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Mean crossover in evolutionary path planning method for maritime collision avoidance

Krzyżowanie uśredniające w ewolucyjnej metodzie planowania ścieżki przejścia w zastosowaniu do problemu unikania kolizji na morzu

Łukasz Kuczkowski, Piotr Kolendo, Bartosz Jaworski, Roman Śmierzchalski

Gdańsk University of Technology, Faculty of Electrical and Control Engineering
Politechnika Gdańska, Wydział Elektrotechniki i Automatyki
80-233 Gdańsk, ul. G. Narutowicza 11/12, e-mail: romsmier@ely.pg.gda.pl

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Abstract
This paper presents the use of mean crossover genetic operator for path planning using evolutionary algorithm for collision avoidance on sea. Mean crossover ensures widening of the possible solutions' set that can be achieved in comparison to exchange crossover variant. The research shown, that the mean crossover allows to achieve results independent from the initial generation and quicker transition of the algorithm from the exploration to the exploitation phase. New version of the algorithm allows for an effective solution search for the problem of a collision scenario on sea.

Słowa kluczowe: algorytmy genetyczne, planowanie ścieżki przejścia, unikanie kolizji

Abstrakt
Artykuł przedstawia zastosowanie operatora krzyżowania uśredniającego do wyznaczania ścieżki przejścia przy użyciu algorytmu ewolucyjnego w zastosowaniu do unikania kolizji na morzu. Krzyżowanie uśredniające zapewnia rozszerzenie zbioru rozwiązań możliwych do uzyskania w porównaniu z wariantem krzyżowania wymieniającego. Przeprowadzone badania wykazały, że zastosowany wariant krzyżowania pozwala na uniezależnienie wyników symulacji od postaci populacji początkowej oraz szybsze przejście algorytmu z fazy eksploracji do eksploatacji obszaru przyciągania optimum. Nowa wersja algorytmu pozwala na skuteczne poszukiwanie rozwiązań w sytuacji kolizyjnej na morzu.

Introduction

The problem of path planning occurs in various ways, such as, motion planning for mobile robots, submarine routing in ocean, or safety path planning for a ship in a collision situation at sea. The problem is defined as follows: having given a moving object and the description of the environment, plan the path for the object that would cross it from the beginning to end location, while avoiding all constraints and meeting certain optimization criteria. The problem can be divided into two basic tasks: the off-line task, in which we look for the path of the object in the unchanging environment, and the on-line task, in which the object moves in the environment that meets the variability and uncertainty restrictions. The on-line mode of the path planning relates to the control of the moving object in the non-stationary environment, in which parts of some obstacles reveal certain dynamics.

The main goal of the present paper is to discuss the application of the mean crossover in the evolutionary method of path planning. In this paper, authors use the navigation problem of avoiding collisions at sea for the testing ground. Taking into account certain boundaries of the manoeuvring region, along with the navigation restrains and other moving ships and other dynamic boundaries, the problem has been reduced to a dynamic optimization task with static and dynamic [1] constrains. Authors consider this an adaptive evolutionary task of estimating the ship's path in the unsteady environment. Based on the Evolutionary (path) Planner / Navigator [2, 3], an updated version has been developed, the υEP/N++ [4, 5, 6] which takes into account specific nature of the process of avoiding collisions. The present version of the system uses different types of static and moving constraints to model the real environment of moving targets and their dynamic characteristics.

The paper has been organized in the following way: in chapters two and three the path planning system is presented. The research on the crossovers is shown in chapter four, while chapter five focuses on the environment research. Chapter six presents simulation examples of the modified version of the path planning algorithm in on-line mode using the mean crossover. The paper closes with the research conclusions.

Path planning system

Following the development of robotics and computer technology, numerous research projects were conducted to develop new methods of planning the paths for passing of moving objects in a known environment [6, 7]. The existing methods analysed come with difficulties that needed solving, including:

– the impossibility to obtain the satisfactory result at a nearly real time (long computing times);
– the inability to respond to changes of the criteria and uncertainties when evaluating the passage path.

To find the way to overcome these difficulties, authors decided to analyse the Evolutionary Planner / Navigator (υEP/N++) system [2, 3]. The advantages of the evolutionary approach can be listed as follows:

– random search is believed to be the most effective in dealing with NP-hard problems and in escaping from local minima;
– intelligent behaviour can be treated as a composition of simple reactions to a complex world;
– a planner can be much more simplified, and still much more efficient and flexible, and increase the quality of the search, if it is not confined to the action within a specific map structure;
– parallel search actions not only secure high speed but also provide opportunities for interactions between search actions, all this acting in favour of better efficiency of the optimization;
– it is better to equip the planner with the flexibility to change the optimization goals than the ability to find the absolute optimum solution for a single particular goal.

