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Motion Path Searches for Maritime Robots

Eiji Morimoto[1 †], Makoto Nakamura[1], Dai Yamanishi[1] and Eiki Osaki[2]

Abstract : A method based on genetic algorithms was investigated for its capability to identify efficient paths for maritime robots. Data for determining robot motion from information obtained in map form regarding regions with topographical features or other obstacles in the control volume, such as structures or navigational markers, or dangerous regions containing such features as ocean currents, tidal currents, or wind, which increase energy consumption and travel time, were encoded as genes. The fitness values of the procedure for finding the optimal motion path after evolution of the population were observed. The motion path was divided into a rectilinear array and 120-bit genes containing motion data as bit information were constructed. A criterion for assessing each gene was calculated from the route length and penalty value and used as the fitness value. The optimal solution was then searched for by driving the evolution of the travel-pattern population. This study generated information about the basic characteristics and the effectiveness of the proposed procedure.

Key words : Robots, Routing, Path, Search, Genetic Algorithms

Introduction

Maritime robots must be capable of moving autonomously[1),2)]. Given a starting point and a destination, they must be programmed with the capability to automatically select the optimal path from among multiple possible paths between the two points on the basis of some pre-determined evaluation function. Generally, an area through which a robot moves (the control volume) contains some variety of impediments to motion. On the ocean surface, these can be local characteristics, such as winds and tides of various directions and strengths, topographical features, such as islands and capes, or artificial structures, such as lighthouses, buoys, markers, and fixed net[3)]. In addition, some zones are subject to legal restrictions. There is a great variety of such obstacles.

Underwater movements are also subject to factors affecting navigation, such as the bottom topography and tides. These must be accounted for in selection of the motion path. Robots that operate inside ships or marine structures also need to avoid a wide variety of obstacles within these operating spaces when they move and work and so their optimal paths should be chosen from the viewpoint of maximizing work efficiency.

The basic criteria for assessing the performance of a robot include the travel time, fuel consumption, and actual distance covered. Optimal motion paths maximize or minimize combinations of these factors. In performing such searches, the operating system of a robot must identify the optimal solution among a large number of candidates satisfying appropriate criteria, but this generally requires an immense number of calculations. Thus, it is key to determine how to efficiently discover this solution[4),5)]. The present study investigates one such method using a genetic algorithm to determine the optimal path.

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1 Department of Ocean Mechanical Engineering, National Fisheries University
2 Emeritus Professor, National Fisheries University
† Corresponding author : morimoto@fish-u.ac.jp

Methods

In genetic algorithms, information expressing the potential solutions to the problem to be solved are encoded at a genetic locus. Evaluation criteria based on the objectives are applied to the series of information encoded at this genetic locus, and each gene is assessed for how well it fits with the objectives. Many chromosomes containing multiple genes are generated, that population then acts as the first generation to generate the genes for the next generation, and this evolutionary process is repeated for multiple generations to generate evolution in the population toward characteristics that agree with the objectives of the problem. During the process of generational turnover, genes having fitness values beneath a certain threshold are eliminated from the population; this raises the mean fitness value of the overall population and enables it eventually to reach the optimal solution[6)-8)].

A genetic algorithm is executed as follows :

Step 1 : Initialization – Individuals are generated at random.

Step 2 : Assessment – The fitness value of each individual is calculated.

Step 3 : Selection – Individuals are classified according to this calculated fitness.

Step 4 : Crossover – Selected individuals are arbitrarily paired and used to create the next generation.

Step 5 : Mutation – Mutations are introduced at a given probability to individuals in this new generation.

Step 6 : Assessment – The fitness value of each individual is calculated.

Step 7 : Judgment – Terminating conditions are checked, and either the process is repeated from Step 3, or the execution terminates.

Figure 1 is a flow chart of the above procedure.

