k} = i)$, is given by $p_{i,j} \triangleq [\mathbf{L}]_{i,j}$, for $i,j \in \mathcal{J}$. Note that $\sum_{j=1}^{J} [\mathbf{L}]_{i,j} = 1$ for all $i \in \{1,\ldots,J\}$.

We define the *augmented state* of PT k as $\mathbf{y}_{n,k} \triangleq [\mathbf{x}_{n,k}^{\mathrm{T}}\, r_{n,k}\, \ell_{n,k}]^{\mathrm{T}}$ and also $\mathbf{y}_n \triangleq [\mathbf{y}_{n,1}^{\mathrm{T}} \cdots \mathbf{y}_{n,K}^{\mathrm{T}}]^{\mathrm{T}}$. The augmented target states $\mathbf{y}_{n,k}$ are assumed to evolve independently according to Markovian dynamic models, and at time $n = 0$, they are assumed statistically independent across k with prior pdfs $f(\mathbf{y}_{0,k}) = f(\mathbf{x}_{0,k}, r_{0,k}, \ell_{0,k})$. Then, the pdf of $\mathbf{y} \triangleq [\mathbf{y}_1^{\mathrm{T}} \cdots \mathbf{y}_n^{\mathrm{T}}]^{\mathrm{T}}$ factorizes as

$$f(\mathbf{y}) = \prod_{k=1}^{K} f(\mathbf{y}_{0,k}) \prod_{n'=1}^{n} f(\mathbf{y}_{n',k}|\mathbf{y}_{n'-1,k})\,. \tag{3}$$

Assuming that the state $\mathbf{x}_{n,k}$ and the existence variable $r_{n,k}$ depends only on the mode parameter $\ell_{n,k}$ of each PT k at time n and due to the Markovian properties of the mode parameter $\ell_{n,k}$, the single-target augmented state-transition pdf $f(\mathbf{y}_{n,k}|\mathbf{y}_{n-1,k})$ factorizes as

$$\begin{aligned} f(\mathbf{y}_{n,k}|\mathbf{y}_{n-1,k}) &= f(\mathbf{x}_{n,k}, r_{n,k}, \ell_{n,k}|\mathbf{x}_{n-1,k}, r_{n-1,k}, \ell_{n-1,k}) \\ &= f(\mathbf{x}_{n,k}, r_{n,k}|\mathbf{x}_{n-1,k}, r_{n-1,k}, \ell_{n,k}, \ell_{n-1,k}) \\ &\quad \times p(\ell_{n,k}|\mathbf{x}_{n-1,k}, r_{n-1,k}, \ell_{n-1,k}) \\ &= f(\mathbf{x}_{n,k}, r_{n,k}|\mathbf{x}_{n-1,k}, r_{n-1,k}, \ell_{n,k}) \\ &\quad \times p_{\ell_{n,k},\ell_{n-1,k}}\,. \end{aligned} \tag{4}$$

An expression for $f(\mathbf{x}_{n,k}, r_{n,k}|\mathbf{x}_{n-1,k}, r_{n-1,k}, \ell_{n,k})$ in terms of the birth probability $p_{n,k}^{b}$, the survival probability $p_{n,k}^{s}$, the mode-dependent state transition pdf $f_{\ell_{n,k}}(\mathbf{x}_{n,k}|\mathbf{x}_{n-1,k})$ and the mode-dependent birth density $f_{\ell_{n,k}}^{b}$, is obtained by following the approach in [9, Sec. II-A].

D. Measurement Model and Likelihood Function

If measurement $\mathbf{z}_{n,m}^{(s)}$ is generated by target k, i.e. $a_{n,k}^{(s)} = m \in \mathcal{M}_n^{(s)}$, then its distribution conditional on the target state $\mathbf{x}_{n,k}$ is described by the pdf $f(\mathbf{z}_{n,m}^{(s)}|\mathbf{x}_{n,k})$. Under commonly used assumptions [1], [9], [17], that given $\mathbf{y}, \mathbf{a}$ and $\mathbf{m}$, the measurements $\mathbf{z}_n^{(s)}$ are conditionally independent across time n and sensor index s, that the different measurements $\mathbf{z}_{n,m}^{(s)}$, $m \in \mathcal{M}_n^{(s)}$ at any given sensor s are conditionally independent given $\mathbf{y}_n$, $\mathbf{a}_n^{(s)}$, and $M_n^{(s)}$ and since in accordance with standard measurement models, the IMM parameters $\ell_{n,k}$ for each target k at time n influence only the modeling of the target dynamics, the total likelihood function $f(\mathbf{z}|\mathbf{y}, \mathbf{a}, \mathbf{m})$ can be written as

$$f(\mathbf{z}|\mathbf{y}, \mathbf{a}, \mathbf{m}) = C(\mathbf{z}) \prod_{n'=1}^{n} \prod_{s=1}^{S} \prod_{k=1}^{K} w\big(\mathbf{x}_{n',k}, r_{n',k}, a_{n',k}^{(s)}; \mathbf{z}_{n'}^{(s)}\big)\,. \tag{5}$$