Taking under consideration the above mentioned evolutionary techniques and using genetic algorithms specific knowledge, EP/N was devised. The systems main elements consist of:

– unique design of the chromosome structure;
– construction of the genetic operators that modify the chromosomes.

Using those in EP/N does not require discretised search map, which is an usual requirement for similar programs. EP/N searches the environment continuously by generating paths with the aid of various evolutionary operators. Environment's objects can be represented using polygons, both for static and dynamic objects.

Based on EP/N, an extended version, the υEP/N++ was developed. In this algorithm dynamic objects of the environment were also included. Non-stationary elements were described by adding the parameters of time and movement. Following genetic operators were used to modify the paths: mutation, soft mutation, speed mutation, adding a gene, gene position exchange, smoothing, gene removal and repairmen of a chromosome fragment [5].

Path Planning in collision scenarios [4, 5, 6]

Collision avoidance problem consists of planning a path P, as a part of the route that ship travels from the current (starting) position (x_0, y_0) to the destination point (x_e, y_e). The path is built from linear segments p_i (i = 1,...,n), connected with one another with the running points (x_i, y_i). The selection of the start and destination points depends on the considered period of time and is chosen by the operator. Taking this under consideration, the path P is feasible (is considered save), if each its segment p_i (i = 1,…,n) remains in the boundaries of the environment and does not cross any static or dynamic constrain. Paths, that have a fragment that does cross the forbidden areas created by those constrains, are considered non-feasible.

Path planning for an own[1] ship in a collision scenario searches for a path that would balance the costs of the necessary course deviation and the constrain (such as other ships, weather conditions, etc.) avoidance safety. Safety conditions are chosen

[1] Own ship is the ship that is carrying out the collision avoidance action, while the other ship (target) is a moving constraint that has to be avoided.

by the operator using the forbidden areas around moving other objects (ships) based on the relation of the speed of the ships performing a passing manoeuvre, as well as considering the visibility, weather conditions, the area of navigation, ship's manoeuvrability etc. The level of the collision risk with other moving object varies and is dependant from parameters such as: the time necessary to achieve minimal distance, relation between ships' speed, the distance and course from the object.

An object is considered insecure when it is placed in the area of observation and when the course of that object crosses the course of the own ship in an insecure distance. Distance secure from the own ship depends on the established level of a collision danger (usually 5–8 nautical miles ahead of the ship's bow and 2–4 behind the stern).

In the evolutionary approach, the dangerous objects that are a potential collision risk are shown as moving objects (other ships) that move with a certain speed and have a certain shape.

According to transport plan, the own ship should travel a specific route in the estimated time. On the other hand, it has to move safely along the path planned in order to avoid objects representing potential collision risk. Therefore, path planning in a collision scenario has to be a compromise between a deviation from planned course and safety of the voyage. Thus, the problem is defined as multi-criterion optimization task which considers both the safety and the economy of the route. Every path is assessed using the fitness function, that considers, both aspects. The path's safety cost is calculated based on the distance of the path from the obstacle. The economical path's cost considers: the total path's length P, maximal turn's angle between p_i segments and the time necessary to complete the journey.

Mean crossover genetic operator

This chapter contains the description and introduction of the mean crossover to path planning genetic algorithm.

Description

One of the crossover methods in evolutionary algorithm is the mean crossover [8, 9]. Its main feature is that it affects the gene's value directly, not only their exchange between particular generation's members.

There are two types of the mean crossover. In the first one, the process of children creation (P'_1, P'_2) is based on linear combination of the members with the mean point selection parameter $\xi_{U(0,1)}$ and is calculated according to equations (1) and (2) [8]:

$$P'_1 = P_1 + \xi_{U(0,1)}(P_2 - P_1) \tag{1}$$

$$P'_2 = P_2 + P_1 - P'_1 \tag{2}$$

where:

P_1, P_2 – parents;
P'_1, P'_2 – offspring;
$\xi_{U(0,1)}$ – uniform distribution variable that returns a integer from the $\langle 0,1 \rangle$ range – the mean point selection parameter.