In the present study, this algorithm is applied by encoding a possible motion path for each gene for moving from the starting point to the destination. The motion search problem was then solved, using an evolutionary process involving many generations, by creating, from a

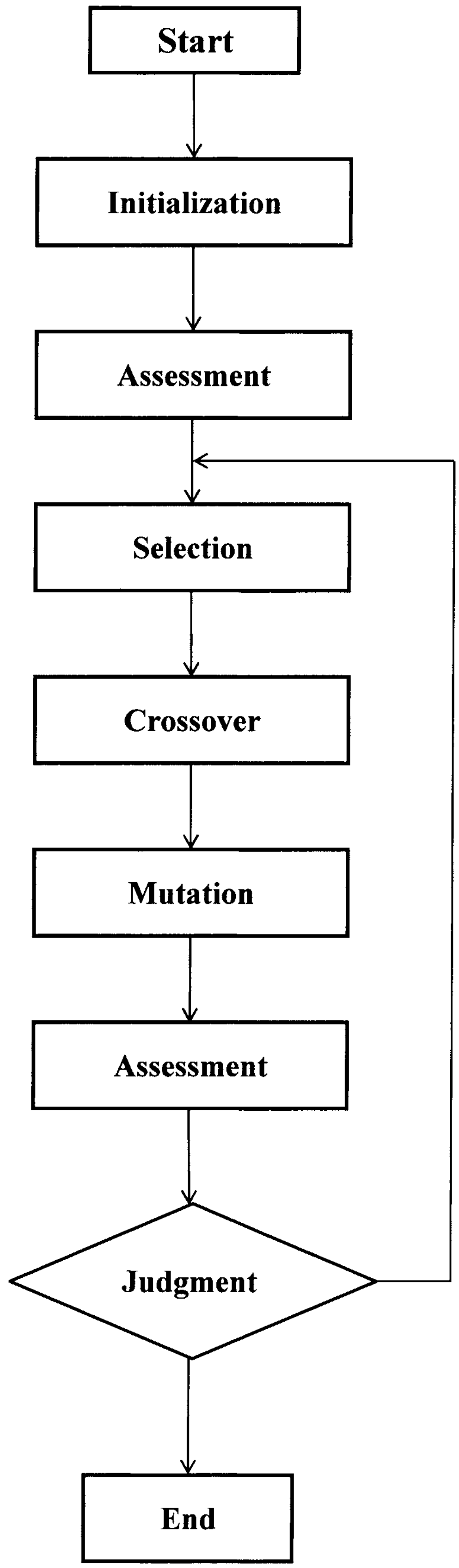

Fig. 1. Getetic algorithm

starting pool of genes encoding different motion patterns, genes that correspond to an optimal motion pattern satisfying the search criteria.

Motion and location data were encoded in binary form at the genetic locus. The simulation range was divided into 2^n divisions in the longitudinal direction and m divisions in the lateral direction. Figure 2 shows the structure of a gene. m segments of n bits each were arranged from the left side. If the k_{th} segment is denoted by p_k, motion is from p_k to p_{k+1}.

n = 6 and m = 20 were used in the simulation, and the control volume was divided into 64 longitudinal and 20 lateral cells. Accordingly, the chromosome consisted of a locus of 6 bits × 20 = 120 bits.

Obstacles and penalty regions were placed in the control volume. These obstacles were topographical features, structures, and other objects that would impede the robot's progress. When the selected path included any of these, it was rejected and replaced with a clear path.

The penalty regions allowed the robot to enter and pass through them; however, the fitness value, which was employed as the evaluation function, was decremented in proportion to the penetration of the penalty region. Also, robots are placed under greater loads as they pass through penalty regions than when operating in ordinary regions. That is, these regions correspond to places where a robot is subject to an ocean current, tidal current, wind, or other factor that increases the travel time and fuel consumption.

The fitness value was evaluated by calculations using the route length and the penetration into the penalty region. The route length was taken to be the total travel distance from the starting point to the destination. The penalty value was set to an appropriate value that differed for every penalty region. The penalty value was calculated using the length of the path through the penalty region. These two quantities were summed for each individual, and the reciprocal of the sum was used to calculate the fitness value for the individual.

