Development of a Motion Planning System for an Agricultural Mobile Robot

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Abstruct: This paper describes the development of a motion planning system which plans an optimal work pass for an autonomous agricultural vehicle in a farm land. This system consists of two parts: a global path planning component and a local motion planning component. The global path planning component works to acquire an optimal work path for a whole field. In this case, the optimal work path is the lowest traveling cost from a start point to a goal point. The local motion planning component acquires the optimal path and plans an optimal control policy in a headland. In this motion planning, an optimal solution is a path with a low traveling cost and soil compaction. These components are implemented with the following algorithm: Simulated Annealing (SA), TABU Search, Genetic Algorithm (GA), and Reinforcement Learning. In this paper, we solve the optimal path problems in the headland using computer simulation.

Keywords: Optimization, Genetic Algorithm, Reinforcement Learning, Motion Planning

1.Introduction

At the present time, there are lots of serious problems in Japanese agriculture. For example, they are a reduction of the number of farmer every year, an increase of advanced aged farmers, and an upsurge of low price import crops from overseas. For solving these problems, there are many researches in agriculture. Recently, Precision Agriculture (PA) 1) was suggested as a new farming way in this area. The objectives of PA are to reduce production costs, materials, and environmental pollution. Also PA considers sustainable agriculture. It is considered that PA receives much attention as a farming way in the 21st century.

On the other hand, in agriculture engineering, researches consider that unmanned and automatic farmwork using agricultural robots is one the of solutions for these problems, because it is considered that the unmanned and automatic farmwork makes a low cost crops production and efficent farming possible. These researches developed an end-effector to yield any corps or fruit [2),3),4)] and agricultural mobile robots or autonomous vehicles [5),6)] and navigation system [6)]. The agricultural mobile robot is equipped with a variety of sensors such as CCD camera, Global Positioning System (GPS), Fiber Optical Gyroscope (FOG) and Geomagnetic Direction Sensor (GDS). These sensors are used to know own position at the present time.

Indeed, when these robots and vehicles are used in a farmland, it is necessary for them to work and move any farmland using the sensors and navigation data automatically. The navigation data are an optimal work path in a farmland. However, in this area, there would be few researches that are related to acquire navigation data in the farmland automatically.

So the objective of this research is the development of a motion planning system for agricultural mobile robots. This system plans the necessary navigation data for mobile robots or vehicles. Proposed system consists of two components which are a global path planning one and a local motion planning one. This paper presents the motion planning system configuration and discusses the effectiveness of the motion planning system.

2.Proposed System

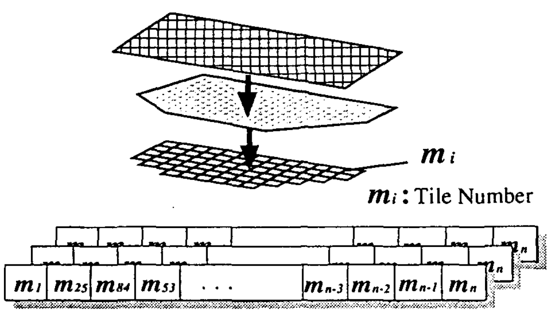
we can consider that generating an optimal work path in a farmland is composed of two phases as mentioned before. One is global path planning which generates a general work path in a farmland. The others is local motion planning which plans path and reference control data in a headland and a turning situation using vehicle model. The following section gives detailed description of the global path planning and the local motion planning.

2.1 Global Path Planning

In a farmland, we consider that the global path planning component needs a flexible planning algorithm, because a path planning system should be able to plan any shapes of farmland. Currently, one of researches which deal with path planning in a farmland particularly, in a rectangular farmland, is based on a numerical expression whose parameters are dimensions of a vehicle and a work width [6]. However this method would be suitable for path planning at any farmland because it has the deficiency of flexibility.

So to solve these problems, we develop a path planning component. The following is the development procedure of this component.

- Retrieve a farmland shape data from map
- Divide a farmland with a work width mesh, approximate a farmland with the mesh
- Assign a number to each meshes
- Input mesh number to path arrangement randomly (Fig.1)
- Computation with several algorithms, then acquire an optimal work path



