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A sampling-based method with virtual reality technology to provide minimum dose path navigation for occupational workers in nuclear facilities

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ABSTRACT

This paper proposes a sampling-based method (SBM) for planning minimum dose path navigation for workers in nuclear facilities. To simulate and avoid obstacles, they were approximated by a combination of basic geometries and detected with the aid of virtual reality. To obtain an optimized walking path with minimum dose without considering the pre-designed road networks, a sampling-based method that utilizes the rapidly exploring random tree star (RRT*) algorithm, applicable in both continuous and discrete radiation fields, was proposed and implemented. The performance of this method was evaluated by simulating walk paths and estimating their radiation dose rates in a hypothetical nuclear facility, and the simulation results were compared with those derived from Dijsktra's algorithm under various radioactive environments.

1. Introduction

The working environments in nuclear facilities are inherently under high radiation that is harmful to human health, and the workers in such facilities face the risk of radiation exposure, especially during the maintenance and decommissioning tasks and during clean-up processes when accidents occur. Hence, under the principle of ALARA (as low as reasonably achievable), it is imperative to provide a minimum dose navigational approach for occupational workers who work in radioactive environments, to help them find a minimum dose walking path before and during their work. As a measure of radiation protection, to improve personnel safety and efficiency, and to avoid unnecessary radiation exposure, the minimum dose path planning is important. Its importance is elaborated when one considers the fact that workers in nuclear facilities spend a considerable amount of time in radiation environment when carrying out tasks such as equipment maintenance, decommissioning of a nuclear facility and during emergency drills. Furthermore, virtual reality (VR) technology has the characteristics of intuition and low cost, and it plays an important role in the assessment of radiation dose exposure and training. Integrating optimized minimum dose path planning into such VR tool will improve the efficiency of the tool and enhance the reliability and users' trust in the use of VR-based technology.

Some researchers have studied the path planning method in radioactive environments.

Pachter and Pachter (2001) introduced a weighted exposure and path length optimization problem to find the optimal trajectory for avoiding a radiating source.

Iguchi et al. (2004) developed a Decommissioning Engineering Support System (DEXUS) to support the decommissioning of Fugen Nuclear Power Station. VRdose software, a part of DEXUS, can simulate the staff activities on a related work scene, to visualize the radiation dose that staff suffered. However, VRdose can only plan a walking path artificially.

Alzalloum (2009) addressed the least cost path problem for a radioactive contaminated area and found the minimum radiation exposure paths using Dijkstra and Bellman-Ford algorithms.

Khasawneh et al. (2009) proposed a graph-coloring-based navigational algorithm for personnel safety in nuclear installations. The algorithm is based on graph coloring theory and

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wireless sensor, and applicable to guide personnel through potentially hazardous radiation areas at nuclear facilities. Also, Khasawneh et al. (2013a,b) addressed a localized navigation algorithm for radiation evasion. A well-designed wireless sensor network infrastructure is distributed to acquire the information needed for path planning.

Mól et al. (2009a,b) used a game engine for virtual reality simulations for the assessment of radiation dose exposure by a nuclear plant's personnel. The simulation platform collects dose rate data from radiation monitors installed in a real plant, then researchers assess dose rate for personnel. Furthermore, Mól et al. (2011) used neural networks to interpolate dose rate values among measured points to improve the simulation of dose received by personnel, and this research provides a feasible way to get interpolated dose rate values.

Jeong et al. (2014) developed a method to simulate and assess the exposure dose to workers during decommissioning of nuclear facilities using virtual reality. Virtual environments of decommissioning and human models were developed with Unity3D. The assessment of exposure doses to workers is accomplished by detecting the amount of collision between the human model and radiation distribution.

Liu et al. (2014) combined particle swarm optimization algorithms with multi-objective decision-making techniques to solve the multi-objective walking path problem in radioactive environments. In addition, Liu et al. (2015) built a road network in the radioactive environment, then use the shortest path algorithm A* to find the minimum radiation exposure path. Based on this research, Liu et al. (2016) solved the walking path-planning problem for multiple radiation areas, and Li et al. (2016) extended the static minimum dose walking path planning method to dynamic radioactive environments.

These methods are mainly achieved by dispersing the configuration space (based, e.g., on a grid) and transforming the environment into a graph offline, and then searching the minimum dose path based on graph search algorithms, such as Dijsktra and A*. However, the structure and the radioactive environment change frequently during the decommissioning and other activities, and certainly, a new road network needs to be generated frequently to adapt to the new environment. Hence, based on the dynamics of decommissioning tasks, it is not sufficient to find the minimum dose path only on pre-designed road networks in this situation.