The second version of the mean crossover is done on particular genes. In this approach genes ($p'_{1,i}$, $p'_{2,i}$,) of the offspring pair (P'_1, P'_2) are created by linear combination of the individual genes with the mean point selection parameter $\xi_{U(0,1),i}$ generated randomly for every gene i separately. The offspring are being created with the equations (3) and (4) [8]:

$$p'_{1,i} = p_{1,i} + \xi_{U(0,1),i}(p_{2,i} - p_{1,i}) \tag{3}$$

$$p'_{2,i} = p_{2,i} + p_{1,i} - p'_{1,i} \tag{4}$$

where:

$p_{1,i}$, $p_{2,i}$ – i genes of the parents (P_1, P_2);
$p'_{1,i}$, $p'_{2,i}$ – i-genes of the children (P'_1, P'_2);
$\xi_{U(0,1),i}$ – uniform distribution variable that returns a value $\langle 0,1 \rangle$ for i gene.

The introduction of a uniform probability distribution of the mean point selection in the schema of offspring creation, ensures the symmetry of the other individuals in accordance to curve that connects the distances between genes. Figure 1 shows parents P_1, P_2, children P'_1, P'_2 and the symmetry curve created with the mean point selection parameter $\xi_{U(0,1)} = 0.2$. The distances of all correlating points between parents and the offspring and the symmetry curve will always be proportional to the mean parameter (5).

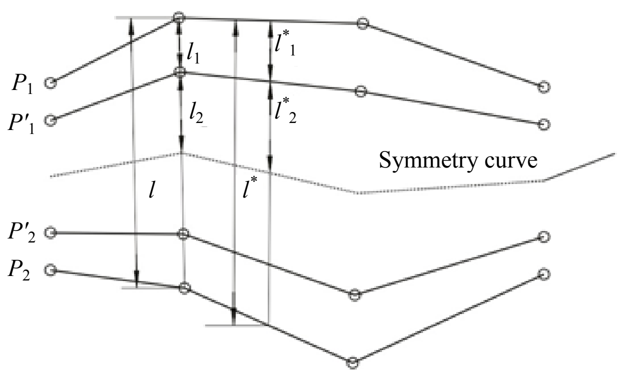

Fig. 1. Symmetry of the individuals during mean crossover
Rys. 1. Symetria jednostek w czasie krzyżowania uśredniającego

$$\frac{l_1}{l} = \frac{l_1^*}{l^*} = \xi_{U(0,1)} \quad \text{and} \quad \frac{l_2}{l} = \frac{l_2^*}{l^*} = \xi_{U(0,1)} \qquad (5)$$

where:

- l – distance between parental genes;
- l_1 – distance between parental gene of the individual P_1 and the offspring gene of the individual P'_1;
- l_2 – distance of the offspring gene P'_1 from the symmetry curve;
- l^* – distance between parental points symmetrical to one another;
- l^*_1 – distance between symmetrical to one another points P_1 and P'_1;
- l^*_2 – distance between the symmetry curve and individual P'_1 generated using it.

Mean and replacement crossover

The main feature distinguishing the mean crossover from the replacement crossover is the introduction of the new genes to the population.

Figure 2a shows the amount of individuals that can be obtained using replacement crossover, that has been achieved using all possible crossover variants. Figure 2b presents the space S of all the possible offspring that can be obtained using the mean crossover. The application of the mean crossover expands the solutions set in comparison to the replacement crossover variant.

Application of the mean crossover in the process of path plannin

The implementation of the mean crossover to the problem of path planning requires to overcome two problems. One of them is the chromosome definition and gene representation. The chromosome in EP/N is built from n genes, which correlates to the number of junctions of the route it represents. Every gene contains information about the coordinates of the turn point and speed. The crossover process is performed separately for each parent coordinates' pair.

The second obstacle is connected to the varied number of genes in chromosome. If the parental pair selected has the same amount of junctions, the crossover is performed with the equations (3) and (4). However, if parents have different amount of genes, algorithm checks which one of them has the least amount of junctions. For the individual having greater amount of genes the dependence (6) is being applied. Because the starting point and the destination point are constant for both individuals, the

