Determination of Robot Drop Location for Military Path Planning Using GIS Application

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Abstract: – Due to the uncertainties and higher risks of fatality in combat situations, Unmanned Ground Robots (UGR) may be proven to be a safer alternative for carrying out critical military missions, such as search and rescue, and reconnaissance operations. Among many issues involved in the Military Path Planning (MPP) problem, this paper discusses factors affecting drop locations of the UGR in the battlefield. A customized GIS-based model which finds suitable drop locations of the UGR is developed accordingly. The objective is to reach a known target location as quickly as possible, while minimizing its energy consumption as well as intervention from the enemies distributed in the battlefield. The model is tested on a complex digital terrain, assuming there is a presence of enemy's surveillance system. The result confirms the capability of the proposed method, by indicating that the candidate drop locations are feasible without violation of the specified constraints.

Keywords: – Robot Drop, Military Path Planning, Unmanned Ground Robot

1. Introduction

Due to the uncertainties and higher risks of fatality, robots (especially unmanned ground robots (UGR)) have become an important part of many applications in combat situations. In the battlefield, the UGR operates in an outdoor environment over a wide variety of terrain to complete a mission. Two classes of UGR (i.e., Teleoperated or Autonomous robot) are generally used in real world. One is Teleoperated UGR controlled by a human operator at a remote location via a communications link, and the other is Autonomous UGR operating itself for extended durations without human intervention. The objective of UGR is to carry out critical missions such as search and rescue, and reconnaissance operations.

Many mathematical models and technologies have been proposed and are being developed for intelligent UGR operation in visual detection of surrounding environment, path planning and controls. Among them the most popular, yet challenging one is the path planning problem. The problem of path planning for mobile robots (i.e., UGR) is generally defined as the search for a path from a starting point to a target location without being destroyed by obstacles (such as enemies). To date, a variety of approaches have been developed to solve the path planning problem, such as analytical methods [1-3], genetic algorithms [4-7] and neural networks [8-10].

It is interesting to note that most approaches dealing with the path planning problem assume that the starting point of the robot is given and fixed. In combat situation, however, finding the start point of the UGR is not a simple problem, and must be preceded before operating it toward the target. Due to the existence of enemies distributed in the battlefield and complex land-use and surface of terrain, factors affecting its initial location are conflicting each other (e.g., minimizing travel time to target and minimizing the risk of exposure to enemies), and thus make the location problem complicated.

Among many issues that need to be considered for an effective use of UGR in the battlefield, this paper seeks to find its initial position for mission operation, assuming that it is dropped from the sky (e.g., from aircrafts and helicopters) to the battlefield. The remainder of this paper begins with investigation of factors affecting the robot drop location. Mathematical formulations of these factors are also discussed in this section. Next, a GIS-based approach for solving the location problem is proposed. An example study to show the performance of the model is demonstrated in the following section. Finally, we conclude with the summary of this study. Future work is also discussed in the conclusion section.

2. Methodology

2.1 Slope Impact

In this study, we should take into consideration the slope of terrain for two different aspects. First, the slope is one of the important factors affecting the robot drop. Areas of relatively flat land are preferred to minimize the risk of accidents due to an unstable landing on an irregular surface. The second aspect of the slope in this problem is that it significantly affects energy consumption of the robot when traveling on the surface of terrain. The robot requires more effort for moving on higher slopes of terrains, while less effort is needed for moving on lower slopes.

Slope Value Affecting Robot Drop Location: A map which contains the elevation of the study area (e.g., DEM) is needed to calculate the slop of terrain. For each cell of the elevation map, changes in elevation over the distance between the cell and its neighbors are calculated, and the maximum value is regarded as the slope (θ) of that cell. In the slop map the lower the slope value, the flatter the terrain, while the higher the slope value, the steeper the terrain. Note that the slope value is calculated using the average maximum technique developed by Burrough and McDonell [13].