Many methods have been proposed for crossover, including multipoint crossover, uniform crossover, cyclic crossover, partial crossover, order-based crossover, and uniform location crossover[9]. In this study, the method selected was multipoint crossover.

Many methods have also been proposed for mutation: random, perturbation, inversion, scramble, rotation, translocation, duplication, insertion, and deletion[10]. In this study, values were changed at randomly selected genetic loci. The range of loci where the changes were made was determined in a preliminary experiment to avoid a deterioration of convergence, and a stop or stagnation of revolution[11]. The effect of mutation has been calculated and is shown in Figure 3.

Results

Path search

Obstacles were placed in the interior of the control volume. Figure 4 shows one of the basic motion paths created by the algorithm. The robot starts from the origin ; coordinate (0,0) to the destination (0, 20) . G shown in the legend means the generation number of genes. In the figure, the location X and Y mean the disance from the origin, and the rectangular painted dark indicates the obstacle which robots cannot move across. The figure shows the number of generational turnovers and variations in the search path. It can be seen that the repetition of generational turnovers shortened the detour paths avoiding obstacles, leading to the optimal path between the two given points.

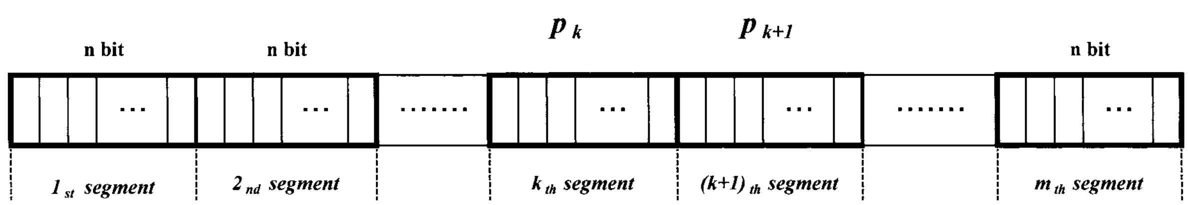

Fig. 2. Structure of gene

Figure 5 shows the results of a path search in a control space with only penalty regions painted thinly and no obstacles. In th figure, the destination is (0,64). Unlike obstacles, penalty regions allow entry, exit, and crossing, but when a robot passes through a penalty region, its fitness value is reduced as a function of crossing distance. In the real world, such areas would be those exposed to strong winds or tidal currents that impede movement. Such factors increase the crossing time and travel energy usage for a robot, and thus entry into these areas should be minimized. In the simulation shown in the figure, it can be seen that a path crossing a penalty region is selected by the initial generation, but as the evolutionary process is repeated, this region is increasingly avoided, resulting in the choice of a path with high fitness value.

