Rao-Blackwellized Particle Filter for Security Surveillance

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Abstract: Nowadays, the necessity of safeguarded environments is stronger than ever. The defence of public areas against terroristic threats requires intelligent security assistance systems that comprise state-of-the-art surveillance technology to localize persons with hazardous materials. The recent progress in the detection of hazardous materials by a new generation of chemical sensors leads to an increasing need of appropriate sensor models. Though, the detection capability of such sensors is quite high, their spatio-temporal resolution is very limited. Hence, a single chemical sensor is not able to localize hazardous material and assign it to a person. This drawback can be compensated by fusing the information of multiple chemical sensors with the location estimates of persons in an observed area. In this work, we are describing a Rao-Blackwellized Particle Filter (RBPF) that fuses person tracks with chemical sensors and thereby localizes persons carrying hazardous material.

1 Introduction

Freedom of movement for people as well as freedom to come together safely in open public events or utilities is vital for each citizen. The defence of this freedom against ubiquitous threats requires the development of intelligent security assistance systems that comprise state-of-the-art surveillance technology and work continuously in time. To satisfy this demand, we recently introduced an indoor security assistance system for the localization of hazardous materials in person streams [7]. Within this system, basic input data for the detection of explosives is provided by a new generation of chemical sensors. However, due to the fact that these sensors have only a limited spatio-temporal resolution, an individual chemical sensor is unable to localize this material and assign it to a potentially threatening person. To compensate this deficiency, our system fuses the output of several distributed chemical sensors with the location estimates of the persons based on laser range data.

The laser data can be assigned to the constructed and successively updated tracks in many ways. Therefore the solution of the assignment problem is crucial for every multiple target tracking algorithm. Traditional approaches to multiple hypothesis tracking rely on the complete enumeration of all possible interpretations of the measurements and avoid an exponential growth of the hypothesis trees by various approximations (MHT: Multiple Hypothesis Tracking [2, 3], (J)PDAF: (Joint) Probabilistic Data Association Filter [1]). Alternatively, the *Probabilistic* Multiple Hypothesis Tracking (PMHT) [5, 6] uses the method of Expectation-Maximization for handling data association conflicts. Furthermore, there exists a multitude of sequential Monte Carlo approaches [10] to solve the tracking task.

However, the simultaneous tracking and classification of persons using complementary types of sensors with differing resolution capabilities is still an open research topic. Our system mentioned above [7] uses an extension of the PMHT [4] to fuse laser output with chemical attributes. Schulz et al. [8] developed a Rao-Blackwellized Particle Filter (RBPF) to combine laser range scanners with infrared and ultrasound receivers. In the following sections we shall extend this RBPF framework by the capability of fusing person tracks with chemical attributes to localize persons with hazardous material.

2 RBPF Design and Algorithm

Let J be the number of persons that are moving in the surveillance area and that are observed by multiple laser range scanners. At each scan k, the scanners generate a set of N_k measurements[1] $\{\mathbf{z}_k^n\}_{n=1}^{N_k}$. The task of tracking consists in estimating the locations $\mathbf{x}_k = \{\mathbf{x}_k^j\}_{j=1}^{J}$ of the observed persons, i.e. in estimating the posterior $p(\mathbf{x}_k|\mathbf{z}_{1:k})$ over the state $\mathbf{x}_k$, based on all the measurements up to time k. Difficulties arise from unknown associations of measurements to persons. These associations are given by $J \times N_k$ assignment matrices Θ_k with: $\Theta_k(j,n) = 1$ if measurement $\mathbf{z}_k^n$ is assigned to person j and $\Theta_k(j,n) = 0$, otherwise.

2.1 RBPF for Multiple Person Tracking

The idea of Rao-Blackwellization is to augment the state by the assignment history $\Theta_{1:k}$ and to consider the posterior $p(\mathbf{x}_k, \Theta_{1:k}|\mathbf{z}_{1:k}) = p(\mathbf{x}_k|\Theta_{1:k}, \mathbf{z}_{1:k})p(\Theta_{1:k}|\mathbf{z}_{1:k})$. This posterior can be approximated by sampling assignments from $p(\Theta_{1:k}|\mathbf{z}_{1:k})$ and then determine the locations $\mathbf{x}_k$ analytically, based on the respective sample.