Tile Arrangement

Fig. 1 Global Path Planning Procedure

This system applies several algorithms to the optimal work path planning. They use planning algorithms that are algorithmic, heuristics, stochastic exploration, and evolutionary computation. These specific methods are hill climbing method, nearest neighbors, simulated annealing method, TABU search, k-OPT and genetic algorithm (GA). The optimal solution is defined as the minimum traveling cost from a start point to a goal point in a farmland. An evaluation function defined as

$$f = \lambda \times D + \eta \times A \quad \cdots (1)$$

$$D = \sum_{i=0}^{n-1} d_{i,i+1} \quad \cdots (2)$$

$$A = \sum_{i=0}^{n-2} \alpha_{i,i+1,i+2} \quad \cdots (3)$$

$$\alpha_{i,i-1,i+2} \equiv \frac{1+\left(d_{i,i+1}^2 + d_{i+1,i+2}^2 - d_{i,i+2}^2\right)}{2 \times d_{i,i+1} + d_{i+1,i+2}}$$

$$2 \geq \alpha_{i,i+1,i+2} \geq 0 \quad \cdots (4)$$

where f is an evaluation value, D is a total distance between point i and $i+1$, A is the amount of direction change among point i, $i+1$, and $i+2$. λ and η are the degree of importance about A and D respectively. $d_{i,i+1}$ is a distance from i to $i+1$, and $\alpha\, i,i+1,i+2$ is degree of change direction among $i,i+1,i+2$, respectively. We apply this evaluation function and these algorithms to a simulation of the path planning. It is the optimal solution that the evaluation value f is minimum.

2.2 Local Motion Planning

The global path planning component deals with generating a whole work path in a farmland with a computer simulation. But, these data are insufficient navigation data, because they have only work path data. So, in the case of a headland and turning situation, it is necessary for a vehicle to plan a precise path and generate motion control data successively. The local motion planning component deals with these problems which are optimal time/path problems of mobile robots on the headland and to decide input motion control data that are steering angle and velocity.

There are researches about a navigation problem in the headland. They applied the principle of a maximum value and optimal control theory [7]. These researches assume that the headland is homogeneity, put in another way, a target space is an ideal one. Then, in this case, it is not considered that heterogeneous soil in the headland affects movement of a mobile robot. So, we have given consideration that when a vehicle model moves it is affected by soil in the simulation. The affect of the soil is a wheel slip.In this paper, the occurrence of the slip is given stochastically when the vehicle model turns and moves in a slope. (Then the farmland data are 3-Dimensions ones)

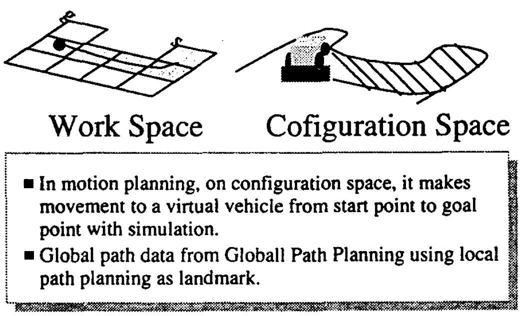


Fig.2 Local Path Planning Procedure

In this research, reinforcement learning is applied to a motion planning method. The reinforcement learning is the problem faced by an agent that learns a behavior through trial-and-error interactions in a dynamic environment. Q-Learning [7),8)] is introduced which is one of reinforcement learning, we consider that it can acquire an optimal motion plan by bottom up approach using the vehicle model.

Evaluation is carried out using the follows function:

$$Cost(i) = \alpha \times \text{Distance} + \beta \times \text{Time} \quad \cdots (5)$$

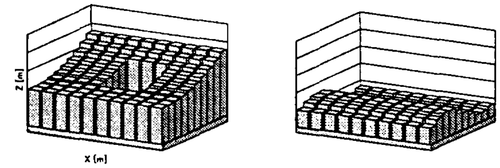
where *cost* is an evaluation function of a movement cost, Distance is a total distance from a start point to a goal point, and Time is movement time. α and β are the degree of importance, respectively. In a simulation, the vehicle model moves in a configuration space, and its evaluation of motion plan is in a work space (Fig.2).

3.Simulation

3.1Simulation Problem

Field maps for a simulation are given as in Fig.3. Field maps have up and down slopes in the z axis. In Field Map 1, it has a depression in the center. It is impossible working in this area.

A non-holonomic vehicle model which is used in the local motion planning is shown in Fig.4.



(a) Field Map1 (b) Field Map2

Fig.3 Field Map

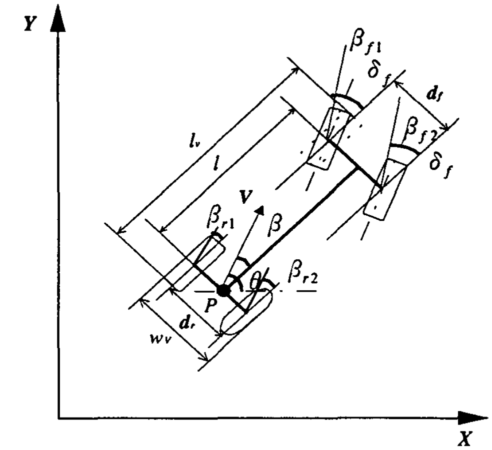


Fig.4 Vehicle Model

This vehicle model describes the following equations of motion:

$$\frac{d\theta}{dt} = \gamma = \frac{V}{l}\tan\delta_f \quad \cdots (6)$$

$$\frac{dY}{dt} = \alpha \times V \sin(\beta + \theta) \quad \cdots (7)$$

$$\frac{dX}{dt} = \alpha \times V \cos(\beta + \theta) \quad \cdots (8)$$

where γ is an angular velocity around a point P, V is a velocity, l is a wheel base, β is a skid angle, θ is a posture angle, and δ_f is a steering angle.