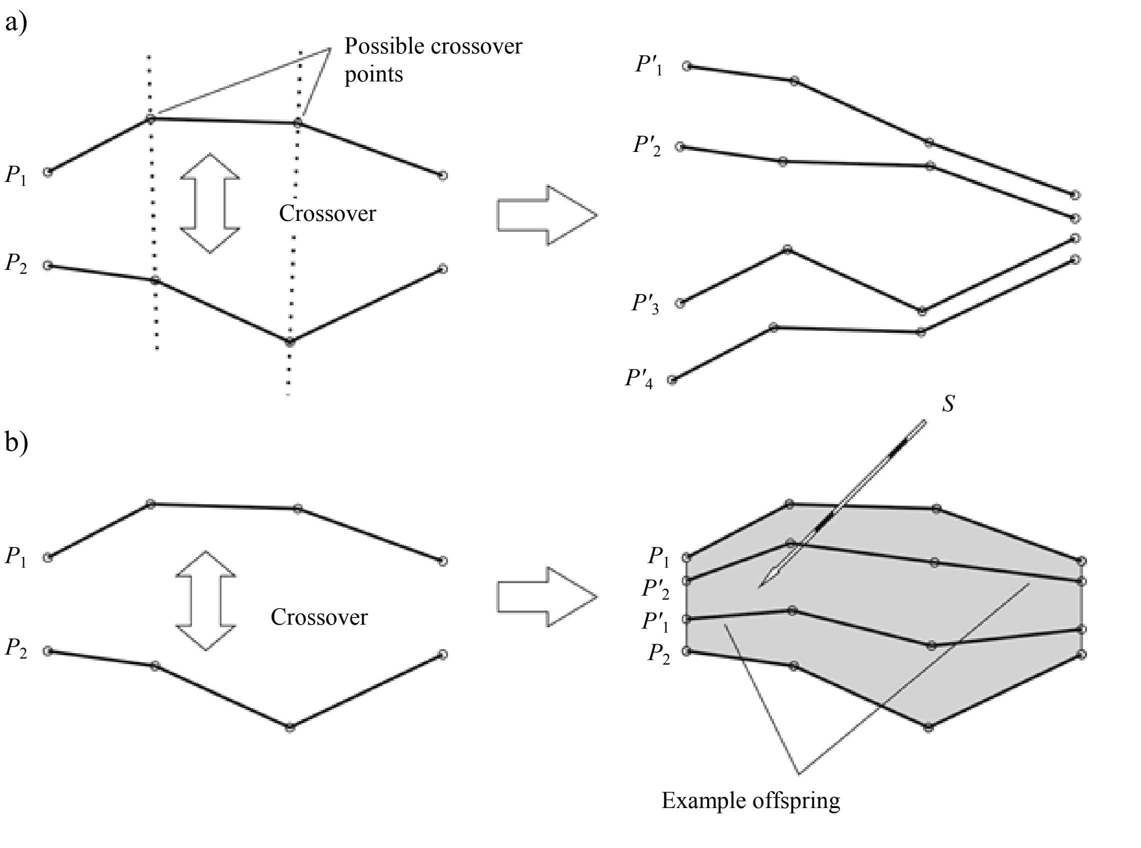

Fig. 2. The set of possible solutions: a) for the replacement crossover, b) for the mean crossover
Rys. 2. Zbiór możliwych rozwiązań: a) dla krzyżowania zastępczego, b) dla krzyżowania uśredniającego

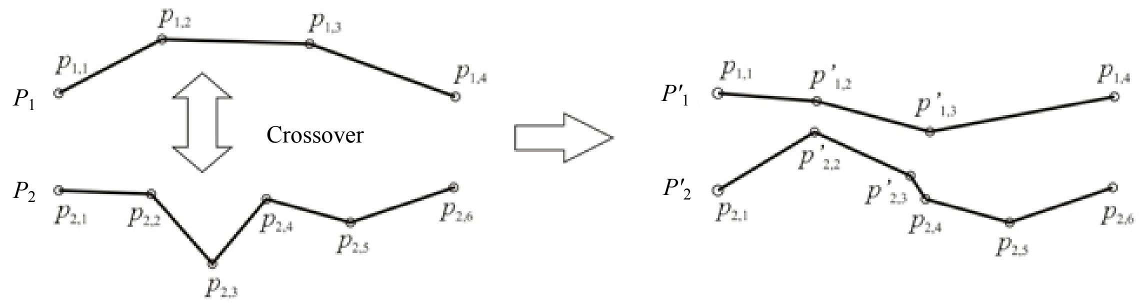

Fig. 3. The operating principle of the mean crossover for individuals with different amount of genes in chromosome
Rys. 3. Zasada operacyjna krzyżowania uśredniającego dla jednostek z różną wielkością genów w chromosomie

genes correlating to those points are not being modified:

$$p'_{2,i} = \begin{cases} p_{2,i} + p_{1,i} - p'_{1,i} & \text{for} \quad i < r \\ p_{2,i} & \text{for} \quad r \le i < t \end{cases} \tag{6}$$

where:
- r – the amount of genes in the shorter chromosome;
- t – the amount of genes in the longer chromosome.

