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Path planning algorithm using the values clustered by k-means

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Abstract: Path planning has been studied focusing on finding the shortest paths or smallest movements. The previous methods, however, are not suitable for stable movements on real environments in which various dynamic obstacles exist. In this paper, we suggest a path planning algorithm that makes the movement of an autonomous robot easier in a dynamic environment. Our focus is based on finding optimal movements for mobile robot to keep going on a stable situation but not on finding shortest paths or smallest movements. The proposed algorithm is based on GA and uses k-means cluster analysis algorithm to recognize the much more information of obstacles distribution in real-life space. Simulation results confirmed to have better performance and stability of the proposed algorithm. In order to validate our results, we compared with a previous algorithm based on grid maps-based algorithm for static obstacles and dynamic obstacles environment.

Keywords: Path Planning, GA, Clustering and static/dynamic obstacles

I. INTRODUCTION

Path planning is a navigation problem that mobile robots should find optimal movements to reach the destination position from the start point. It has been one of the complex problems on NP-Complete or NP-Hard domains that must have been solved for autonomous robots. Many researchers have studied for decades to construct robots that are capable of moving around autonomously.

Path planning is divided into the hierarchical maps-based and the grid maps-based[1]. The hierarchical maps-based method has an advantage of faster path planning because robot has simplified map data structures and can easily understand them. Thereupon the robot can't recognize the detailed information in working environments. On the other hand, the grid maps-based may have the detailed information with the grid resolution on entire map, however the problem is the usage of much operating memory. In this paper, we focused on the grid-maps based approach to represent much more information that is helpful to autonomous robots in a dynamic real environment. The method is based on such a A*[1], potential field[1] and the Genetic Algorithm(GA).

Recently, many autonomous robot researches have approached on evolutionary computing by employing GA, ACS (Ant Colony System) to solve the heuristic optimal problem for path planning. The researches based on evolutionary computing have mainly used the GA[3][4][5][6].

In [3], it was suggested that a path planning operated with the chromosome structure have sufficient information, such as movement direction and so on. Though, its drawback of static chromosome size is that it has not been applied in dynamic space information. In [5][6], authors suggested the knowledge-based path planning that the chromosome of path routes could be dynamically resizable and that could be operated with the modified GA operators with the additional operators for faster processing than traditional GA. There are no approaches for various dynamic obstacles. Also, there is limitation for the real-life space application. In other study [7][8], it was suggested that ACSs can be applied to find shortest paths using pheromone that ants lay on for moving paths. They also focused on finding shortest paths and with no consideration of dynamic obstacles like Fig. 1.

Fig.1. Motivation of this paper

As it was mentioned above, most of the researches still focused on finding shortest paths or smallest movements as be shown in Fig. 1. Besides the previous methods may be limited for mobile robots to avoid the various dynamic obstacles and make a stable path route in real-life space.

Clustering method is one of data-mining techniques. Clustering is a set of methodologies for automatic classification of samples into a number of groups using a measure of association, so that the samples in one group are similar and samples belonging to different groups are not similar. Owing to the features of clustering, if it is adopted into path planning, it can be utilized for recognizing a workspace of a mobile robot while it is operating. It also reduces searching space and is helpful to find out optimal paths with more detailed information[2].

We suggest a path planning algorithm that makes the movement of an autonomous robot easier in a dynamic environment. We focus on finding optimal movements for mobile robot to keep going, on a stable situation but not on finding shortest paths or smallest movements. The proposed algorithm is based on GA and uses k-means of cluster analysis to recognize the much more information of obstacles distribution in real-life space. Simulation results confirmed to have better performance and stability of the proposed algorithm. The obtained results is validated and compared with previously proposed algorithms which are based on grid maps algorithm for static obstacles and dynamic obstacles environment.

The rest of this paper is organized as follows: Section 2 describes an overview of k-means as one of clustering analysis and building clustered information, included into the chromosome structure, for the proposed algorithm. We explain the proposed path planning algorithm in Section 3. Section 4 presents the experimental results for static and dynamic environment that is similar to the layout of official room to show efficiency of the proposed algorithm. Finally, section 5 concludes the paper.