Vertical Factor Affecting Energy Consumption: The energy consumption of the robot may vary depending on the slope of terrain on which the robot is traveling. If the robot is traveling downhill, its energy consumption will decrease; if it is going uphill, the energy consumption will increase. To represent such an effect of slope for estimating travel cost of the robot (see Section 2.4 for more detail), a vertical factor is introduced in this study. The vertical factor (denoted as F^V) is computed based on the slope between two adjacent points, and is normalized with an equation expressed as:

$$F^V_{i-1,i} = \begin{cases} \alpha_1 \times \theta_{i-1,i} + \alpha_2 & \text{if } \theta_{min} \le \theta_{i-1,i} \le \theta_{max} \\ \infty & \text{otherwise} \end{cases} \quad (1)$$

$$\theta_{i-1,i} = \tan^{-1}\left(\frac{z_i - z_{i-1}}{\sqrt{(x_i - x_{i-1})^2 + (y_i - y_{i-1})^2}} \right) \quad (2)$$

where, $F^V_{i-1,i}$ = Vertical factor between two adjacent points

α_1, α_2 = Parameters used for calculating vertical factor

$\theta_{i-1,i}$ = Slope between two adjacent points

θ_{max} = Maximum allowable slope between two adjacent points

θ_{min} = Minimum allowable slope between two adjacent points

λ_i = xyz coordinates of i^{th} location; $\lambda_i = (x_i, y_i, z_i)$

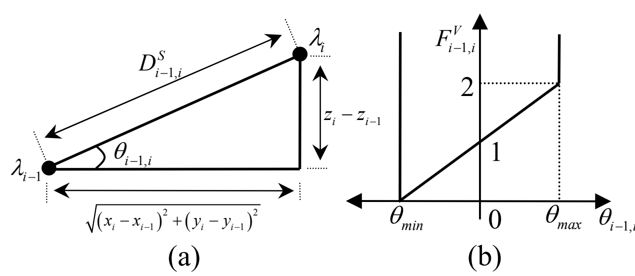


Figure 1: (a) Slope and (b) Vertical Factor between Two Adjacent Points

2.2 Land-Use Impact

Undesirable Land-Use for Robot Drop and Travel: Various land-uses; for example, desert, forest, river, and agricultural areas, may exist in the battlefield. Among them, there might be areas to which the robotic agents should not travel and at which dropping the robot is not recommended. These land-use types (e.g., lake, wetlands, and enemy facilities) should be regarded as "No-Go" areas (Λ_{NG}) and be removed from the candidate locations of the robot drop and traveling.

Friction Factor Affecting Energy Consumption: Different land-uses provide different values of bumpiness on their surfaces. More energy consumption is needed for the robot to travel on irregular surface compared to when it travels on a relatively flat surface. Thus, we use a land-use map to compute the degree of bumpiness (i.e., friction factor) of various surfaces in the battlefield. Figure 2 shows the relation between land-use and friction factor. Note that such a relation is reflected when we calculate the weighted-travel cost of the robot in Section 2.4. The friction factor (denoted as F^F) is calculated with an equation expressed as:

$$F_i^F = \beta_1 + \beta_2 \times \exp\left(LU_i\right) \tag{3}$$

where, β_1, β_2 = Land-use parameter
LU_i = Discrete land-use variable at i^{th} location in the battlefield (e.g., 0: open space without obstacles; 1: Agricultural area, farmland; 2: Desert; 3: Forest; 4: Built-up; 5: Rocky mountain)

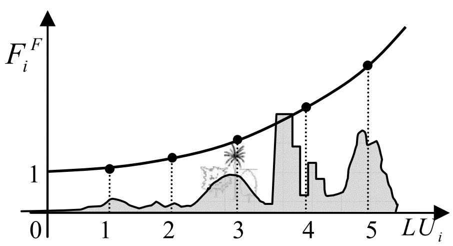


Figure 2: Relationship between Land-Use and Friction Factor

2.3 Exposure to Enemy

Limit of Radar Detecting Objects in the Sky: Recall that we assume the robotic agent being dropped from the Sky. Thus, if there is an enemy base which has radar system designed to detect air carriers (e.g., aircrafts and helicopters) transporting the robotic agent, its drop location must be outside the detectable limit of the radar. In this study, the areas within the detectable limits of the enemy radars are regarded as "No-Drop" areas (Λ_{ND}), and are removed from the candidate robot locations.

