Design and Comparison of a Passive and Active Multiple Radiological Point Source Localisation Algorithm

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***Abstract*— Over the past years, automated, robotic radiation source localisation has become of emerging interest due to a variety of reasons, e.g. disaster response, homeland security, or dismantling and decommissioning of nuclear contaminated areas. Nowadays, to perform in-the-field measurements, radiation protection officers are tasked with characterising an environment before dismantling and decommissioning can take place. This is challenging because of the absence of a priori information on the potentially contaminated area. Besides the health risks involved, this preparatory task is very time-consuming and prone to errors concerning the taken measurements and the post-processing of these measurements. To further automate this key preliminary task, this paper presents two search algorithms to localise multiple radiological point sources in the environment: a passive localisation algorithm where a robotic platform scans a surface using a predefined pattern, and an active source localisation algorithm that chooses the next best position to take a measurement in order to characterise an environment. The developed approaches are first tested in a simulation environment and then validated using in-situ laboratory measurements using a Kromek CZT sensor and a two-dimensional linear guidance system. The experiments show that a correct representation of the environment is contained both for the passive and active localisation approach. Furthermore, the active localisation approach demonstrates that a large reduction in the amount of measurements to characterise an environment can be obtained without compromising on the estimation accuracy.**

I. INTRODUCTION

Since a couple of years, robots are being employed in the nuclear scene. The first generation of robots in the nuclear scene were employed in the 1980s. Most of them were teleoperated [1]. More recently, new research has focused on fully autonomous robots [2]–[4]. One of the potential tasks for which autonomous robots can be adopted in the nuclear scene is the dismantling and decommissioning (D&D) of nuclear facilities, nuclear power plants, or factories. Currently, an important a priori step towards dismantling and decommissioning activities is a screening of the radiation, and localising local maxima of radiation, caused by radiation point sources, generally called hot spots, in the environment where the dismantling and decommissioning activities will take place. Determining the locations of these point sources has become of high importance, e.g. for homeland security, leakage detection, and dismantling and decommissioning. Radiation protection officers are sent out in the field to characterise the environment by taking ambient dose rate, atmospheric, and surface contamination measurements. Many risks are associated with this task. The physical state of the personnel needs to be continuously monitored to prevent potential, future health damage. Moreover, this task is very time-consuming, and in practice, these measurements can vary from several minutes up to a few hours, depending on the geometric properties of the environment to be dismantled. The use of (semi-)autonomous robots and state-of-the-art algorithms during this preliminary key task could lead to a minimisation in operator costs and keeping the operator risks as low as reasonably achievable (ALARA). The remainder of this paper is organised as follows. Section II discusses the implementation and results of the passive radiation source localisation algorithm. Next, section III deliberates the approach and the results of the active source localisation. Next, section IV compares the two approaches. Lastly, section V concludes this work and delineates some tracks for future work.

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II. PASSIVE LOCALISATION

The word *passive* implies that the measurement pattern is independent from the already acquired measurements to localise the sources in an environment. Nevertheless, this approach can be used to estimate the position of the sources, the amount of sources available in the environment, and their respective radiological intensity. The first step in the passive localisation process is to create a *data set* of an environment. In this work, a data set of a two-dimensional environment has been created using a Kromek GR1 spectrometer, and a two-dimensional linear guidance system, as depicted in figure 1. The data set consists of a count rate information at a specific 2D position, 50mm perpendicularly removed away from the scanned environment. The measurement time at each data point is 5s. The next step is to determine the background radiation based on the whole data set. This is determined by primarily creating a histogram of the count rates in the data set. The maximum of the histogram function will lead to the amount of background radiation in the environment. The second step in the passive localisation process is applying *Gaussian smoothing* on the sensor data in the data set. This step will diminish noisy data, which is crucial for the next step in the localisation approach. The third step consists of an interpolation of the sensor data. This is used to convert a

Fig. 1: Setup of the in-situ experiments, depicting the used XY linear guidance system, Kromek GR1 spectrometer, and used sources [6].

discrete data set into a continuous function, where for each continuous 2D position in the data set an accompanying count rate is available. As an interpolation technique, the inverse distance weighting (IDW) interpolation has been chosen, since it represents the inverse distance character of radiation correctly [5].