Figure 6 shows the performance of the algorithm after

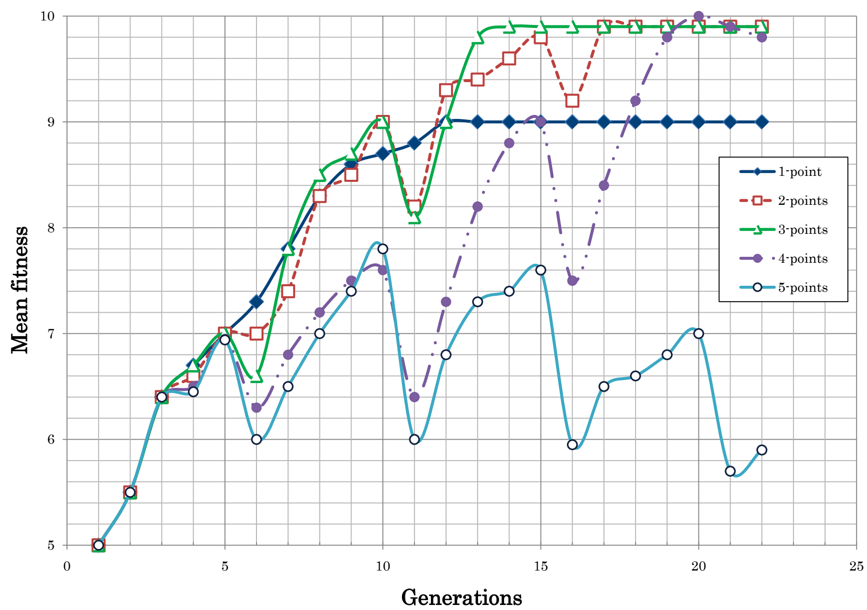

Fig. 3. Effect of mutation

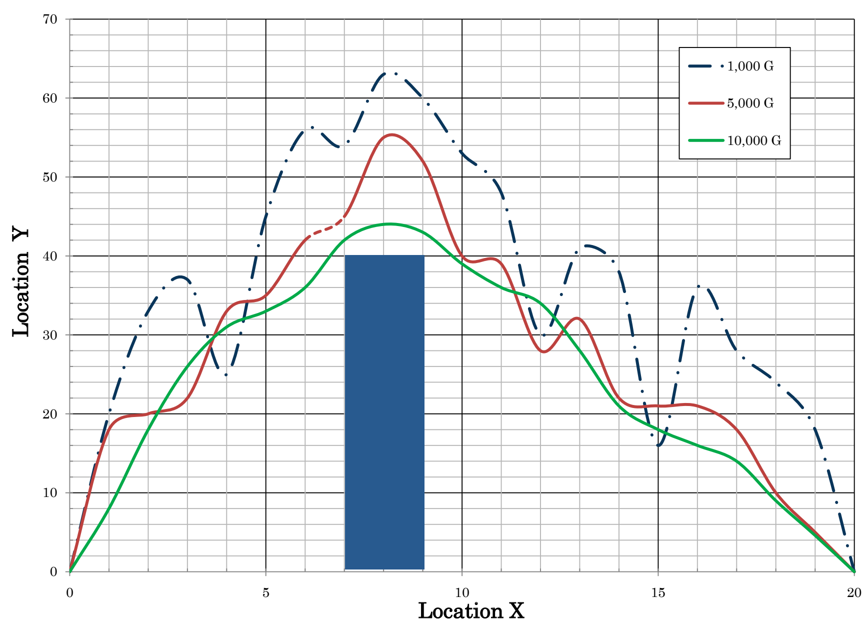

Fig. 4. Results of path search in the area with an obstacle

obstacles were added to the control volume in a complicated pattern, along with additional penalty regions. The optimal path will from (0,0) to (0,64) avoiding two obstacles and penalty areas.

Calculation of the fitness value

To see how each would affect the fitness value, each quantity related to penalties or path length was multiplied by a coefficient, and differences in search conditions were investigated using these coefficients as parameters. Of course, the results for regions given with few penalty regions were different from those for regions with many. The destination is set up at the point (50, 40), and the optimal path is took as moving just 4 distance higher than the position following along the warning area from sea bottom.