The RBPF uses a fixed number of S particles. Each particle $s_k(\iota)$ consists of an assignment history $\Theta_{1:k}(\iota)$, J Kalman Filters (one for each person) and an importance weight $w_k(\iota)$. Given the samples of scan $k-1$, the algorithm proposed in [8] can be summarized as follows: **Step 1:** Use the Metropolis-Hastings algorithm [9, 11] to efficiently generate an ergodic Markov chain with M^L assignment matrices[2] for each particle $s_{k-1}(\iota)$. **Step 2:** Update the importance weights $w_{k-1}(\iota)$ with respect to each track's ability to predict the current observation $\mathbf{z}_k$. **Step 3:** Resample from the previous sample set using the updated weights. For each sample, draw an assignment from the corresponding Markov chain. Finally, update the location estimates of all samples and set each weight $w_k(\iota)$ to $\frac{1}{S}$. Restart the algorithm for scan $k+1$. Details can be found in [8, 9].

[1] Measurements are assumed to be preclustered.

[2] L refers to the location phase. In the chemical assignment phase the length of the Markov Chain is M^C.

2.2 RBPF for Chemical Assignment

In this section we describe how the RBPF framework of section 2.1 can be extended to assign chemical attributes to person tracks. Therefore, we introduce a *chemical assignment vector* (CAV) $\Phi_k \in \{0,1\}^J$ with the following meaning: $\Phi_k(j) = 1$ if person $j \in \{1, \dots J\}$ is supposed to carry hazardous material and $\Phi_k(j) = 0$, otherwise. The initial CAV Φ_0 is set to $\mathbf{0} \in \mathbb{R}^J$. Furthermore, let $\mathbf{c}_k = \{\mathbf{c}_k^i\}_{i=1}^C$ be the set of outputs provided by C chemical sensors at scan k. There exists a threshold that breaks down each chemical concentration measurement to a binary output $\mathbf{c}_k^i \in \{0,1\}$.

Assume that the location phase for scan k has already been finished. Thus, we have estimates $\mathbf{x}_k^j(\iota)$ for each person j of each particle $s_k(\iota)$. In the following, we outline the chemical assignment phase, in which the persons carrying hazardous material are estimated for a fixed particle $s_k(\iota)$. For the sake of simplicity we do not denote the sample index ι in this context anymore. To this end, the posterior

$$\pi(\Phi_k) := p(\Phi_k|\mathbf{c}_k, \mathbf{x}_k, \Phi_{k-1}) = \frac{p(\mathbf{c}_k|\Phi_k, \mathbf{x}_k) \cdot p(\Phi_k|\mathbf{x}_k, \Phi_{k-1})}{p(\mathbf{c}_k|\mathbf{x}_k, \Phi_{k-1})} \tag{1}$$

has to be estimated. Analogously to the location phase, we sample from the posterior by applying the Metropolis-Hastings algorithm [11]. The sampling procedure works as follows: Let Φ_{k-1} be the CAV at scan $k-1$. Then, an ergodic Markov chain $\{\Phi_k^r\}_{r=0\dots M^C-1}$ with M^C elements is created. We initialize the chain with the previous CAV, i.e. $\Phi_k^0 := \Phi_{k-1}$. For a given element r, a new CAV Φ is proposed using the *proposal density* $Q(\Phi|\Phi_k^r)$. This can be easily realized by flipping some values of the given CAV proportional to their probability [9]. For the new CAV Φ, an acceptance ratio

$$\alpha := \min\left(1, \frac{\pi(\Phi) \cdot Q(\Phi_k^r|\Phi)}{\pi(\Phi_k^r) \cdot Q(\Phi|\Phi_k^r)}\right) \tag{2}$$

is calculated, where $\pi(\Phi)$ is the intended stationary distribution. With probability α, we accept Φ, i.e. we set $\Phi_k^{r+1} := \Phi$. If Φ is rejected, we keep the previous CAV, i.e. we set $\Phi_k^{r+1} := \Phi_k^r$. When the Markov chain is fully created, the new assignment Φ_k can be sampled out of it, proportional to the occurrences.