where $C(\mathbf{z})$ is a normalization factor that depends only on $\mathbf{z}$ and $w\big(\mathbf{x}_{n,k}, r_{n,k}, a_{n,k}^{(s)}; \mathbf{z}_n^{(s)}\big)$ is defined as

$$w\big(\mathbf{x}_{n,k}, 1, a_{n,k}^{(s)}; \mathbf{z}_n^{(s)}\big) = \begin{cases} \dfrac{f\big(\mathbf{z}_{n,m}^{(s)}\big|\mathbf{x}_{n,k}\big)}{f_{\mathrm{FA}}\big(\mathbf{z}_{n,m}^{(s)}\big)}, & a_{n,k}^{(s)} = m \in \mathcal{M}_n^{(s)} \\ 1, & a_{n,k}^{(s)} = 0 \end{cases}$$

$$w\big(\mathbf{x}_{n,k}, 0, a_{n,k}^{(s)}; \mathbf{z}_n^{(s)}\big) = 1.$$

E. Joint Prior Distribution of Association Variables and Numbers of Measurements

Let $1(a)$ denote the indicator function of the event $a = 0$, i.e., $1(a) = 1$ if $a = 0$ and 0 otherwise. Under commonly used independence assumptions [1], [9], [17], that given $\mathbf{y}$, the $\mathbf{a}_n^{(s)}$ and the $M_n^{(s)}$ are conditionally independent across n and s, that the measurement $\mathbf{z}_{n,m}^{(s)}$, $m \in \mathcal{M}_n^{(s)}$ at sensor s are randomly ordered, with each possible order equally likely, and since for each PT k and sensor s, the association variables $a_{n,k}^{(s)}$ are independent from $\ell_{n,k}$ given $\mathbf{x}_{n,k}$ and $r_{n,k}$, the joint prior pmf of $\mathbf{a}$ and $\mathbf{m}$ given $\mathbf{y}$ and $\mathbf{q}$ can be expressed as

$$\begin{aligned} &p(\mathbf{a}, \mathbf{b}, \mathbf{m}|\mathbf{y}, \mathbf{q}) \\ &\quad = C(\mathbf{m}) \prod_{n'=1}^{n} \prod_{s=1}^{S} \prod_{k=1}^{K} h\big(\mathbf{x}_{n,k}, r_{n,k}, a_{n,k}^{(s)}, q_{n,k}^{(s)}; M_n^{(s)}\big) \\ &\qquad \times \prod_{m=1}^{M_n^{(s)}} \Psi\big(a_{n,k}^{(s)}, b_{n,m}^{(s)}\big)\,. \end{aligned} \tag{6}$$

where $C(\mathbf{m})$ is a normalization factor that depends only on $\mathbf{m}$, $h\big(\mathbf{x}_{n,k}, r_{n,k}, a_{n,k}^{(s)}, q_{n,k}^{(s)}; M_n^{(s)}\big)$ is defined as

$$h\big(\mathbf{x}_{n,k}, 1, a_{n,k}^{(s)}, q_{n,k}^{(s)}; M_n^{(s)}\big) = \begin{cases} \dfrac{q_{n,k}^{(s)}}{\mu^{(s)}}, & a_{n,k}^{(s)} \in \mathcal{M}_n^{(s)} \\ 1 - q_{n,k}^{(s)}, & a_{n,k}^{(s)} = 0 \end{cases}$$

$$h\big(\mathbf{x}_{n,k}, 0, a_{n,k}^{(s)}, q_{n,k}^{(s)}; M_n^{(s)}\big) = 1\big(a_{n,k}^{(s)}\big)\,.$$

and $\Psi\big(a_{n,k}^{(s)}, b_{n,m}^{(s)}\big) \in \{0, 1\}$ is an indicator function defined as

$$\Psi\big(a_{n,k}^{(s)}, b_{n,m}^{(s)}\big) \triangleq \begin{cases} 0, & a_{n,k}^{(s)} = m,\ b_{n,m}^{(s)} \neq k \\ & \quad \text{or } b_{n,m}^{(s)} = k,\ a_{n,k}^{(s)} \neq m \\ 1, & \text{otherwise.} \end{cases}$$

As already reported in [9], [17] $\Psi\big(a_{n,k}^{(s)}, b_{n,m}^{(s)}\big)$ enforces the data association assumption, i.e., a target can generate at most one measurement at sensor s, and a measurement at sensor s can be generated by at most one target. Moreover, the resulting association is a key to obtaining an algorithm that scales well in the number of targets and in the number of measurements per sensor [9].

III. The Proposed Method

In this section, we describe the adaptive BP-based multisensor-multitarget tracking algorithm.