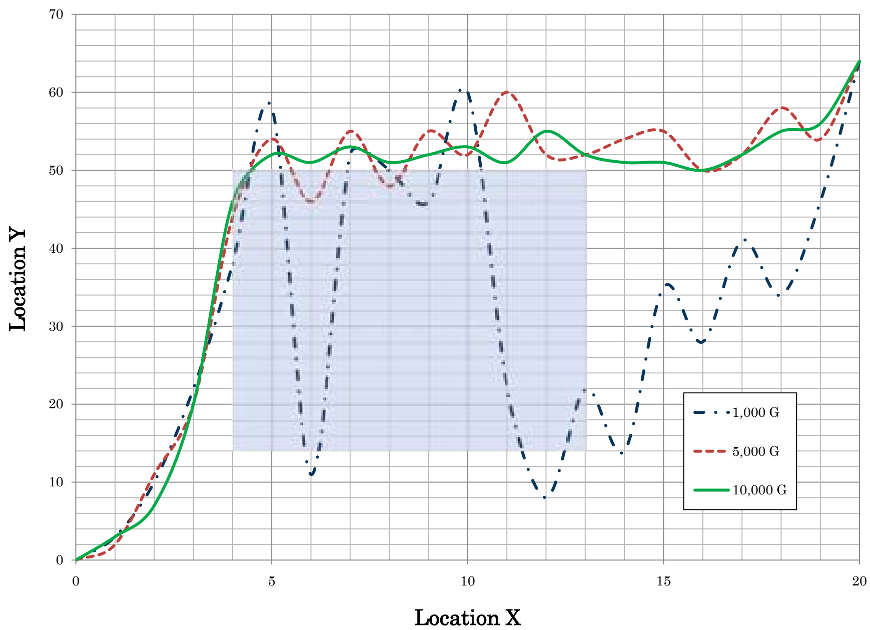

Fig. 5. Results of path search in the area with penalty regions

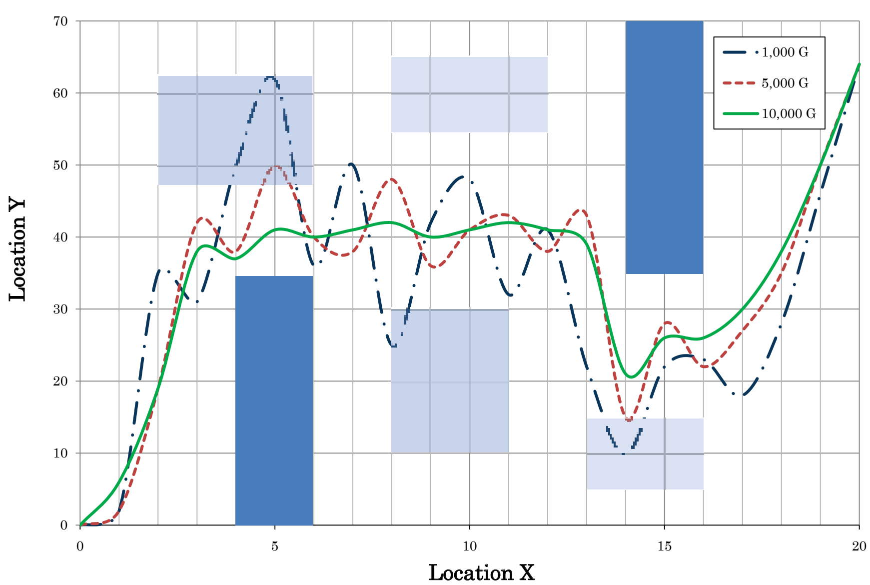

Fig. 6. Results of path search in the area with complicated configurations

And the way in which a penalty was assessed also varied with the settings, for regions with multiple characteristics. Therefore, we could not identify any qualitative tendencies, but we found that we could increase the sensitivity of the search by weighting these parameters in a way appropriate to the degree and distribution of the penalties included in the area.

Movement in the ocean

This simulation also modeled the unevenness of the ocean bottom, in addition to obstacles and penalty regions. The results are shown in Figure 7. In the figure, thinly painted region indicates penalty area, and dark painted region is sea bottom. As in the above results, the greater the number of generations, the more efficient the identified path became. It was verified that raising the assessed value on passage through a penalty region reinforced the tendency to avoid such regions.

Movement of land-based robots

Using our algorithm, the same procedure can be applied to robots designed to work on land surfaces. In the present study, it was envisaged that the typical environment for the robot would be the deck of a ship or marine structure. Such locations are full of objects that can impede free movement, such as stacks of materials, equipment, pillars, and cables, so the robot will be forced to avoid these objects when moving. It will be possible to search for and realize efficient motion paths in such environments by applying a method like that shown in this study.