The control outputs are defined as a pair of the velocity V and the steering angle δ_f. Input data at each step for these parameters are generated by a local motion planning simulation with Q-Learning.

Finally, the whole work path in the farmland synthesizes the global path planning data and the local motion planning data. Local motion planning is applied to a turning part on headland and other turning data point in the global path planning data. The final evaluation of the

Action

Velocity	V: {1. 0, 0. 5, 0, -0. 5, -1. 0} [m/s]
Steering angle	α : {0. 785, 0. 349, 0, -0. 349, -0. 785} [rad]

Set of Reword R

Goal-1(Posture angle = π [rad]) = 2.0
Goal-2(Posture angle = except π [rad]) = 1.0
Take a plunge into ridge = -0.4
The others = 0.0

Q-Learning Parameters : α = 0.5, γ = 0.9

Fig.5 Setting Q-Learning Parameters

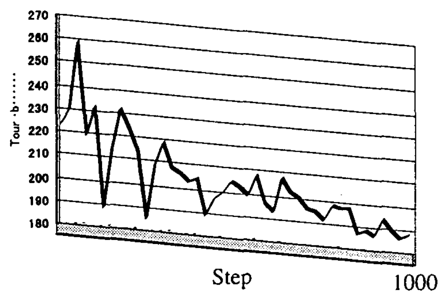
whole work path takes account into a total cost of each turn cost.

$$Total\_Cost = \sum_{i=1}^{n} Cost(i) \quad \cdot \cdot \cdot (9)$$

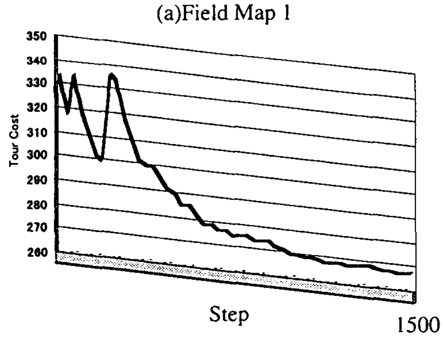
3.2 Result of Simulation

First, a total cost of an optimal work path in each step is shown in Fig.5. These results show a synthesizing value of the global path planning costs and the local motion planning costs each calculation step. Fig.5-(a) gives the result of field map 1, and (b) is the result of field map 2. Cost of (a) converges to the 189.4 at 1000 steps and (b) is convergent 267.0 at 1500 steps.

The results of the global path planning is shown in Fig.6, (a-1) and (b-1). A global work path which covers the whole of the farmland is acquired. The other figures, (a-2) and (b-2) in Fig.6 show the results of synthesizing global path planning and the local motion planning which is based on the global path planning data. From these results, it is



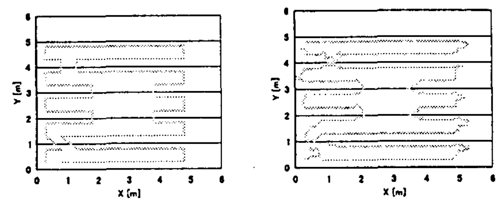
(a)Field Map 1



(b)Field Map 2

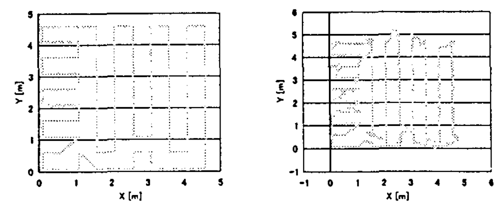
Fig.5 Total Cost of Work Path

verified that this planning system generate a work path tentatively. However these results satisfy the evaluation function which a system developer considered. Therefore, we would consider that this system is necessary to interact with a user because of using users expert knowledge.



(a-1) Global Path Planning (a-2) Local Path Planning

(a) Simulation Result : Field Map1



(b-1) Global Path Planning (b-2) Local Path Planning

(b) Simulation Result : Field Map2

Fig.6 Results of Simulation

4.Conclusions

This paper discussed a motion planning problem in a farmland, and constructed an automatic optimal motion planning system for an agricultural mobile robots. This system was to plan an optimal work path, then it was confirmed to generate a work path.

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