On figure 3 the crossover has been performed only for genes $p_{1,2} - p_{2,2}$ and $p_{1,3} - p_{2,3}$, because only they have their counterparts. Genes $p_{2,4}$, $p_{2,5}$, have been assigned to individual P'_2 without any modification.

Environment

The environments under consideration are populated both with static and dynamic objects, that simulate the ships' movement on the sea. The first environment presents the problem of island avoidance and the dynamic objects encountered. It contains five static obstacles represented by polygons and three dynamic objects, represented by moving hexagons:

target 1 – speed = 3 knots, course 45°;
target 2 – speed = 2 knots, course 135°;
target 3 – speed = 2 knots, course 90°.

The hexagon representation is described in [4]. The second environment is a scenario with a peninsula crossing with the necessity of moving by two other ships: "target 1" moving in the same direction and "target 2" coming from the opposite direction. The targets' parameters are:

target 1 – speed = 2 knots, course 85°;
target 2 – speed = 2 knots, course 245°.

On figures below, the position of the dynamic objects is displayed only for the best adjusted path. Starting positions of the objects were shown on the figure 4 for the first environment and figure 5 for

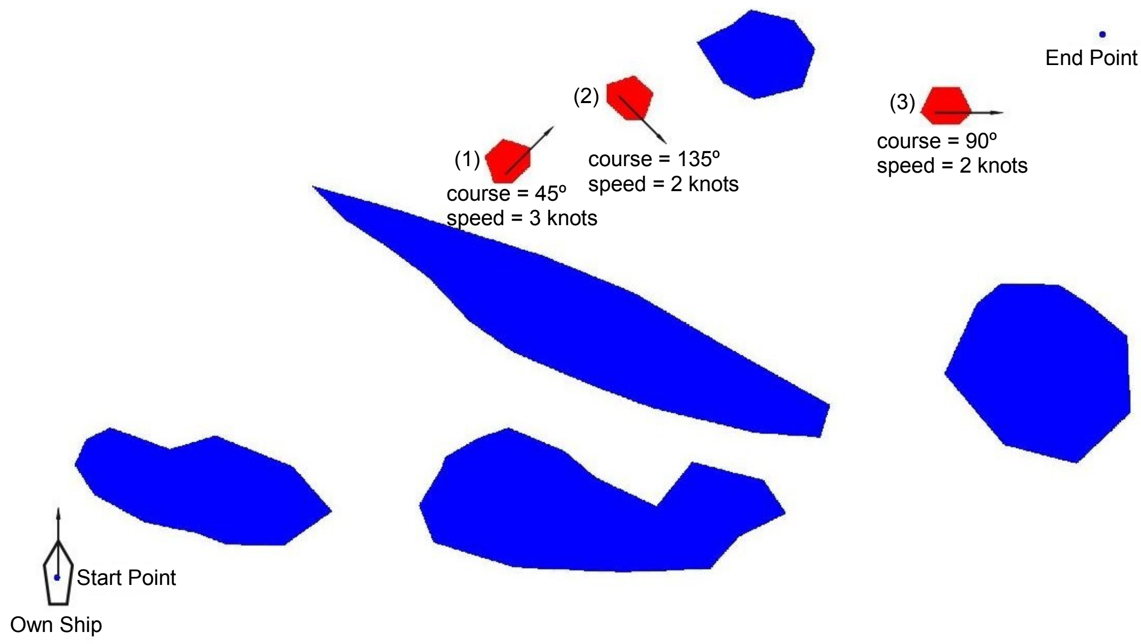

Fig. 4. Environment 1 – Island avoidance
Rys. 4. Środowisko 1 – unikanie kolizji z wyspą