In general, the quality of the Markov chain, and thus of the sampled assignment, strongly depends on the proposal density Q, because it is in charge of exploring the state space of the CAV. However, in our application the state space is not that big consisting of 2^J elements. Therefore, the posterior function of a given assignment $\pi(\Phi_k)$ becomes more important and has to be modeled in a proper manner.

2.2.1 Modeling the Posterior of a CAV

As derived in equation (1), the posterior of the CAVs can be found by estimating the sensor model $p(\mathbf{c}_k|\Phi, \mathbf{x}_k)$ and the evolution model $p(\Phi_k|\mathbf{x}_k, \Phi_{k-1})$.

Let us first have a look at the sensor model. Using the evidence of a given assignment Φ, we can directly calculate the expected value $E\left[c^i\right]$ of the measurement c^i for sensor

i, which is located at the position coordinates P^i. Without loss of generality, it can be assumed that the associations of hazardous material are independent for different tracks. Thus, we can sum up the likelihoods of each track and obtain:

$$E\left[c^i\middle|\,\Phi\right] = \frac{\sum_{j=1}^{T} \Phi(j) \cdot e^{-\frac{\left|P^i - x_k^j\right|}{2\sigma^2}}}{\sum_{\tilde{j}=1}^{T} \Phi(\tilde{j})}, \tag{3}$$

where σ describes the sensor variance and depends on the sensing range. Based on our assumption that the measurement c_k^i has a binary state space, we can now easily derive the posterior probability by setting the evidence on a given output value c_k^i:

$$p(c_k^i|\Phi, \mathbf{x}_k) = c_k^i E\left[c_k^i|\Phi\right] + (1 - c_k^i)(1 - E\left[c_k^i|\Phi\right]) \tag{4}$$

If we further assume that the chemical outputs are stochastically independent, we get:

$$p(\mathbf{c}_k|\Phi, \mathbf{x}_k) = \prod_{i=1}^{C} p(c_k^i|\Phi, \mathbf{x}_k). \tag{5}$$

For the evolution model, we introduce a parameter P_c, which describes the probability of an association to be altered. Thus, we have for the j^{th} track:

$$\Phi_k^-(j) := p(\Phi(j)|x, \Phi_{k-1}) = \Phi_{k-1}(j) + (-1)^{\Phi_{k-1}(j)} \cdot P_c. \tag{6}$$

It can be easily seen, that a small parameter value for P_c leads to a greater stability, whereas a high value results in a faster approximation. Putting it all together, equation (1) leads to:

$$p(\Phi_k|\mathbf{c}_k, \mathbf{x}_k, \Phi_{k-1}) = \Phi_k^- \cdot \frac{p\left(\mathbf{c}_k|\Phi_k^-\right)}{p\left(\mathbf{c}_k|\Phi_{k-1}\right)}. \tag{7}$$

2.2.2 Transition Model

The algorithm presented in the previous section can be extended by modeling the fact, that a value flipping of a CAV is likely to happen at certain spatial points near the chemical sensors. Let P^i be the position of a chemical sensor with a sensing range r. We expect that an assignment value changes most likely at points lying on a sphere of radius r around the sensor. This leads to a model, which only depends on the distance from a person's position $\mathbf{x}$ to the sensor at P^i. So, if we look at a projection to a half plane cut vertically at P^i, the probability function $P_c(\mathbf{x})$ describes a truncated Gaussian with its peak at r and a width controlled by a parameter σ_c. As this parameter is angle independent, we get:

$$P_c(\mathbf{x}) = e^{-\frac{\left|\|\mathbf{x} - P^i\| - r\right|^2}{2\sigma^2}} \tag{8}$$

Furthermore, we consider σ_c to be proportional to the radius r, i.e. $\sigma = ar$. Now we substitute the ratio of the distance to the radius by a new variable $u := \frac{\|\vec{x} - P^i\|}{r}$ and obtain

$$P_c(u) = e^{-\frac{u^2 - 2u + 1}{2a^2}} = e^{-\frac{(u-1)^2}{2a^2}}. \tag{9}$$

For a usual environment, we propose to set the *full width at half maximum* (FWHM) of the Gaussian to the radius r. Using the well-known approximation formula for the FWHM, this results in a proportionality constant $a = \frac{1}{2\sqrt{2 \cdot ln(2)}}$.