A. Target Detection and State Estimation

The ultimate objective of the proposed multisensor-multitarget tracking algorithm is to determine the existence of a PT $k \in \mathcal{K}$ (i.e., to detect the binary target existence variables $r_{n,k}$) and to estimate the states $\mathbf{x}_{n,k}$ of the detected PTs. This detection-estimation step is based on the past and present measurements of all the sensors, i.e., on the total measurement vector $\mathbf{z}$. In the Bayesian setting, target detection and state estimation essentially amount to calculating the marginal posterior existence probabilities $p(r_{n,k}=1|\mathbf{z})$ and the marginal posterior state pdfs $f(\mathbf{x}_{n,k}|r_{n,k}=1,\mathbf{z})$, respectively. PT k is detected if $p(r_{n,k}=1|\mathbf{z})$ is larger than a suitably chosen threshold P_{th} [18, Chapter 2]. Furthermore, for each detected PT k, an estimate of $\mathbf{x}_{n,k}$ is provided by the minimum mean square error estimator (MMSE) given by [18, Chapter 4]

$$\hat{\mathbf{x}}_{n,k}^{\text{MMSE}} \triangleq \int \mathbf{x}_{n,k} f(\mathbf{x}_{n,k}|r_{n,k}=1,\mathbf{z})\,\mathrm{d}\mathbf{x}_{n,k}\,. \quad (7)$$

The marginal statistics $p(r_{n,k}=1|\mathbf{z})$ and $f(\mathbf{x}_{n,k}|r_{n,k}=1,\mathbf{z})$ used for target detection and state estimation can be obtained from the marginal posterior pdf of the augmented target state, $f(\mathbf{y}_{n,k}|\mathbf{z}) = f(\mathbf{x}_{n,k}, r_{n,k}, \ell_{n,k}|\mathbf{z})$, according to

$$p(r_{n,k}=1|\mathbf{z}) = \sum_{\ell_{n,k}\in\mathcal{J}} \int f(\mathbf{x}_{n,k}, r_{n,k}=1, \ell_{n,k}|\mathbf{z})\,\mathrm{d}\mathbf{x}_{n,k} \quad (8)$$

and

$$f(\mathbf{x}_{n,k}|r_{n,k}=1,\mathbf{z}) = \frac{\sum_{\ell_{n,k}\in\mathcal{J}} f(\mathbf{x}_{n,k}, r_{n,k}=1, \ell_{n,k}|\mathbf{z})}{p(r_{n,k}=1|\mathbf{z})}\,, \quad (9)$$

respectively. The marginal posterior pdf $f(\mathbf{y}_{n,k}|\mathbf{z})$ is a marginal of the joint posterior of $f(\mathbf{y},\mathbf{a},\mathbf{b},\mathbf{q}|\mathbf{z})$. This calculation can be performed in an efficient manner by means of the BP algorithm described in what follows.

B. Joint Posterior Distribution and Factor Graph

In the conditional pdf $f(\mathbf{y},\mathbf{a},\mathbf{b},\mathbf{q}|\mathbf{z})$, the measurements $\mathbf{z}$ are observed and thus fixed. As a consequence, the numbers of measurements $M_n^{(s)}$ and the corresponding vector $\mathbf{m}$ are fixed as well. We then have

$$\begin{aligned} f(\mathbf{y},\mathbf{a},\mathbf{b},\mathbf{q}|\mathbf{z}) &= f(\mathbf{y},\mathbf{a},\mathbf{b},\mathbf{q},\mathbf{m}|\mathbf{z}) \\ &\propto f(\mathbf{z}|\mathbf{y},\mathbf{a},\mathbf{b},\mathbf{q},\mathbf{m})\, f(\mathbf{y},\mathbf{a},\mathbf{b},\mathbf{q},\mathbf{m}) \\ &= f(\mathbf{z}|\mathbf{y},\mathbf{a},\mathbf{m})\, f(\mathbf{y},\mathbf{a},\mathbf{b},\mathbf{m},\mathbf{q}) \\ &= f(\mathbf{z}|\mathbf{y},\mathbf{a},\mathbf{m})\, p(\mathbf{a},\mathbf{b},\mathbf{m}|\mathbf{y},\mathbf{q})\, f(\mathbf{y})\, p(\mathbf{q})\,. \end{aligned}$$

Inserting (1) for $p(\mathbf{q})$, (3) for $f(\mathbf{y})$, (6) for $p(\mathbf{a},\mathbf{b},\mathbf{m}|\mathbf{y},\mathbf{q})$ and (5) for $f(\mathbf{z}|\mathbf{y},\mathbf{a},\mathbf{m})$ and omitting the constants $C(\mathbf{m})$ and $C(\mathbf{z})$, we obtain the final factorization