To detect the potential sources in the environment, an approach has been designed to amplify local maxima and normalise it. Based on the original input data set, two separate Gaussian smooting operations will be performed on the input data set. This results in two smoothing matrices, where one is strongly smoothed, while the other matrix is less smoothed. The window size of each smoother is again empirically chosen. Next, the least smoothed matrix is divided by the most smoothed matrix in such a way that a new matrix is created where plains have a value of one, valleys a value between zero and one, and peaks have a value of greater than one. Thereafter, all the values in the newly created matrix are reduced by one, and values under zero are set to be zero. To create a difference between large maxima coming from the actual sources and low peaks originating from noise, the matrix is squared and normalised. This approach results in the amplification of the maxima.

The following step in the passive localisation routine consists of a weighted K-means clustering algorithm to retrieve the two-dimensional position of the sources in the environment. The amount of sources to estimate in the environment is iteratively enlarged, until the algorithm converges to the correct amount of sources. When the amount of sources and each source position is determined using the weighted K-means clustering, the radiological intensity of each source is calculated using the inverse distance properties of radiation. Finally, a gradient descent algorithm, with as error function the root mean square error between the estimated measurements and the actual measurements, is performed to optimise the intensity of each individual source

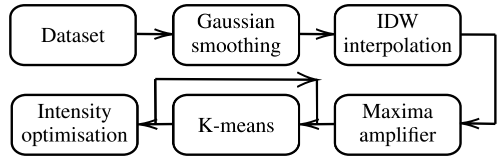


Fig. 2: Flowchart representation of the passive radiological source localisation algorithm.

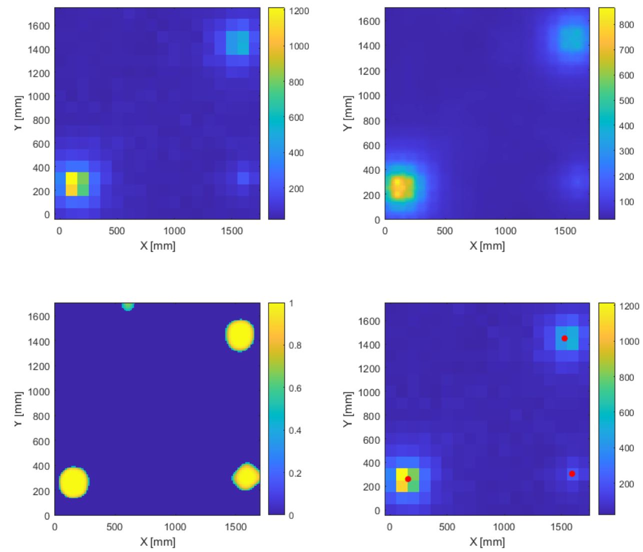


Fig. 3: Results of the passive localisation routine. The upper left figure depicts the raw input data set. The upper right figure shows the output of the inverse distance weighting (IDW) interpolation technique. The amplified source maxima are displayed in the lower left figure. The output of the passive source localisation approach is illustrated in the bottom right subfigure.

based on the calculated intensity at the source location and the actual measurement in the data set close to the estimated position. Figure 2 shows a flowchart representation of the overall passive source localisation process. The results of the passive localisation framework are depicted in figure 3 and can numerically be consulted in table I.

TABLE I: Results of the passive localisation framework. The actual source parameters are compared against the estimated ones.

Radionuclide	X_{act} [mm]	Y_{act} [mm]	E_{act} [KBq]	X_{est} [mm]	Y_{est} [mm]	E_{est} [KBq]
Cs-137	1560	1450	162	1542	1446	178
Am-241	135	255	392	158	262	380
Co-60	1615	315	20	1591	306	24

III. Active localisation

Next to the passive source localisation routine, an active approach towards autonomous source localisation has been developed. The expression *active* is understood to mean that during the measurement process the location of the next measurement is determined based on the previous measurements. In the field of state estimation and control within the robotics community, this approach is also known as *active sensing* or *active localisation*. The purpose of active localisation is to get a maximum amount of information gain while minimising the amount of measurements. As stated in the introductory section I, the process of characterising an environment, and therefore localising the potential radiological sources in an environment before dismantling and decommissioning activities can take place, is very time-consuming. An active localisation approach could help to optimise this process.