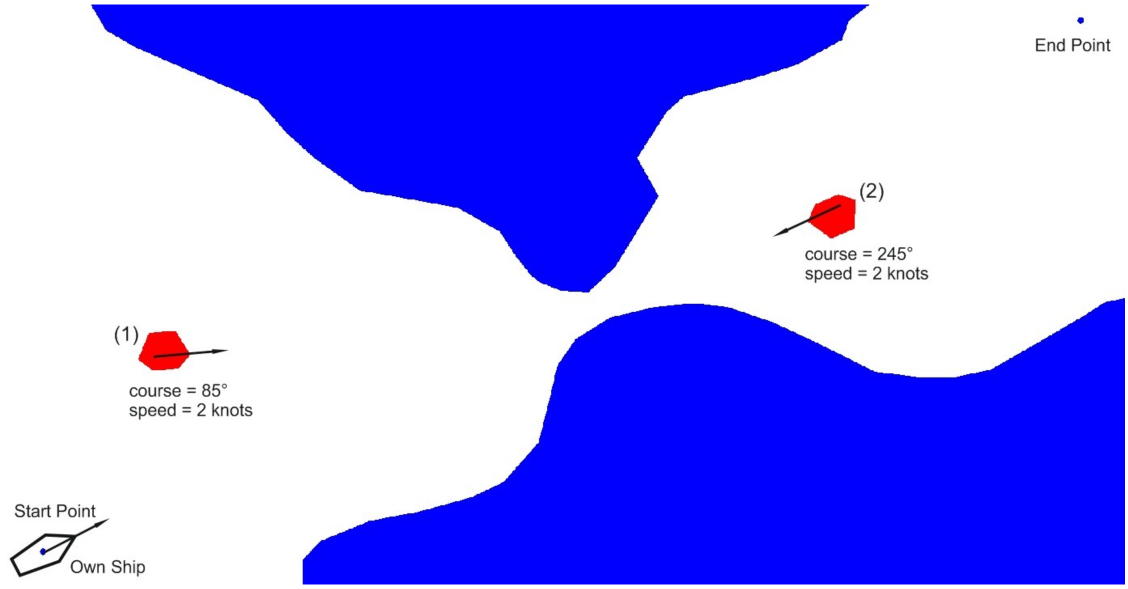

Fig. 5. Environment 2 – Peninsula crossing
Rys. 5. Środowisko 2 – przechodzenie przy półwyspie

the second one. The results were taken for three random initial populations that consisted of 70 individuals. The probability of crossover p_c has been set to 0.8 and the probability of mutilation p_m to 0.05. Calculations were performed with the GALib [10] library and a Steady-State Algorithm with the population replacement on the 0.2 level.

Simulations

The results of the simulations of the mean crossover operator for the two environments previously described can be found below.

Figure 6a presents the initial population for the first environment. Figure 6b shows the beginning of