$$\begin{aligned} & f(\mathbf{y},\mathbf{a},\mathbf{b},\mathbf{q}|\mathbf{z}) \\ &\propto \prod_{k=1}^{K} f(\mathbf{y}_{0,k}) \prod_{n'=1}^{n} f(\mathbf{y}_{n',k}|\mathbf{y}_{n'-1,k}) \\ &\quad\times \prod_{s=1}^{S} p\big(q_{n',k}^{(s)}|q_{n'-1,k}^{(s)}\big)\, \upsilon\big(\mathbf{x}_{n',k}, r_{n',k}, a_{n',k}^{(s)}, q_{n',k}^{(s)}; \mathbf{z}_{n'}^{(s)}\big) \\ &\quad\times \prod_{m=1}^{M_{n'}^{(s)}} \psi\big(a_{n',k}^{(s)}, b_{n',m}^{(s)}\big)\,, \end{aligned} \quad (10)$$

with

$$\begin{aligned} & \upsilon\big(\mathbf{x}_{n,k}, r_{n,k}, a_{n,k}^{(s)}, q_{n,k}^{(s)}; \mathbf{z}_n^{(s)}\big) \\ &\triangleq w\big(\mathbf{x}_{n,k}, r_{n,k}, a_{n,k}^{(s)}; \mathbf{z}_n^{(s)}\big)\, h\big(\mathbf{x}_{n,k}, r_{n,k}, a_{n,k}^{(s)}, q_{n,k}^{(s)}; M_n^{(s)}\big)\,. \end{aligned}$$

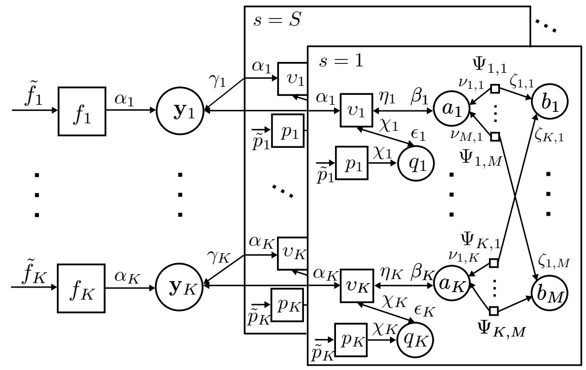

Fig. 1. Factor graph describing the factorization of $f(\mathbf{y},\mathbf{a},\mathbf{b},\mathbf{q}|\mathbf{z})$ in (10), shown for one time step. For simplicity, the time index n and sensor index s are omitted, and the following short notations are used: $f_k \triangleq f(\mathbf{y}_{n,k}|\mathbf{y}_{n-1,k})$, $p_k \triangleq p\big(q_{n,k}^{(s)}|q_{n-1,k}^{(s)}\big)$, $\upsilon_k \triangleq \upsilon\big(\mathbf{x}_{n,k}, r_{n,k}, a_{n,k}^{(s)}, q_{n,k}^{(s)}; \mathbf{z}_n^{(s)}\big)$, $\tilde{f}_k \triangleq \tilde{f}(\mathbf{y}_{n,k})$, $\tilde{p}_k \triangleq \tilde{p}\big(q_{n,k}^{(s)}\big)$, $\Psi_{k,m} \triangleq \Psi\big(a_{n,k}^{(s)}, b_{n,m}^{(s)}\big)$, $\alpha_k \triangleq \alpha(\mathbf{y}_{n,k})$, $\beta_k \triangleq \beta\big(a_{n,k}^{(s)}\big)$, $\eta_k \triangleq \eta\big(a_{n,k}^{(s)}\big)$, $\gamma_k \triangleq \gamma^{(s)}(\mathbf{y}_{n,k})$, $\chi_k \triangleq \chi\big(q_{n,k}^{(s)}\big)$, $\epsilon_k \triangleq \epsilon\big(q_{n,k}^{(s)}\big)$, $\nu_{m,k} \triangleq \nu_{m\to k}^{(p)}\big(a_{n,k}^{(s)}\big)$, and $\zeta_{k,m} \triangleq \zeta_{k\to m}^{(p)}\big(b_{n,m}^{(s)}\big)$.

The factor graph describing the factorization (10) is shown for one time step in Fig. 1.

C. BP Message Passing Algorithm

Following the approach in [9], approximations of the marginal posterior pdfs $f(\mathbf{y}_{n,k}|\mathbf{z}) = f(\mathbf{x}_{n,k}, r_{n,k}, \ell_{n,k}|\mathbf{z})$, known as *beliefs* and denoted as $\tilde{f}(\mathbf{x}_{n,k}, r_{n,k}, \ell_{n,k})$, can be calculated at each time n for all PTs k in an efficient way by running iterative BP message passing on the factor graph in Fig. 1. In addition, the beliefs $\tilde{p}\big(q_{n,k}^{(s)}\big)$, the mode beliefs $\tilde{g}(\ell_{n,k})$ and the beliefs $\tilde{f}(\mathbf{x}_{n,k}, r_{n,k}|\ell_{n,k})$, approximating respectively, the posterior pmfs of the detection probabilities, $p\big(q_{n,k}^{(s)}|\mathbf{z}\big)$, the posterior pmfs of the modes, $p(\ell_{n,k}|\mathbf{z})$, and the posterior distributions of $\mathbf{x}_{n,k}$ and $r_{n,k}$ conditional on the the modes $\ell_{n,k}$, $f(\mathbf{x}_{n,k}, r_{n,k}|\ell_{n,k},\mathbf{z})$, are also calculated for all PTs $k \in \mathcal{K}$ and all sensors $s \in \mathcal{S}$. Since the obtained factor graph contains loops, there is no unique order of calculating the individual messages, and different orders may result in different sets of beliefs. In our algorithm, the order is defined by the following two rules: first, messages are not sent backward in time, and second, *iterative* message passing is only performed for data association, and separately at each time step and at each sensor. The second rule implies that for loops involving different sensors, only a single message passing iteration is performed. Combining these rules with the generic BP rules for calculating messages and beliefs [19], [20], one obtains the BP message passing operations at time n, which are reported in Algorithm 1.