Exposure to Enemy's Visible Sensor: Besides the radar systems, which are designed to detect the robot carrier in the sky, the robotic agent should try not to be detected by individual enemies distributed in the battlefield when it travels on the surface of terrain. Such an individual enemy can detect the robotic agent based on its eyes and/or visible sensors (e.g., periscope, telescope, and binocular) equipped in it. To estimate the robotic agent's degree of exposure to the individual enemy, several assumptions are made in this study. These are:

- There are a set of enemies (denoted as $\mathbf{E}^{\text{known}}$) distributed in the battlefield, and their location is known at the time of the robot drop.
- The specification of visible sensors (e.g., maximum and effective limit of detecting boundary) is given for enemies whose location is known.
- The performance (i.e., detectable limit) of the robotic agent's visible sensor is better than that of the enemies.
- The robotic agent prefers to avoid the enemies until it reaches the target location rather than fighting with them.

Taking all these considerations into account, the degree of exposure to the enemy (called the enemy factor, and denoted as F^E) can be expressed as:

$$F_i^E = \sum_{k=1}^{n\left(\mathbf{E}^{\text{known}}\right)} p_i^{e^k} \tag{4}$$

$$p_i^{e^k} = \begin{cases} 1 & \text{if } d_i^{e^k} \le R_e^{e^k} \\ \left(1 - \dfrac{d_i^{e^k}}{R_{max}^{e^k}}\right) \times \left(\dfrac{R_{max}^{e^k}}{R_{max}^{e^k} - R_e^{e^k}}\right) & \text{if } R_e^{e^k} < d_i^{e^k} \le R_{max}^{e^k} \\ 0 & \text{if } R_{max}^{e^k} < d_i^{e^k} \end{cases} \tag{5}$$

where, F_i^E = Robotic agent's degree of exposure to enemies at i^{th} location
$p_i^{e^k}$ = Probability of being detected by k^{th} enemy at i^{th} location
$d_i^{e^k}$ = Visible distance from the location of k^{th} enemy to i^{th} point

F_i^E is the sum of the exposure probabilities to all enemies detected at i^{th} location. Figure 3 shows robotic agent's exposure probability to an individual enemy (e^k). Note that F^E is also used for calculating the weighted-travel cost of the robotic agent in Section 2.4.

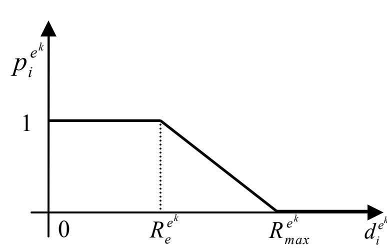


Figure 3: Probability of Exposure to Individual Enemy

2.4 Weighted Travel Cost to Target

Distance to target location would be the most important factor affecting the decision of robot drop location. If there is no enemy including individual units and facilities (e.g., enemy bases) in the battlefield, the best robot drop location would be exactly at the target location. However, due to the existence of enemies and complexity in terrain and land-use in the battlefield, finding the robot drop location based on the minimum distance is an oversimplification. Therefore, a weighted travel cost is introduced here which not only represents surface distance from the robot drop location to target but also reflects the effect of its energy consumption and exposure to enemies distributed in the battlefield. A weighted travel cost between two adjacent points can be expressed as:

$$C_{i-1,i}^{w} = \left(D_{i-1,i}^{S}\right) \times \left(F_{i-1,i}^{V}\right) \times \left(\frac{F_{i-1}^{E} + F_{i}^{E}}{2}\right) \times \left(\frac{F_{i-1}^{F} + F_{i}^{F}}{2}\right) \quad (6)$$

where, $C^{w}_{i-1,i}$ = Weighted travel cost between two adjacent points

$D^{S}_{i-1,i}$ = Surface (i.e.,3D) distance between two adjacent points

Other parameters are defined earlier.