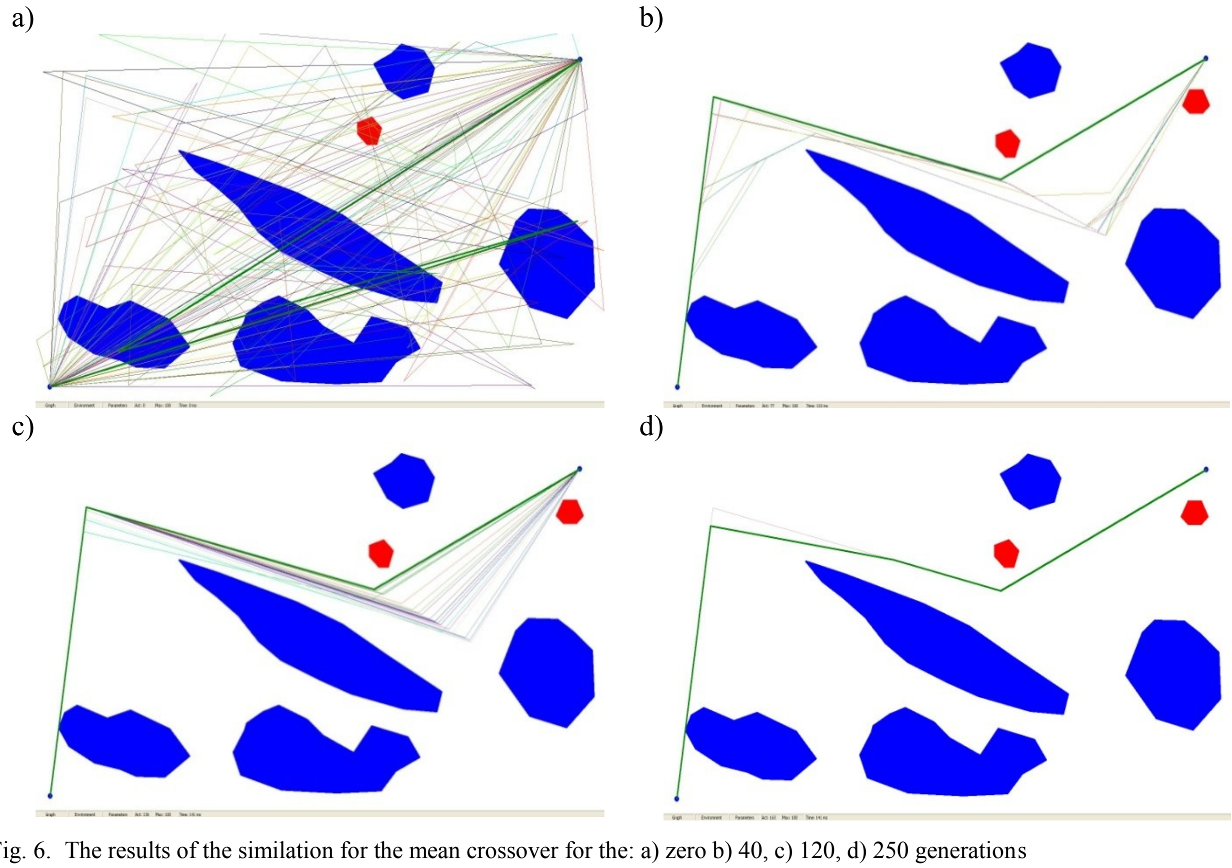

Fig. 6. The results of the similation for the mean crossover for the: a) zero b) 40, c) 120, d) 250 generations
Rys. 6. Wyniki symulacji dla krzyżowania uśredniającego dla: a) zero, b) 40, c) 120, d) 250 generacji

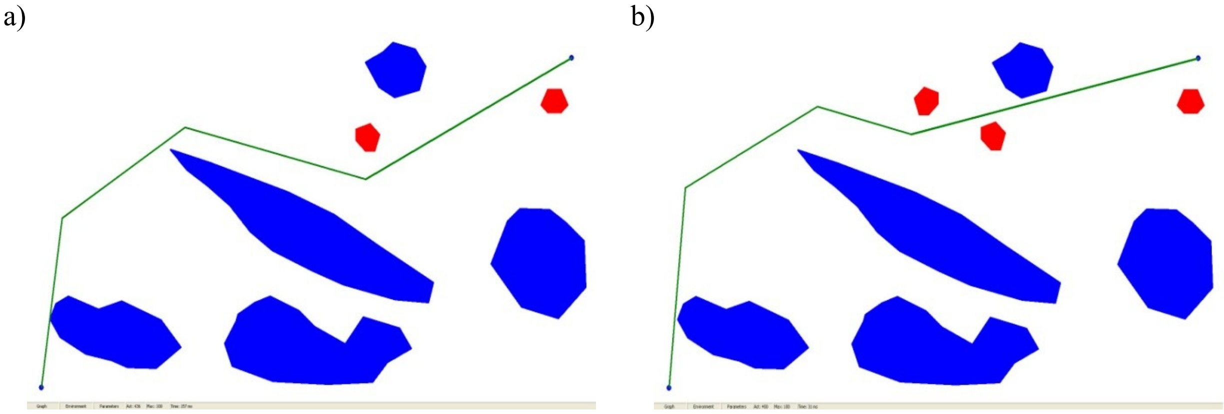

Fig. 7. Environment 1 simulation results for a), b) different initial populations
Rys. 7. Wyniki symulacji dla środowiska 1: a), b) różne początkowe populacje