First, a *prediction step* is performed for all PTs $k \in \mathcal{K}$. This comprises the calculation of the messages $\alpha(\mathbf{y}_{n,k}) = \alpha(\mathbf{x}_{n,k}, r_{n,k}, \ell_{n,k})$ and the messages $\chi\big(q_{n,k}^{(s)}\big)$ for all sensors $s \in \mathcal{S}$. Next, the following steps are performed for all PTs $k \in \mathcal{K}$ and for all sensors $s \in \mathcal{S}$ in parallel: a *measurement evaluation* step, where the messages $\beta\big(a_{n,k}^{(s)}\big)$ are calculated; a

Input (from previous time $n-1$):
$\tilde{f}(\mathbf{x}_{n-1,k}, r_{n-1,k}|\ell_{n-1,k})$, $\tilde{g}_{n-1,k}(\ell_{n-1,k})$, $\tilde{p}(q^{(s)}_{n-1,k})$

Prediction:
for $k \in \mathcal{K}$, $s \in \mathcal{S}$ **do**

$$\alpha(\mathbf{x}_{n,k}, r_{n,k}, \ell_{n,k}) = \sum_{\substack{r_{n-1,k},\\ \ell_{n-1,k}}} \int f(\mathbf{x}_{n,k}, r_{n,k}, \ell_{n,k}|\mathbf{x}_{n-1,k}, r_{n-1,k}, \ell_{n-1,k}) \times \tilde{f}(\mathbf{x}_{n-1,k}, r_{n-1,k}|\ell_{n-1,k})\tilde{g}_{n-1,k}(\ell_{n-1,k})\, \mathrm{d}\mathbf{x}_{n-1,k}$$

$$\chi(q^{(s)}_{n,k}) = \sum_{q^{(s)}_{n-1,k} \in \mathcal{Q}} p(q^{(s)}_{n,k}|q^{(s)}_{n-1,k})\, \tilde{p}(q^{(s)}_{n-1,k})$$

end

for *all* $k \in \mathcal{K}$, *all* $s \in \mathcal{S}$ *(in parallel)* **do**

Measurement evaluation:

$$\beta(a^{(s)}_{n,k}) = \sum_{q^{(s)}_{n,k} \in \mathcal{Q}} \chi(q^{(s)}_{n,k}) \int v(\mathbf{x}_{n,k}, 1, a^{(s)}_{n,k}, q^{(s)}_{n,k}; \mathbf{z}^{(s)}_n) \times A(\mathbf{x}_{n,k}, 1)\, \mathrm{d}\mathbf{x}_{n,k} + 1(a^{(s)}_{n,k})\, \alpha_{n,k}$$

with $A(\mathbf{x}_{n,k}, 1) \triangleq \sum_{\ell_{n,k}} \alpha(\mathbf{x}_{n,k}, 1, \ell_{n,k})$ and $\alpha_{n,k} \triangleq \sum_{\ell_{n,k}} \alpha(\mathbf{x}_{n,k}, 0, \ell_{n,k}) \mathrm{d}\mathbf{x}_{n,k}$

Data association (same as in [9]):

$$\beta(a^{(s)}_{n,k}) \longrightarrow \eta(a^{(s)}_{n,k})$$

Measurement update:

$$\gamma^{(s)}(\mathbf{x}_{n,k}, r_{n,k}) = \sum_{\substack{a^{(s)}_{n,k},\\ q^{(s)}_{n,k} \in \mathcal{Q}}} v(\mathbf{x}_{n,k}, r_{n,k}, a^{(s)}_{n,k}, q^{(s)}_{n,k}; \mathbf{z}^{(s)}_n) \times \chi(q^{(s)}_{n,k})\, \eta(a^{(s)}_{n,k})$$