II. MAP REPRESENTATION

In this section, we describe the k-means as non-hierarchical clustering one to make groups using similarity among scattered data. We also see how one can build grouping information, included into the chromosome structure, when computed into the level of GA processing. Subsection A briefly presents the k-means algorithm. Subsection B presents how to build combined groups with the same similarity.

A. *k-means clustering*

k-means (MacQueen, 1967) is one of the simplest unsupervised learning algorithms that solve the well-known clustering problem. The procedure follows a simple and easy way to classify a given data set through a certain number of clusters (assume k clusters) fixed a priori. The main idea is to define k centroids, one for each cluster **Error! Reference source not found.**. As an example the basic algorithm is as follows:

Set $D = \{ (x_i, y_i) \mid x_i \in N, y_i \in N \}$

Step 1) For k point, Select the initial centroid point(x,y) of Set D randomly and set a new group(k) where k is a random value.

Step 2) For all unsigned point, calculate the distance between one point and all k's centroid point and assign one point into the closest centroid group(any k). After assigned, recalculate the centroid point for any k .

Step 3) Iterate the Step 2 until not assigned newly any one point into other groups

B. *Map representation using k-means*

Fig. 2 shows the map where a mobile robot moves around. As you see Fig. 2, we divide the map into the grid unit cells of *X* x *Y* matrix. Let C_{xy} be the set of the cells. Also C_{xy} includes various values such as the points of Cells, the center point of Cells, the obstacles-occupied density of the grid unit and the mean density of the *k* centroid for the grid unit. The detailed attributes is shown in table I. Let C_{xy}^{d} be the density of the grid cell and $C_{k}^{k\_centroid\_d}$ be the mean density of the *k* centroid for the grid cell. Then we can describe these equations as below:

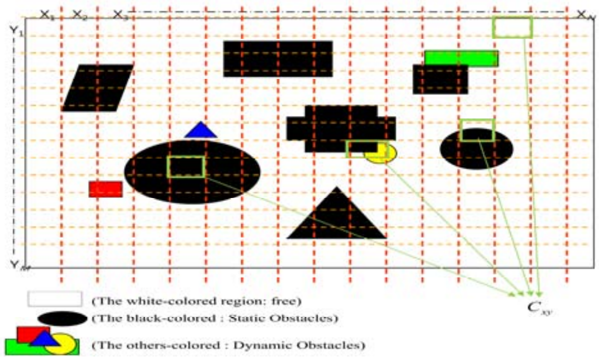


Fig.2. Grid-based representation for a work-space

$$C_{xy}^{d} = \frac{Number\ of\ \text{(the bright colored pixels)}}{Number\ of\ \text{(all of pixels)}}$$

, where *x* and *y* is index value of cells.

$$C_k^{k\_centroid\_d} = \frac{\text{Sum of the density of all } C_{xy}}{Count\ of \text{ all } C_{xy} \text{ allocateed in } k \text{ centorid)}}$$

, where k is a constant index of centroids.

First, we calculate all C_{xy}^{d} for each cell to represent a map using k-means algorithm and then $C_k^{k\_centroid\_d}$ is calculated by using k-means algorithm. The calculated clustering **values** hold on the constructed data structure until all path planning procedures have been completed.

Fig. 3 shows the represented maps using k-means algorithm with the distance vector equation (1) which is modified from Euclidean distance.

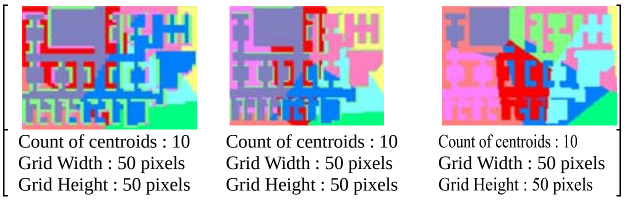


Fig. 3. Examples of represented map using *k*-means

The Function is defined as

$$D(C_i, C_j) = |C_i^d - C_j^d| + \frac{\sqrt{(C_{i,x} - C_{j,x}) + (C_{i,y} - C_{j,y})}}{\beta}$$

-------- (1)

where β is a constant to scale the distance value down.