The initial step in the active source localisation process is the execution of an amount of measurements randomly distributed over the environment to be characterised. In this work, the amount of initial measurements has been empirically set to 10. Next, the algorithm performs a thin-plate-spline (TPS) interpolation based on the input measurements [7]. This interpolation technique has been chosen over the IDW interpolation as used in section II due to its better performance with non-ordered, limited data inputs. Based on the interpolated result, a belief matrix and a penalty matrix are constructed. The belief matrix represents the probability of the location of a possible radiological source over the environment space. The position where the interpolated data maximises, receives a probability equal to 1, while the other locations are represented with a probability that decreases inversely quadratically. Next to the belief matrix, a penalty matrix is created based on the positions where a measurement has been sampled. Positions, where a measurement has been performed, receive a probability equal to 0, where unexplored positions are granted with a larger probability. The calculation of the belief and the penalty matrix is given by equations 1 and 3, where l_x is the distance between the coordinate of the maximum value and position x, and s is a scaling factor. By combining the belief matrix with the penalty matrix using the element-wise Hadamard product for matrices, a measurement location matrix is created. An example of this measurement location matrix is depicted in figure 4.

$$P_{belief}(x) = \frac{1}{1 + (l_x \cdot s)^2} \tag{1}$$

$$s = \frac{l_{max}}{100 \cdot res} \tag{2}$$

$$P_{penalty}(x) = \frac{1}{1 + (l_x \cdot s)^{-2}} \tag{3}$$

The position which corresponds with the largest probability in the measurement location matrix, is chosen as the next best measurement point. This approach is executed an adjustable amount of iterations. The maximum of the belief matrix at the last iteration is chosen as the estimated location of a single radiological source. At this point, the intensity of the estimated source is determined as discussed in section II. The next step in the active localisation process is the suppression of the found source in the environment. By doing this, the influence of the found source is subtracted from the environment, and thus the algorithm will not be attracted by the already found source. This approach will run until an iteration criterion is met. The following iteration criteria are implemented:

- the maximum amount of iterations is reached;
- the interpolated area at iteration $i + 1$ has not changed drastically with the interpolation at iteration i;
- the measurements are spread over the entire space. This criteria is met when no unexplored areas exist in the environment.

The final step in the active localisation routine is the same as can be found in the passive localisation framework explained in section II, i.e. the optimisation of the locations and intensities of the estimated sources using a gradient descent algorithm. A flowchart representation of the overall active source localisation process can be found in figure 5.

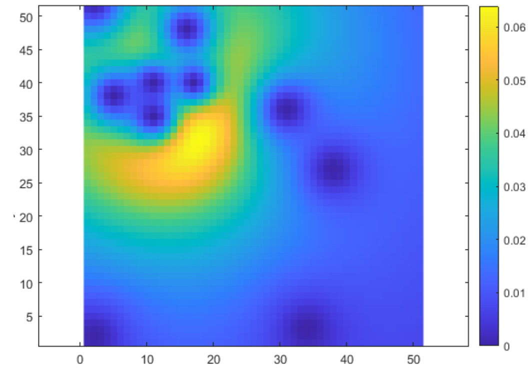


Fig. 4: Example of a measurement location matrix. This matrix is the element-wise (Hadamard) matrix product of the belief matrix and the penalty matrix.

IV. Comparison between passive and active approach

Both the passive and active localisation frameworks have been validated and compared in a simulation environment, as well as conducted to a series of in-situ laboratory experiments. For these experiments, a two-dimensional linear guidance system is used. The commercial Kromek GR1 CZT spectrometer is used as radiological measurement unit, and three samples of radioisotopes (two Cs-137 sources and one Am-241 source) will serve as point sources to be detected.