Detection probability update:

$$\epsilon(q^{(s)}_{n,k}) = \sum_{a^{(s)}_{n,k}} \int v(\mathbf{x}_{n,k}, 1, a^{(s)}_{n,k}, q^{(s)}_{n,k}; \mathbf{z}^{(s)}_n)\, \eta(a^{(s)}_{n,k}) \times A(\mathbf{x}_{n,k}, 1)\, \mathrm{d}\mathbf{x}_{n,k} + \eta(0)\, \alpha_{n,k}$$

$$\tilde{p}(q^{(s)}_{n,k}) = \chi(q^{(s)}_{n,k})\, \epsilon(q^{(s)}_{n,k}) \tag{11}$$

end

Belief calculation:
for $k \in \mathcal{K}$ **do**

$$\tilde{f}(\mathbf{x}_{n,k}, r_{n,k}, \ell_{n,k}) = \frac{1}{C_{n,k}}\, \alpha(\mathbf{x}_{n,k}, r_{n,k}, \ell_{n,k}) \times \prod_{s \in \mathcal{S}} \gamma^{(s)}(\mathbf{x}_{n,k}, r_{n,k})$$

$$\tilde{g}_{n,k}(\ell_{n,k}) = \sum_{r_{n,k}} \int \tilde{f}(\mathbf{x}_{n,k}, r_{n,k}, \ell_{n,k})\, \mathrm{d}\mathbf{x}_{n,k} \tag{12}$$

$$\tilde{f}(\mathbf{x}_{n,k}, r_{n,k}|\ell_{n,k}) = \frac{\tilde{f}(\mathbf{x}_{n,k}, r_{n,k}, \ell_{n,k})}{\tilde{g}_{n,k}(\ell_{n,k})}$$

$C_{n,k}$: normalization constant

end

Algorithm 1: Adaptive BP algorithm for a single iteration at time n.

data association step, that closely follows [17] and is the same as in [9], in which the messages $\beta(a^{(s)}_{n,k})$ are converted into messages $\eta(a^{(s)}_{n,k})$; a *measurement update* step, in which the messages $\gamma^{(s)}(\mathbf{x}_{n,k}, r_{n,k})$ are computed; a *detection probability update* step, in which the updated detection probabilities beliefs $\tilde{p}(q^{(s)}_{n,k})$ are obtained. Finally, in the *belief calculation* step, the beliefs $\tilde{f}(\mathbf{x}_{n,k}, r_{n,k}, \ell_{n,k})$, $\tilde{g}(\ell_{n,k})$, $\tilde{f}(\mathbf{x}_{n,k}, r_{n,k}|\ell_{n,k})$ are computed for all PTs $k \in \mathcal{K}$ and used as input to the next time $n+1$[2].

The detection of each PT k and state estimation of the detected PTs is carried out by using $\tilde{f}(\mathbf{x}_{n,k}, 1, \ell_{n,k})$ instead of $f(\mathbf{x}_{n,k}, r_{n,k}=1, \ell_{n,k}|\mathbf{z})$ in Eqs. (8) and (9), respectively. A particle-based implementation of this BP message passing algorithm that avoids an explicit evaluation of integrals and message products can be obtained by extending the implementation presented in [9].

IV. Simulation Results

The performance of the proposed adaptive multisensor-multitarget tracking method has been validated in a simulated scenario and compared with the performance of the original nonadaptive BP algorithm from [9].

A. Basic simulation setup

In the simulated scenario, the number of PTs K is set to 8, and the state of each PT k consists of two-dimensional (2D) position and velocity, i.e., $\mathbf{x}_{n,k} = [x_{1,n,k}\ x_{2,n,k}\ \dot{x}_{1,n,k}\ \dot{x}_{2,n,k}]^{\mathrm{T}}$. We consider dynamic models (DMs) $\mathbf{f}_j$ of the nearly-constant velocity type, i.e. (cf. (2))

$$\mathbf{x}_{n,k} = \mathbf{f}_j(\mathbf{x}_{n-1,k}, \mathbf{u}_{n,k}) = \begin{bmatrix} 1 & \Delta T \\ 0 & 1 \end{bmatrix} \otimes \mathbf{I}_2\, \mathbf{x}_{n-1,k} + \begin{bmatrix} \Delta T^2/2 \\ \Delta T \end{bmatrix} \otimes \mathbf{I}_2\, \mathbf{u}^{(j)}_{n,k} \tag{13}$$

where $\mathbf{I}_2$ denotes the 2D identity matrix and $\Delta T = 20\,\mathrm{s}$ is the sampling period, i.e., the duration of one time step n; furthermore, the driving process $\mathbf{u}^{(j)}_{n,k} \sim \mathcal{N}(\mathbf{0}, \sigma_j^2 \mathbf{I}_2)$ is a sequence of 2D Gaussian random vectors that is iid across n and k. We note that the DMs $\mathbf{f}_j(\cdot)$ differ solely in the driving process variance σ_j^2. Higher values of σ_j^2 are typically used to model maneuvering targets. In the simulated scenario, the number of different DMs is chosen as $J = 2$.