3. GIS-Based Model

3.1 Distance Transformation Algorithm

The weighted travel cost to target location is calculated with Distance Transformation (DT) [11], which is widely used to transform an initial value of image into another representation. DT propagates from the source cell (i.e., the target location in this study), marking all free cells with an incrementing value. Once all cells that are not prohibited have been marked, a search from a selected start position can be made. If the start has been marked with a DT value, a path is possible; otherwise a path does not exist [12].

Three GIS input layers (i.e., elevation map, exposure to enemy (F^{E}), land-use friction factor (F^{F})) are employed to develop a weighted travel cost map, which is the output of the DT process. Figure 4 shows the input and output of the DT process. Note that surface distance (D^{S}) and vertical factor (F^{V}) between two adjacent points are computed during the DT process with xyz coordinates in the elevation map. DT algorithm is processed as follows:

Step 1: Initialization

- Identify the selected cell as the target cell, and assign its value to be 0.
- Make the active cell list empty.

Step 2: Calculating weighted travel cost between two adjacent cells.

- Calculate C^{w} between the selected cell and its neighborhood cells
- Add the neighborhood cells in the active cell list
- Find the lowest cost cell in the active cell list

Step 3: Calculating accumulated travel cost

- Add the selected cell value to the lowest cost cell value
- Store the sum in the output cell

Step 4: Update the selected cell

- Identify the selected cell as the lowest cost cell
- Delete the lowest cost cell from the active cell list
- Go to *Step 2*

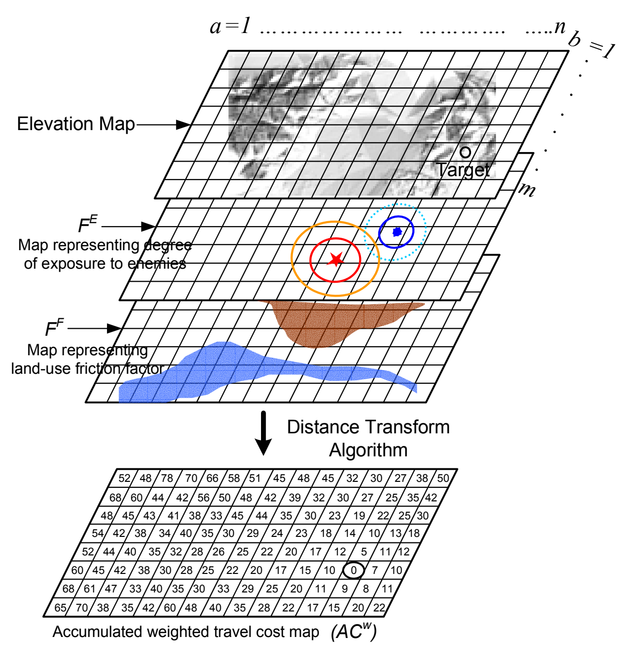


Figure 4: Input and Output of DT Process

3.2 Find Suitable Location for Robot Drop

It should be noted that the accumulated weighted travel cost to target location is stored in each cell of the resulting map of the DT process. Thus, the location problem (which finds the suitable robot drop point) can now reduce to:

Objective: Finding the lowest cost cells in the output map ($\boldsymbol{AC}^w$) of the DT process

Subject to: 1. Min/max allowable slopes for robot drop (i.e., $\theta_{min} < \theta_i < \theta_{max}$)