Figure 6 shows a single result of the conducted experiments. As can be seen, both results correctly characterise the environment, i.e. estimating the amount of sources and the location of each individual source. Quantitative results from the conducted experiments are shown in table II. From table II it is clear that the active approach gives a better estimation in intensity, while the passive approach gives a better estimation regarding the location of each individual source. The entire execution time in the active localisation approach is larger than the one during the passive localisation process, due to the fact that the two-dimensional linear guidance system has to travel more distance between each individual measurement. However, the amount of measurements that results in the outcome of the active localisation framework

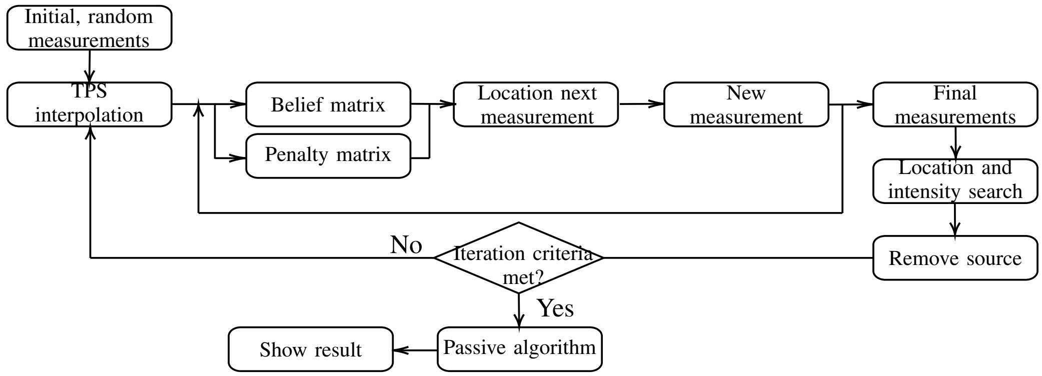
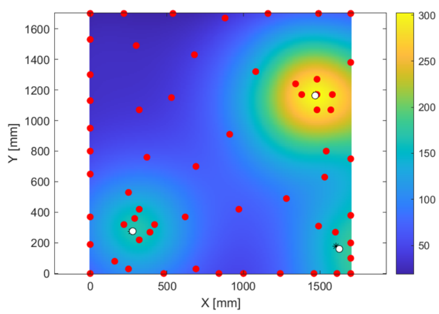


Fig. 5: Flowchart representation of the active source localisation algorithm

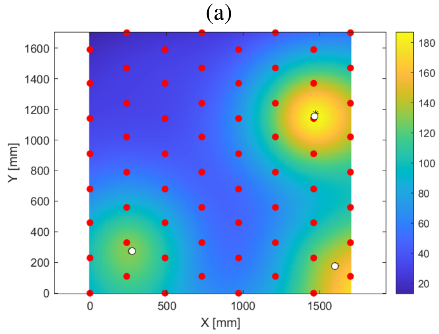
TABLE II: Numerical results of the comparison between the passive and active approach.

Approach	Location error [mm]	Intensity error [kBq]	Number of measurements	Execution time [s]
Active localisation	15.19 ± 7.5	21.34 ± 5.13	48	551.3 ± 141.4
Passive localisation	10.33 ± 7.01	23.90 ± 9.63	324	493.5 ± 120.9

is by a factor of 6 lower than the amount of measurements needed to obtain the results from the passive localisation framework.



(a)



(b)

Fig. 6: Results of the in-situ laboratory experiments. Red dots represent the points where a measurement has been taken. Crosses indicate the estimated position of the sources, and white dots represent the actual source locations. Subfigure (a) shows the results of the active localisation routine, while subfigure (b) depicts the outcome of the passive localisation approach.

V. Conclusion and Future Work

This work presents a passive and active localisation framework towards autonomous radiological source localisation. Experiments show that an active source search approach is beneficial in mitigating the amount of measurements needed to characterise an environment. Instead of a full data set of 324 measurements, the active approach results in a good estimation of the radiological hotspot locations with only 48 measurements. Tracks for future work concern the optimisation of the active search framework. Moreover, an optimisation in terms of measurement time is envisaged. Besides, the exploitation of Bayesian approaches towards the active sensing problem of characterising a radiological environment faster will be explored. Finally, in-situ measurements covering a larger area will be executed with a mobile manipulator robotic platform.

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