Sampling-based algorithms are popular algorithms because they are less computationally complex. The rapidly exploring random tree star (RRT*) is one of the recent sampling based algorithms, which have both probabilistic completeness and asymptotic optimality. Since the introduction of the RRT* algorithm, it has been widely applied in various fields such as holonomic robots (Webb and Berg, 2013). Seif (2015) used RRT* to plan paths for mobile robots in dynamic environments, and Jeong et al. (2015) proposes RRT*-Quick, an improved version of RRT* with faster convergence rate. However, there is almost no literature describing minimum dose path-planning with the sampling-based methods in a nuclear facility.

Consequently, this paper proposes a sampling-based method (SBM) using RRT* to find the minimum dose path in nuclear facilities without relying on pre-designed road networks, and explains how the method can avoid obstacles and find optimal, or near optimal, paths in virtual environments. This work also illustrates how the sampling based method can work both in continuous and discrete environments. Finally, the effectiveness of the proposed method is verified via simulation experiments and the results are compared with the one derived from Dijsktra's algorithm.

The paper is organized as follow: Section 2 briefly describes Dijkstra's algorithm and the sampling based algorithm RRT*. Section 3 focuses on the implementation of the proposed method. Section 4 is allotted to describing the simulation experiments. Section 5 analyzes the results of simulation experiments. Section 6 presents the concluding remarks.

2. Algorithms used for path planning

The two algorithms evaluated in this paper are the Dijkstra's and RRT* algorithms. Both algorithms are of great importance to solve the problem of finding optimal paths. The following section provides a brief description of Dijkstra's and RRT* algorithms.

2.1. Dijsktra's algorithm

Dijkstra's algorithm was originally proposed in Dijkstra (1959). It is a graph search algorithm to find the minimum weight for a path on a graph with non-negative edges.

Dijkstra's algorithm operates as follows: it uses an Open list to store unchecked nodes and a Closed list to store checked nodes. Initially, the Closed list only has the source vertex v, and the other vertices are added to the Open list, and the distances from v to all other vertices is set to infinity. It then calculates the distance from v to all the closest vertices and adds the vertex v_{new} with the smallest distance to the Closed list. Meanwhile, it removes v_{new} from the Open list. It then updates the distance to the neighbor of v_{new}. It keeps repeating the process until the destination vertex is reached.

2.2. The RRT* algorithm

The RRT* algorithm is conceived by Karaman and Frazzoli (2011), and is proven to be asymptotically optimal. RRT* builds a roadmap of feasible trajectories made by connecting together a set of points sampled from the obstacle-free space. The pseudo code of RRT* is shown in Algorithm 1.

Algorithm 1: RRT*

$V \leftarrow \{q_{\mathrm{init}}\};\ E \leftarrow \emptyset;$
for $i = 0, 1, \cdots, n$ **do**
  $q_{\mathrm{rand}} \leftarrow \mathrm{SampleFree}(i);$
  $q_{\mathrm{nearest}} \leftarrow \mathrm{Nearest}(T, q_{\mathrm{rand}});$
  $q_{\mathrm{new}} \leftarrow \mathrm{Steer}(q_{\mathrm{nearest}}, q_{\mathrm{rand}});$
  if $\mathrm{ObstacleFree}(q_{\mathrm{nearest}}, q_{\mathrm{new}})$ **then**
    $Z_{\mathrm{near}} \leftarrow \mathrm{Near}(T, q_{\mathrm{new}}, r);$
    $V \leftarrow \mathrm{AddNode}(q_{\mathrm{new}});$
    // Get node that makes the cost reach to q_{new} minimum in Z_{near}
    $z_{\mathrm{min}} \leftarrow \mathrm{ChooseParent}(Z_{\mathrm{near}}, q_{\mathrm{new}});$
    $E \leftarrow \mathrm{AddEdge}(z_{\mathrm{min}}, q_{\mathrm{new}});$ // Connect along a minimum-cost path
    foreach $z_{\mathrm{near}} \in z_{\mathrm{near}}$ **do** // Rewire the tree
      if $\mathrm{CollisionFree}(z_{\mathrm{near}}, q_{\mathrm{new}})$ and
        $\mathrm{Cost}(q_{\mathrm{new}}) + c(\mathrm{Line}(q_{\mathrm{new}}, z_{\mathrm{near}})) < \mathrm{Cost}(z_{\mathrm{near}})$
      then $q_{\mathrm{parent}} \leftarrow \mathrm{GetParent}(z_{\mathrm{near}});$
        $E \leftarrow \mathrm{DeleteEdge}(q_{\mathrm{parent}}, z_{\mathrm{near}});$
        $E \leftarrow \mathrm{AddEdge}(q_{\mathrm{new}}, z_{\mathrm{near}});$
return $T = (V, E)$

RRT* algorithm maintains a tree structure, T, by adding points to the vertex set V sampled from an obstacle-free space, and each sample has a unique parent vertex except the starting point (as the root of the tree), q_{init}. First, a random vertex q_{rand} is created by