2. Undesirable land-use for robot drop (i.e., $\lambda_i \notin \boldsymbol{\Lambda}_{NG}$)

3. Limit of enemy radars designed to detect air carriers transporting the robotic agent (i.e., $\lambda_i \notin \boldsymbol{\Lambda}_{ND}$)

where, $AC_i^w = i^{th}$ cell value in the $\boldsymbol{AC}^w$; $AC_i^w \in \boldsymbol{AC}^w$

θ_i = Slope of i^{th} cell

λ_i = Geographic location of i^{th} cell; $\lambda_i = (x_i, y_i, z_i)$

$\boldsymbol{\Lambda}_{NG}$ = A set of "No-Go" areas

$\boldsymbol{\Lambda}_{ND}$ = A set of "No-Drop" areas

4. Case Study

This section presents an example study to demonstrate the performance of the proposed method. Figure 5 shows the land-use and terrain information of the example study area in which the target location, individual enemies, and enemy bases with their limits of radar search boundaries are displayed. The mission assigned to the robot is to reach the destination (i.e., target) as quickly as possible, while avoiding "No-Go" areas and highly risky regions being detected by the enemy. Key input parameters used for this example study are also presented in Figure 5. The total size of the study area is about 440 km^2 (22 km long and 20 km wide), and various land-uses (e.g., river, agricultural, and mountainous areas) are comprised in it. A Pentium Core 2 duo desktop PC with ArcGIS 9.3 is used for preparing and manipulating input GIS maps and finding suitable locations of the robot drop.

Several robot drop locations that satisfy the constraints (specified in Section 3.5) are identified after massive processing of GIS data with the proposed method (See Figure 6(a)). As shown in the figure, darker areas represent undesirable regions for dropping the robotic agents, while the areas with the lighter color represent relatively suitable regions for the robot drop. All the robot drop locations are outside the radar search limit of the enemy bases, and are located in the open space rather than mountainous areas. In addition, slopes at those drop locations are within minimum and maximum allowable limits specified. Figure 6(a) also shows minimum weighted cost paths at the candidate drop locations. These are initial paths which connect the drop locations to the target, and are found based on current information obtained from the battlefield. It should be noted however that the initial paths might be relocated when the robotic agent starts moving along the paths and the enemy positions are redistributed.

Number of enemy bases	7
Number of individual enemies	10
Max. limit of enemy radar search boundary	3k m
Max. limit of enemy's visible sensor	0.5 km
Effective limit of enemy's visible sensor	0.1

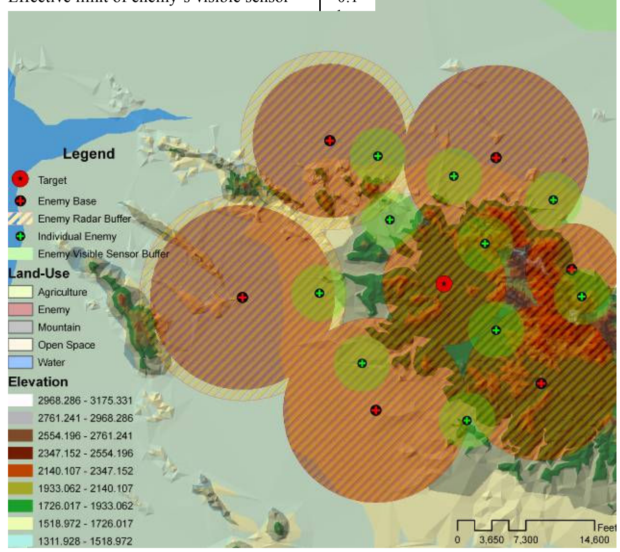
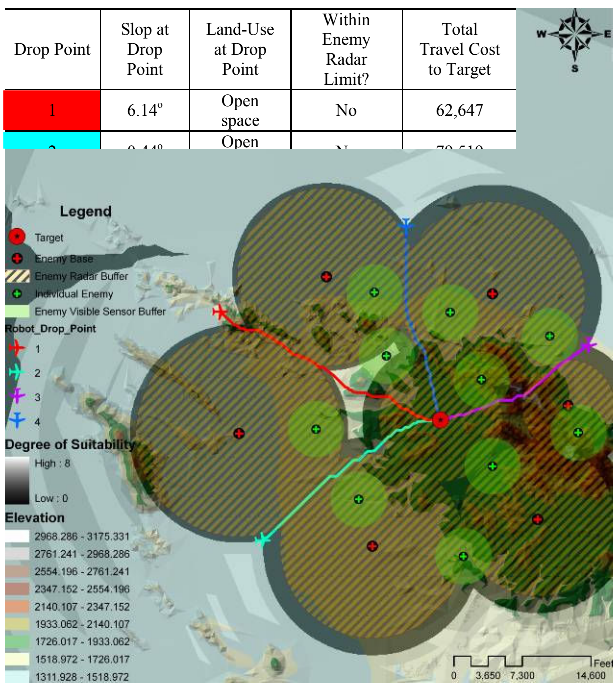


