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UGV Radiation Mapping using a Particle Filter

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Abstract. *We present and evaluate a particle filter based approach to predict the location and emission intensity of an arbitrary and unknown number of stationary nuclear radiation sources from measurement data taken by an autonomously navigating unmanned ground vehicle (UGV).*

1. Introduction

Due to the threat for humans caused by radiation and the associated difficulties after a nuclear disaster it is crucial to establish save methods of estimating the radiation distribution in certain affected areas. For this purpose we suggest to record radiation measurement using an autonomous UGV. These measurements are then processed by an adapted particle filter to generate a detailed radiation distribution model of the affected area. The approach presented in this paper has been successfully tested in realistic conditions at the *ENRICH 2019 — European Robotics Hackathon*, where live radiation sources had to be detected inside the nuclear power plant in Zwentendorf, Austria.

2. Related Research

In [1] Eric T. Brewer used an autonomously flying aerial platform to detect and locate a single radioactive point source using a particle filter. In [2] M. Morelande et al. compare the performances of a maximum likelihood estimator and a Bayesian estimator approach to deal with an unknown number of sources. D. Shah et al. present a particle filter in [3] that manages to locate multiple radiation sources.

3. Problem Description

The setting is represented by a set Θ of unknown radiation sources s and a set Γ of radiation measurements m. The goal is to generate a set Ψ of estimated sources $\hat{s}$, that fits the number and intensities of the real sources accurately. Each set holds elements defined by a certain location x_i and y_i and an equivalent radiation dose rate α_i in $\mathrm{Sv\,s^{-1}}$ that either represents the actual measurement for the set Γ or the theoretical dose rate that would be measured at the exact position of a source for the sets Θ and Ψ. In general for modelling the radiation intensity at a certain location l based on a set of sources Θ, we assume that the radiation follows the principle of *superposition* and the *inverse-square-law* which has been shown to be applicable by multiple former approaches. [1, 2]:

$$\alpha(l) = \alpha_{bgr} + \sum_{s\in\Theta} \frac{\alpha_s}{4 \cdot \pi \cdot d_s(l)^2} \tag{1}$$

where α_{bgr} denotes the known background radiation and $d_s(l)$ the euclidean distance between the location l and the source s.

4. Particle Filter

In contrast to common particle filter use cases in robotics (e.g., estimating a robots position), it is now necessary to detect multiple sources that can co-exist at the same time at different positions. In this context particles are predictions of potential sources [3] with each particle $p \in P$ being represented similar to real sources by $p =< x_p, y_p, \alpha_p, w_p >$ with an additional weight w_p that is related to the probability that a certain particle has the parameters of a real source. At first the particles are initialized uniformly distributed on the plane where the measurements took place and given a random intensity within the same range of the measurement results. The algorithm then iteratively performs the two steps of *weighting* and *re-sampling* and adds estimated sources $\hat{s}$ to the growing set Ψ until a maximum number of iterations T is reached and Ψ represents a consistent estimation for Θ based on the measurements Γ.

4.1. Weighting

First an intensity estimation $\hat{\alpha}_m$ for a certain measurement m is calculated based on the single particle $p \in P$ to be weighted and the influence of all already defined sources $\hat{s} \in \Psi$ assuming the model presented in Equation 1:

$$\hat{\alpha}(m) = \alpha_{bgr} + \frac{\alpha_p}{4 \cdot \pi \cdot d_p(m)^2} + \sum_{\hat{s} \in \Psi} \frac{\alpha_s}{4 \cdot \pi \cdot d_s(m)^2} \tag{2}$$

Using Equation 2 the relative mean square error considering all measurements is calculated like:

$$e_{rmse} = \frac{1}{|\Gamma|} \sum_{m \in \Gamma} \left(\frac{\hat{\alpha}_m - \alpha_m}{\hat{\alpha}_m} \right)^2 \tag{3}$$

where $|\Gamma|$ is the number of measurements. The weight for a single particle is then calculated like:

$$w_p = \frac{1}{1 + e_{rmse}} \tag{4}$$

After all particle weights have been updated the weights are normalized such that $\sum_{p \in P} w_p = 1$.

4.2. Re-Sampling and Clustering

During re-sampling a certain percentage of particles with the highest weights stay the same, while another percentage of particles with the smallest weights are omitted and newly drawn from a uniform distribution over the search space. The remaining particles are re-sampled by adding Gaussian Noise to the intensity α_p and position based on the particles weight:

$$[x'_p, y'_p, \alpha'_p]^T \sim \mathcal{N}\left([x_p, y_p, \alpha_p]^T, \frac{\text{diag}(\sigma_{pos}, \sigma_{pos}, \sigma_{int})}{1 + w_p} \right) \tag{5}$$

The total number of particles stays the same. After a defined number of iterations k the particles are clustered using the mean shift algorithm as suggested by [3]. The cluster centroids have the same structure as a single particle and are then evaluated by the weighting algorithm described in section 4.1. If the weight of a cluster surpasses a defined threshold φ the centroid is believed to be a real source and added to the growing set of predicted sources Ψ.

5. Experimental Evaluation - ENRICH 2019

As part of the TU Graz Robotics Team TEDUSAR we participated in the European Robotics Hackathon

Total Particles	2000
Random New Particles	10 %
Sustain Particles	10 %
Max Iterations T	1000
Confidence Threshold φ	0.9
Clustering Interval k	20 iter
Position Deviation σ_{pos}	0.5
Intensity Deviation σ_{int}	0.4

Table 1: Hyper-parameters used for the ENRICH 2019

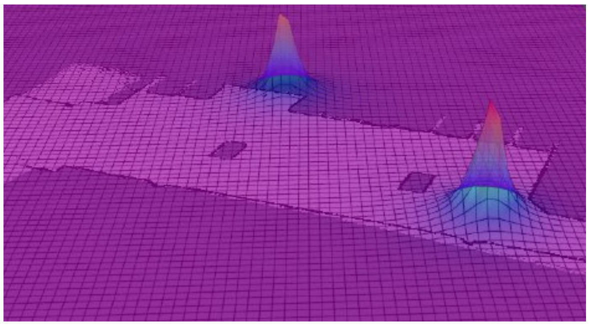

Figure 1: Source estimation based on live measurement data during the ENRICH 2019 in Zwentendorf.

- ENRICH 2019 at the nuclear power plant Zwentendorf, Austria[1] and were able to test our particle filter approach under real world conditions. An autonomous robot created a 3D map of the interior while our approach created the mathematical model of the real radiation sources and the radiation contamination. The parameters used are shown in Table 1.

An experimental result can be observed in Figure 1. In this experiment two sources were placed in a larger room. After traversing the room and collecting radiation measurements our approach correctly predicted the location and intensity of the two sources.

6. Conclusion and Future Work

In this paper we presented the adaptation of an approach based on a particle filter to determine the location and intensity for an arbitrary and unknown number of stationary radiation sources. This approach has been successfully tested and proven to be applicable in real world scenarios, like an accident in a nuclear facility. Future work will focus on reducing the number of hyper-parameters.

[1] www.enrich.european-robotics.eu

References

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