III. Path Planning Algorithm

A. *Outline of whole processing procedure*

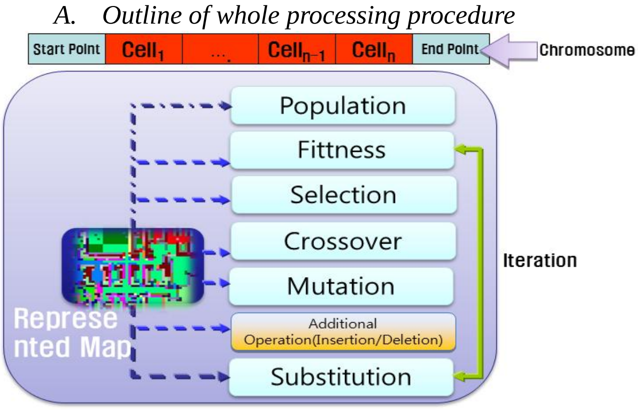


Fig.4. Whole scheme of the proposed algorithm

The entire scheme of the proposed algorithm is given in Fig. 4. The distribution information of static/dynamic obstacles is constructed as the initial step. In the next step, some random populations are generated subsequently fitness procedure is processed using the equation to find the optimal paths. The equation is explained in subsection C. In the Selection Operation, we use the tournament method proposed in the previous studies. In the next step, The Crossover Operation is processed to make better population generations than the pre-generated. The Mutation Operation is achieved to explore the low-rate searching spaces. The Additional Operations, which are the Insertion and the Deletion, are processed to smooth the chromosome and to cut them into the cycled paths off. In the final step, the proposed algorithm substitutes the old generation populations with the new generations which is done by this paper's GA. The scheme iterates until the best optimal paths are found out.

B. *Chromosome*

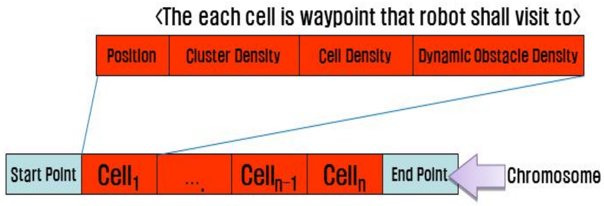


Fig.5. Chromosome structure

As mentioned above, each chromosome consists of various fields like Fig. 5. The first's cells mean a start location and the last's cells mean a destination location. The remained cells are random location to explore the optimal paths. Each cell of a chromosome is composed by selection, mutation, insertion and deletion operation and it has the information of cell's map point, density of static/dynamic obstacles of k-means index value and its mean density.

C. *Fitness Operation*

Fitness function which is defined in conventional GA is an important thing to find the best optimal path. In this paper, we made a fitness function as in the equation (2) in order to calculate cluster information to apply to GA. The fitness function is defined as

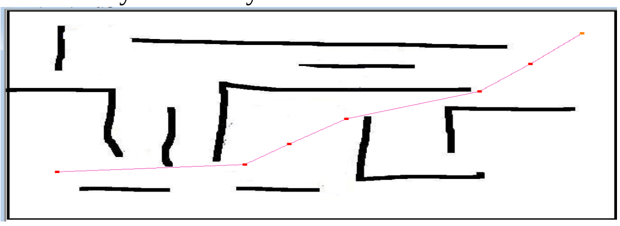
$$\left(\sum_{i=1}^{ch\_s} FC_i\right) \times \alpha + \sum_{i=0}^{ch\_s-1} E(C_i, C_{i+1}) + \sum_{i=0}^{ch\_s-1} \left[\left|C_i^{k\_means\_d} - C_{i+1}^{k\_means\_d}\right| + \left|C_i^d - C_{i+1}^d\right| + \frac{\sqrt{(C_{i,x}^d - C_{i+1,x}^d)^2 + (C_{i,y}^d - C_{i+1,y}^d)^2}}{\beta} \right]$$

------------ (2)

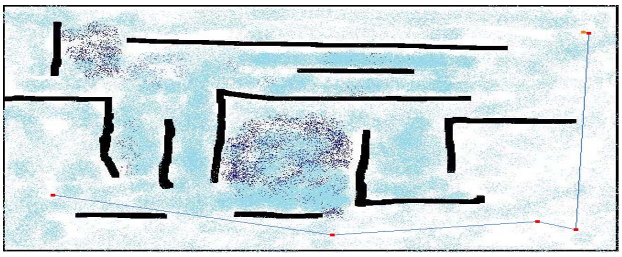
Where *ch_s* is array size of the chromosome, *k_mean_d* is mean value of obstacles density's distribution on a cluster, α is a constant value to scale fitness values up with infeasible paths, *FC* is the number of infeasible paths, β is a constant to scale fitness values down.