Discussion

In the present paper, a method for searching for the motion path of a maritime robot using a genetic algorithm was proposed, and the characteristics and effectiveness of the method were investigated. The proposed search method used as the fitness value of the genetic algorithm the overall route length and criteria for motion over a region subdivided into a rectilinear array. The chromosomes used in the genetic algorithm contain genetic loci with lengths equal to the total length of a sequence of 6-bit data representing locations in space. The present study shows that it is possible to conduct a search for the shortest motion path that avoids dangerous regions and regions containing impediments to motion.

The following issue was identified in the course of the

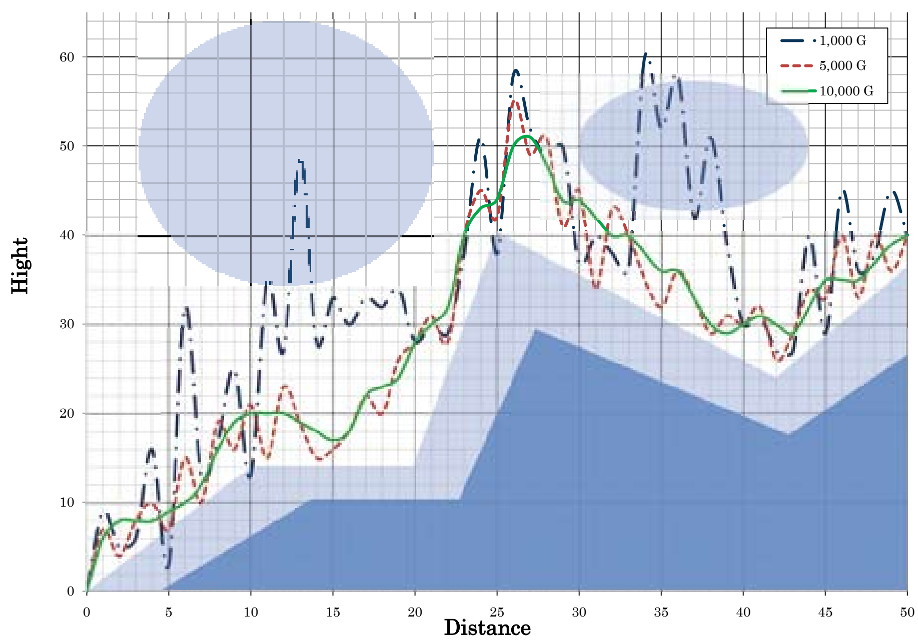

Fig. 7. Results of path search in the ocean

present study: When the robot is passing through a sector, the allowed range of motion includes all of the next contiguous sector, so the amplitude of lateral oscillations in the path tended to become large. It is necessary to suppress this oscillation amplitude in order to reduce the search time; therefore, a technique is needed to limit the permitted range of motion in the region ahead.

The following are other points that should be addressed in future research. First, the effect of variation in the criteria used for crossover and mutation on the search outcome from this algorithm should be explored. In this study, however, both crossover and mutation were employed as a single method, and so these were not subjects of study in the simulations. This aspect should be addressed in a preparatory study in the future in order to identify qualitative tendencies. One can anticipate that land-based robots other than those used in simple applications may well need spatial data in addition to two-dimensional data. This will necessitate construction of genetic information for three-dimensional paths, which must be addressed in future investigations.

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海洋作業ロボットの移動経路探索

森元映治，中村　誠，山西　大，大崎榮喜

海洋作業ロボットの移動経路を効率よく探索するために、遺伝的アルゴリズムを用いる方法について検討した。移動領域の地形、構造体、標識などの障害物、海流、潮流、風などの影響により通過するエネルギーや時間の消費を増大させる領域、移動に危険を伴う領域等に関する情報をマップとして得るとき、移動を決める情報を遺伝子に配し、群の進化により最適移動経路を求める手法の適応性について調べた。移動領域を格子状に区切り、移動地点情報をビット情報として持つ120ビットの遺伝子を構成し、適応度に経路長とペナルティ量から算出する評価量を用い、経路パターン母集団を進化させる事により、最適解を求めた。この結果、提案する手法の基礎的特性と有効性に関する知見が得られた。