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Reconstruction of radiation dose rate profiles by autonomous robot with active learning and Gaussian process regression

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A B S T R A C T

This work proposes an approach to use autonomous intelligent robots to reconstruct 2D dose rate profiles in radioactive environments. The main idea is to use Gaussian process (GP) regression to model the radiation dose rate distribution and active learning (AL) to dynamically improve estimation of GP parameters. A differential evolution (DE) algorithm, guided by the GP entropy is used to find the next measuring point to be visited by the robot in order to improve the GP estimation. Euclidean distances are used as penalizations to minimize the robot's trajectory and, consequently, to speed-up the reconstruction of the dose rate profile. The intelligent algorithm was tested through computational simulations considering 2 hypothetical scenarios with increasing complexity. Results demonstrate that the approach is able to reconstruct the dose rate profile with good accuracy and reduced number of measurements.

1. Introduction

Nowadays, a great variety of robotic applications can be seen in many fields of knowledge. The motivation is generally process automation, reliability and precision of operations and safety issues. Not differently, in the nuclear engineering area, the use of robots has been explored.

There are several robotic prototypes being applied in the nuclear field, such as: the wall climber inspection robots (Briones et al., 1994), the Robug IIS (Luk et al., 2005), which is a robotic vehicle on legs to overcome obstacles in more complex terrain, Robot Snake (Buckingham and Graham, 2005), used to make repairs on nuclear pipes, Korean robots Kaerot (Kim et al., 2010), used for inspection and detection in nuclear plants, underwater robots (Nawaz et al., 2009) to inspection and detection of nuclear waste, and the robotic vehicle called EQUIPA NIPPON (Ohno et al., 2011), designed to measure radiation at the Fukushima Daiichi Nuclear Power Plant, developed by the Japan Atomic Energy Agency (JAEA), Tohoku University, and Tokyo Electric Power Company (TEPCO).

The use of autonomous robots is sometimes very interesting when remote operation is not possible. In order to operate autonomously, robots are required to have some intelligent capabilities to support decision making without human assistance.

Some intelligent algorithms has been investigated in order to provide certain degree of autonomy to robots. Martinez-Cantin et al. (2009) proposed a Bayesian approach for optimal online sensing and planning. Stachniss et al. (2009) investigated the possibility of learning gas distribution models using sparse Gaussian process mixtures. Recently (Deisenroth et al, 2015) also investigated the use of Gaussian process and machine learning applied to robotics and control.

In this work, an adaptive intelligent algorithm is used to drive a robot in the task of reconstruction of dose rate profiles in a radioactive environment. The main idea is to use Gaussian process (GP) regression (Rasmussen and Williams, 2006; Gu and Hu, 2011) to model the radiation dose rate distribution and active learning (AL) (Settles, 2010) to dynamically improve estimation of the GP parameters.

The approach is inspired in the works from Gu and Hu (2011), which proposes a general use of GP and active learning and Stachniss et al. (2009), which proposed GP learning to learn gas distribution models. More precisely, the approach proposed by Gu and Hu (2011) has been adapted to be used by a mobile terrain robot with radiation measurement capability.

Results shown here are computational experiments in which a real existing facility (a programmable robot) is computationally modeled (all features and characteristics such dimensions, velocity, possible movements etc) to operate in a hypothetical radioactive environments.

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Algorithm 1 GP Active Learning

```
GP = initialize_GP()
x = robot initial position;
y = measure_radiation();
GP.add_data({x,y});
NIter = 1;
while (NOT stopping criterion) do
    α_n^P = get_acquisition_function(GP,x);
    x = optimize(α_n^P)
    move_to(x);
    y = measure_radiation();
    GP.add_data({x,y})
    NIter = NIter + 1
    if (Niter mod 10 equals 0) then GP.update_parameters()
end
GP.save()
```

Fig. 1. The GP active learning algorithm.

Algorithm 2 Differential Evolution

```
NIter = 0;
Initialize();
while (NOT stopping criterion) do
    NIter = NIter + 1
    mutate();
    crossover();
    evaluate();
    select();
end
```

Fig. 2. The differential evolution algorithm.

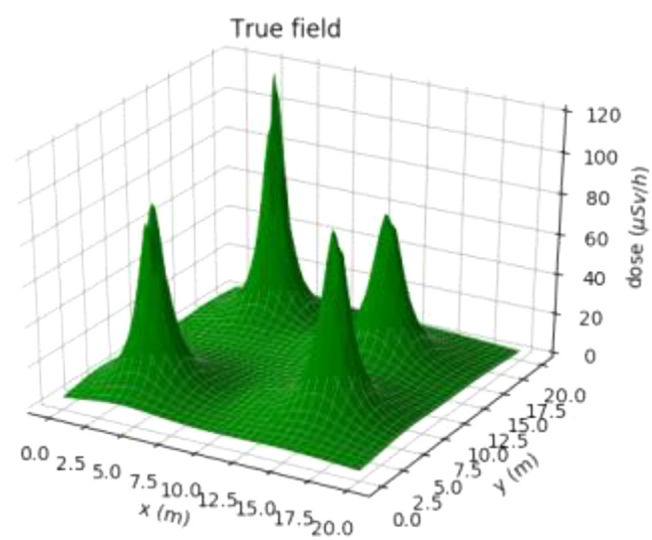

Fig. 3. The 4-peak radiation profile.

Section 2 describes the proposed approach, including an overview of the GP regression and AL. Section 3 shows the method application, results and discussions, and, finally, Section 4 presents concluding remarks and discussions about future works.

2. Proposed approach

In this work, an autonomous robot is aimed to explore a given area in which the radiation profile must be evaluated. To accomplish that, an intelligent algorithm guides the robot through optimized pathways, aiming to provide adequate exploration in the shortest period of time. Such algorithm is based in Gaussian process regression and active learning.

The robot has a radiation detector, which enables it to measure the dose rate at its current position. Considering that the dose rate is function of the position, $f(x, y)$, the objective of the GP regression is to reconstruct/approximate such function starting from a given set of observed points (robots measurements).

The quality of the reconstruction is strongly dependent on the set of observed points and the choice of such set of points is role of the active learning (AL) algorithm. Before each robot movement the AL algorithm is responsible to estimate which is the most profitable point to be visited (and measured).

2.1. Gaussian process regression

Let $X \subset \mathbb{R}^2$ be the map containing the dose radiation field, and $g : X \rightarrow \mathbb{R}^+$ the unknown dose radiation field function. The problem