IV. Experimental Results

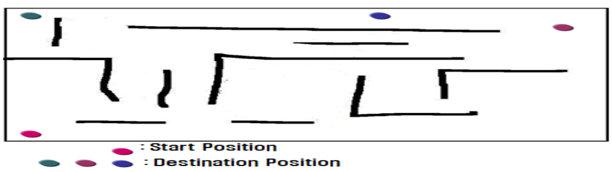
To confirm the better performance and stability of the proposed algorithm, we compared with a previously studied methods based on grid maps-based algorithm for static obstacles as well as for dynamic obstacles environment. The algorithm has been developed using CxImage Open Library as the image processing tool and Visual Studio 2008 as the development toolkit on Windows system family.



(a) Map resolution : 674x461x24b, Path finding result without dynamic obstacles



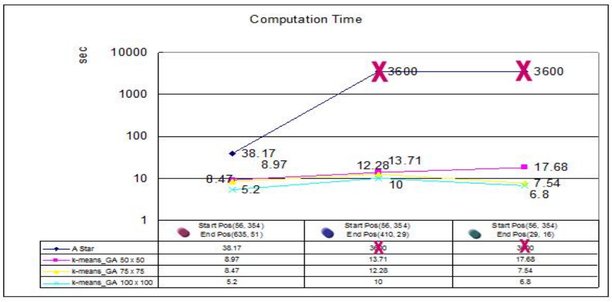
(b) Map resolution : 674x461x24b, Path finding result with distributions of dynamic obstacles



(c) The pink-colored point : start position and the violet-colored point : destination position

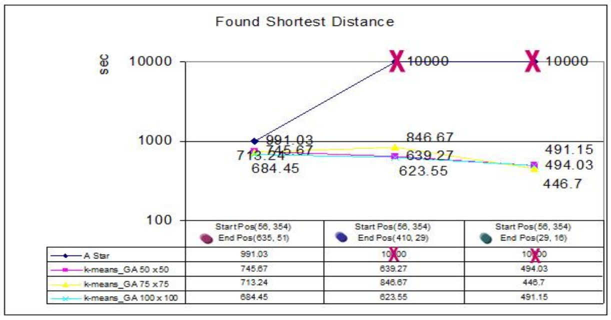
Fig.6. Comparison of path planning results between non-dynamic obstacles space and dynamic obstacles space

Fig. 6 shows the comparative result when the proposed algorithm is processed with and without dynamic obstacles. The results demonstrate that the optimal and stable path can be achieved in the environment with various dynamic obstacles. Certainly, one can confirm that the proposed algorithm has better performance than the previous grid-based approach(A*) in the space with static obstacles as Fig.7 and Fig. 8 show.



	Start Pos(56, 354) End Pos(635, 51)	Start Pos(56, 354) End Pos(410, 29)	Start Pos(56, 354) End Pos(29, 16)
A Star	38.17	3600	3600
k-means_GA 50 x 50	8.97	13.71	17.68
k-means_GA 75 x 75	8.47	12.28	7.54
k-means_GA 100 x 100	5.2	10	6.8

Fig.7. Comparison of processing speed with A*



	Start Pos(56, 354) End Pos(635, 51)	Start Pos(56, 354) End Pos(410, 29)	Start Pos(56, 354) End Pos(29, 16)
A Star	991.03	10000	10000
k-means_GA 50 x50	745.67	639.27	494.03
k-means_GA 75 x75	713.24	846.67	446.7
k-means_GA 100 x 100	684.45	623.55	491.15

Fig.8. Comparison of found shotest path with A*

V. CONCLUSION

As the result of simulation, the proposed algorithm produces to process the optimal path by the order of routes having much less obstacles distribution with the clustered information when is compared with the previous grid-based approach.

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