We simulate two targets which move inside a surveillance square region given by $[-80\,\mathrm{km}, 80\,\mathrm{km}] \times [-80\,\mathrm{km}, 80\,\mathrm{km}]$. The nominal DM of both targets is $\mathbf{f}_1$ with driving process variance $\sigma_1^2 = 0.01^2$, and this DM is used by the nonadaptive algorithm. However, the true target trajectories conform to DM $\mathbf{f}_1$ only in the time intervals $[1, 190]$ and $[230, 400]$, whereas in the intermediate time interval $[191, 229]$, the targets perform a coordinated turn with nearly constant speed and constant angular rate. The proposed adaptive algorithm switches adaptively between DM $\mathbf{f}_1$ and a second nearly-constant velocity DM $\mathbf{f}_2$ with driving process variance $\sigma_2^2 = 0.1^2$. It uses the

[2]A deeper description and derivation of all calculated messages at each time n will be provided in future work.

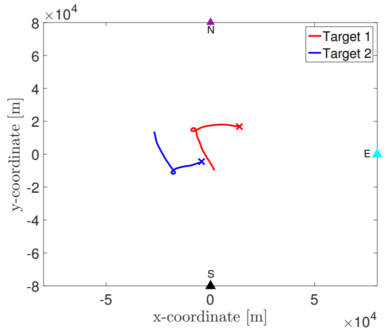

Fig. 2. Target trajectories and sensor positions for the simulated scenario.

DM transition probabilities $[\mathbf{L}]_{1,1} = [\mathbf{L}]_{2,2} = 0.9975$ and $[\mathbf{L}]_{1,2} = [\mathbf{L}]_{2,1} = 0.0025$.

There are $S=3$ monostatic sensors (i.e., source and receiver are colocated). The three sensors are located at North, South and East and measure the target position in polar coordinates, i.e., range and bearing, with a maximum range of 160 km. The range and bearing standard deviations are $\sigma_r = 150$ m and $\sigma_b = 1.5°$, respectively. The target trajectories and sensor positions are depicted in Fig. 2. The false-alarm pdf $f_{\text{FA}}\big(\mathbf{z}_{n,m}^{(s)}\big)$ is linearly increasing on $[0\,\text{km}, 160\,\text{km}]$ and zero outside that interval with respect to the range component, and uniform on $[0°, 360°)$ with respect to the bearing component. The simulated detection probabilities depend on the distances of the targets from the sensors and thus are time-varying. They are estimated by the proposed adaptive algorithm with set of detection probabilities $\mathcal{Q} = \{0.01, 0.1, 0.2, \ldots, 0.9, 1\}$. The transition matrix $\mathbf{Q}^{(s)} = \mathbf{Q}$ is as follows: for $2 \le i \le Q-1$, $[\mathbf{Q}]_{i,i-1} = 0.03$, $[\mathbf{Q}]_{i,i} = 0.92$ and $[\mathbf{Q}]_{i,i+1} = 0.05$; furthermore, $[\mathbf{Q}]_{1,1} = 0.95$, $[\mathbf{Q}]_{1,2} = 0.05$, $[\mathbf{Q}]_{Q,Q-1} = 0.03$ and $[\mathbf{Q}]_{Q,Q} = 0.97$, and $[\mathbf{Q}]_{i,j} = 0$, otherwise. The nonadaptive algorithm uses instead for all $q_{n,k}^{(s)}$ the fixed value of 0.8. The mean number of false alarms $\mu^{(s)}$ is set equal to 10. The birth and survival probability are $p_{n,k}^{s} = p^{s} = 0.999$ and $p_{n,k}^{b} = p^{b} = 0.001$, respectively. The detection threshold is $P_{\text{th}} = 0.5$. We used particle-based implementations of the adaptive and nonadaptive methods with a number of particles $M_{\text{p}} = 5000$. We performed 200 simulation runs, which differ in the initialization of the random seed used to simulate the sensor measurements and generate the random particles.

B. Results

Fig. 3 shows the Euclidean distance based mean optimal sub-pattern assignment (MOSPA) error with order $p = 1$ and cutoff parameter $c = 1000$ [21], for the two methods, averaged over the 200 simulations. The MOSPA error takes into account both the estimation errors for correctly detected targets and the errors due to incorrect target detections. One can see that the MOSPA error of the proposed adaptive method is typically lower than that of the nonadaptive method during the turn interval $[191, 229]$. Indeed here, the time-averaged MOSPA error is 252 m for the adaptive method versus 561 m for the

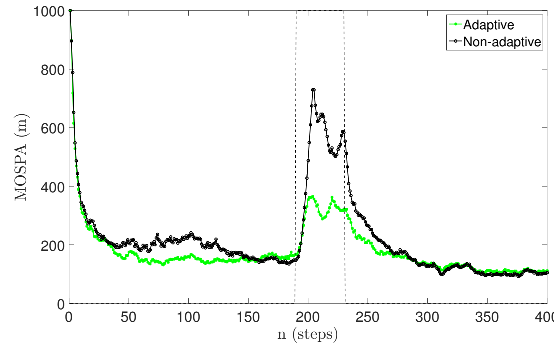

Fig. 3. MOSPA error for the simulated scenario. The dashed line indicates the times when the DM changes.