Figure 5: Example Study Area

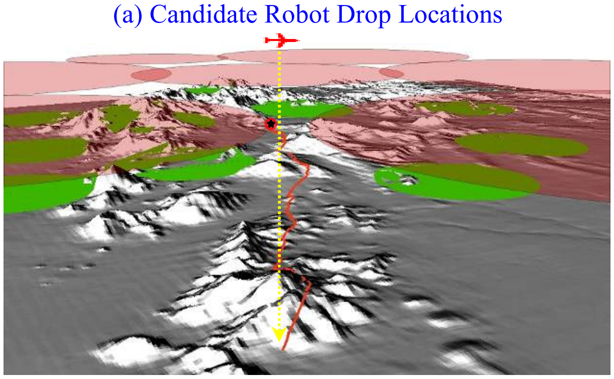
Among the four candidate robot drop locations, Drop Point 1 seems the best one since its path to the target location requires the least total travel cost compared to the others. Figure 6(b) shows 3D view of its path displayed with digital terrain elevation data (DTED) using ArcScene Tool by ESRI.

5. Conclusion and Future Work

A customized GIS-based model is developed to find suitable drop locations of unmanned ground robots (UGR) in combat situations. The objective of the UGR is to reach a known target location as quickly as possible, while minimizing intervention from the enemies distributed in the battlefield. The unique feature of the proposed method is that actual land-use information, terrain profile, and location of enemies spatially distributed in the battlefield are modeled to evaluate robotic agent's energy consumption and its degree of exposure to the enemies, and eventually suitable drop locations with their corresponding minimum cost paths to the target location are identified. An example study tested on a complex digital terrain map with presence of enemy's surveillance system confirms the capability of the proposed method in searching for the robot drop locations. The result clearly indicates that the candidate drop locations are feasible without violation of the specified constraints for the robotic agent to start moving toward the target location.



(a) Candidate Robot Drop Locations



(b) 3D View of the Initial Path from Drop Point 1 to Target

Figure 6: Result of the Example Study

Our future plan is to advance navigating the robotic agent in the battlefield in various combat situations over time. To achieve this goal, a dynamic military path planning strategy in a highly automated fashion is desired. Many technical and methodological improvements that must be considered are:

- Automatic map rectification based on enemy positions dynamically changed over time.
- Development of a stochastic model which measures survival probability of the robotic agent (by defeating enemies and/or by avoiding enemies) based on the line-of-sight analysis.
- Development of a knowledge intensive model which guides robotic agents' movements based on historic data and uncertain territory of the enemy location.
- Modeling various enemy moving strategies (such as, random patrol, scheduled patrol, and unknown patrol).

Acknowledgements
The authors at the Morgan State University would like to thank the US Test Resource Management Center (TRMC) Test and Evaluation/Science and Technology (T&E/S&T) Program for their support. This work is funded by the T&E/S&T Program through the Scientific Research Corporation (SRC) contract W91CRB-07-D-0044 and by SRC subcontract SR20091527 (T309).

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