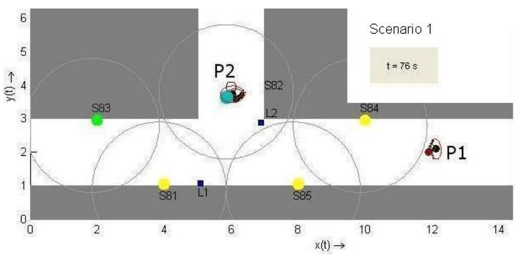
2.2.3 Extended Transition Model

As a further extension, we propose to regard the current motion direction of a given track, as well. It is an important fact that the chemical assignment is only likely to change when the person *enters* the sensing area of a fixed sensor i at P^i. To this end, we construct a cosinusoidal filter using the scalar product, which truncates the transition model $P_c(u)$ described above. Thus, let v_k^j be the velocity vector of person j at the position x_k^j. Then, we the extended transition model is defined as

$$P_c^e(u,v) = \max\left\{0, \frac{\left(x_k^j - P^i\right) \cdot v_k^j}{\|x_k^j - P^i\| \|v_k^j\|}\right\} \cdot P_c(\frac{\|x_k^j - P^i\|}{r}). \tag{10}$$

3 Examples

This section discusses two simulated scenarios. The setup consists of an intersection of two corridors. The screenshots in fig. 1 and 2 show the positions of the chemical sensors (S81-S85), of the laser range scanners (L1 and L2), and of the simulated persons at a scan k. The tables show the results of the corresponding Markov Chain that has been created according to section 2.2. The resulting CAV was sampled afterwards. If the CAV Φ_k associates hazardous material to a person we set a dot into the corresponding column. The percentages denote the relativ occurrences of a certain CAV in the Markov Chain. The examples are discussed for a single particle $s_k(\iota)$.

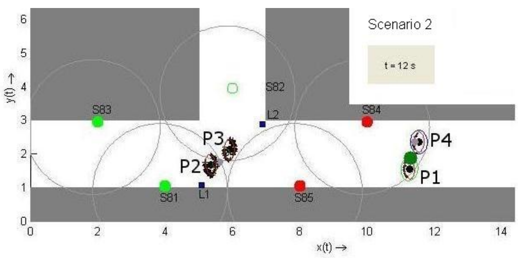


Scenario 1		
P1	P2	occurrences
	•	83%
•	•	17%

Figure 1: Scene with two persons on well separated positions.

Case 1 – Distinct positions: This is an easy-to-decide-situation. The positions of the two persons are well separated. The person marked with the big blue dot (P2) is correctly classified as a dangerous person. As we can see, the probability for P2 to have a positive association is 100%. Still with 83% probability, it is the only person to be associated in this case. As indicated by the gray row, the correct CAV was sampled out of the chain.

Case 2 – Almost colliding positions: In this case we simulate four persons, two of them being dangerous (P1 and P4). In particular, the positions of those two nearly coincide. As the table in fig. 2 shows, 11 out of 16 possible states were accepted at least once. Furthermore, there are three CAVs that are likely to arise out of the sampling procedure. These involve exactly the two persons carrying the dangerous material, namely P1 and P4. The results clearly show that the association is not easy to resolve. As indicated by the green row, the sampling resulted in a CAV that supposes only P1 as dangerous.



Scenario 2				
P1	P2	P3	P4	occurrences
				1%
			•	28%
		•	•	5%
	•		•	4%
•				23%
•			•	24%
•		•	•	2%
•	•			3%
•	•		•	6%
•	•	•		1%
•	•	•	•	3%

Figure 2: Complicated scenario with almost colliding positions.

The discussion shows, that in a simple scenario, as in case one, the probability of the result is quite high. In contrast, the second case describes a situation, in which it is not easy to resolve the association. This results in a Markov chain that has more than one probable output.

4 Conclusion

For the safety in public environments, surveillance technology with complementary types of sensors is needed. In this work we showed how persons can be simultaneously tracked and classified in a network of laser range scanners and chemical sensors. The association of chemical detections to person tracks is carried out by a Monte Carlo Markov Chain procedure. We discussed exemplary results for two simulated scenarios.

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