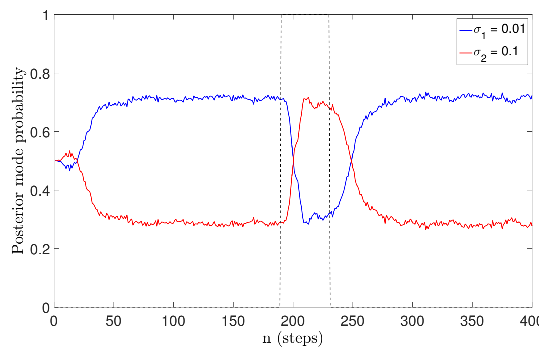

Fig. 4. Averaged mode beliefs $\tilde{g}_{n,k}(\ell_{n,k})$ of the proposed method for the DMs $\mathbf{f}_1$ and $\mathbf{f}_2$. The dashed line indicates the times when the DM changes.

nonadaptive method. In general, the time-averaged MOSPA error is 181 m for the adaptive method versus 221 m for the nonadaptive method.

Fig. 4 shows the mode beliefs $\tilde{g}_{n,k}(\ell_{n,k})$ (cf. (12) in Algorithm 1) for the DMs $\mathbf{f}_1$ and $\mathbf{f}_2$ calculated by the proposed method, averaged over the 200 simulations and the two targets. It is seen that the mode beliefs correctly picture the DM actually in force, albeit with a transition delay of approximately 20 time steps in switching between the DMs. This delay is probably caused by the high values of the range and bearing standard deviations ($\sigma_r = 150$ m, $\sigma_b = 1.5°$).

Finally, Fig. 5 shows the detection probabilities $q_{n,2}^{(s)}$ estimated by the proposed method of target $k=2$ for each of the three sensors s, along with the true detection probabilities and for a single simulation run. Approximate MMSE estimates of the $q_{n,k}^{(s)}$ were obtained as $\hat{q}_{n,k}^{(s)} = \sum_{i=1}^{Q} \omega_i \tilde{p}(q_{n,k}^{(s)} = \omega_i)$, with $\tilde{p}\big(q_{n,k}^{(s)}\big)$ calculated as in (11) in Algorithm 1. It is seen that the estimates roughly approximate the true detection probabilities, which depend on the distance between the target and the respective sensor.

V. Conclusions

This paper extends previous work [9] by showing how the belief propagation (BP) message passing scheme can be exploited to develop an adaptive Bayesian multisensor-

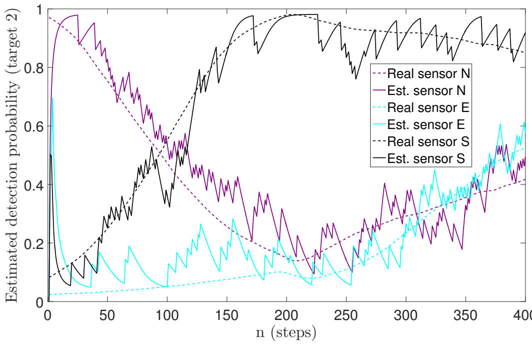

Fig. 5. Estimated detection probabilities for target 2 at the three sensors, for the simulated scenario. The dotted lines indicate the true detection probabilities.

multitarget tracking algorithm. The proposed adaptive algorithm is able to cope with time-varying changing conditions, i.e. maneuvering targets, varying detection probabilities and clutter profiles, by estimating online multiple unknown model parameters. The evolution of the unknown parameters is described by a Markov chain and the parameters are tracked together with the target states using a BP-based tracking methodology. The BP approach provides a principled way to reduce complexity by exploiting conditional statistical independencies, which leads to quasi-optimum Bayesian multisensor-multitarget tracking algorithms with excellent scalability.

As a concrete example, we addressed the case of motion model indices (IMM parameters) and unknown detection probabilities. Simulation results showed that our algorithm is able to track multiple targets during coordinated turns and for time-varying detection probabilities, and that it achieves a significant reduction of the time-averaged MOSPA error relative to the nonadaptive BP-based algorithm (e.g., a time-averaged MOSPA error of 181 m versus 221 m for the nonadaptive algorithm).

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Title

Online estimation of unknown parameters in multisensor-multitarget tracking: a belief propagation approach

Abstract

We propose a Bayesian multisensor-multitarget tracking framework, which adapts to randomly changing conditions by continually estimating unknown model parameters along with the target states. The time-evolution of the model parameters is described by a Markov chain and the parameters are incorporated in a factor graph that represents the statistical structure of the tracking problem. We then use the belief propagation (BP) message passing scheme to calculate the marginal posterior distributions of the targets and the model parameters in an efficient way that exploits conditional statistical independencies. As a concrete example, we develop an adaptive BP-based multisensor-multitarget tracking algorithm for manoeuvring targets with multiple dynamic models and sensors with unknown and time-varying detection probabilities. The performance of the proposed algorithm is finally evaluated in a simulated scenario.

Keywords

Multitarget tracking, online self-tuning algorithm, adaptive processing, probabilistic data association, belief propagation, message passing, factor graph

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