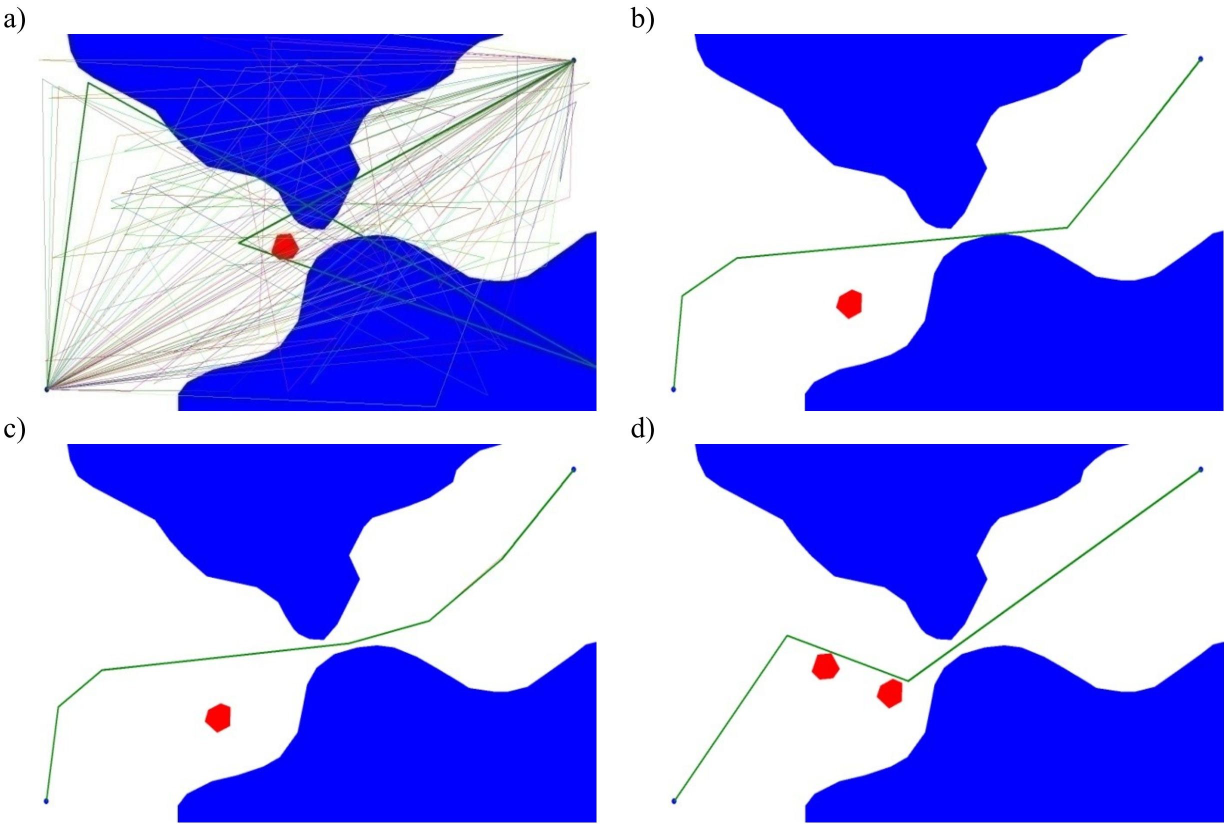

Fig. 8. Environment 2 simulation results: a) example initial population, b), c), d) for other initial populations
Rys. 8. Wyniki symulacji dla środowiska 2: a) przykładowa populacja początkowa, b), c), d) inne populacje początkowe

the mean process (after 40 generations). Between the extreme members of the population, the paths are created in accordance to the distribution of the variable $\xi_{U(0,1)}$ across the generations. Figure 6c presents the maximum number of population members generating a significant number of all possible offspring (after 120 generations). From that moment the algorithm reaches the exploitation phase and the non-optimal solutions are being reduces to finally establish the final path on figure 6d (after 250 generations).

Although different initial populations were used, the end results seen on figure 7 were similar. Only the way that dynamic constrains were avoided differs the two final paths. The results are therefore repeatable, which suggest that they are independent from the initial conditions. This is due to the widen are of search which mean crossover introduces (Fig. 2b).

The environment 1 research shown swift transition of the algorithm from the exploration to the exploitation phase. With the higher crossover parameter in comparison to mutation (p_c / p_m = 1600) the search area is contained to the area between two most distant individuals in the population. The newly generated offspring begin to further widen the solution space by appearing closer and closer to the symmetry curve (Fig. 1). Thus, using only the mean crossover results in convergence quicker than when only the replacement crossover is applied.

Further research was performed on enviroment 2, representing the peninsula crossing.

The results achieved on figures 8b and 8c are similar, though a different amount of generations was necessary to plot the final solution (Fig. 8b – 5500, Fig. 8c – 4300). Therefore, it would appear that the algorithm is resistant to the initial condition, though their unfavourable setting might extend the calculation time. The iteration from figure 8d presents a different solution that was achieved after the 6000th generation. Algorithm was not able to further improve it beyond that point.

The mean crossover contributed in achieving a good result in the case from figure 8c. After 2000 generations the algorithm found a route that met the collision avoidance requirements. After that the algorithm, using the mean mechanism, smoothen the path during the next 2300 generations. This leads to the conclusion that the mean operator is beneficial in the exploitation phase.

Conclusions

The implementation of the mean crossover in the evolutionary path planning allowed the results to become independent from the initial conditions. The simulations presented for environment 1 and 2 (Figs 4 and 5) were performed for various initial populations and the results achieved can be considered similar. This leads to a conclusion that the operator introduced reduced the algorithm's vulnerability to the initial random population's conditions.

The simulations for environment 2 shown an increase in effectiveness of the exploitation phase of the algorithm. The search of the area of optimum attraction with the use of the mean crossover causes the shape of the path to be "smoother" which improves the quality of the solution. In the exploration phase the genetic operator in subject causes the solutions to converge by the attraction area of the local optimum. Therefore, the authors recommend reducing the frequency of the mean crossover utilization in the exploration phase.

Further research will introduce the uniform exchange crossover and compare its results with the mean crossover. In the next step the probability of crossover parameter p_c will be set separately for each genetic operator, so that the proper crossover will be initiated during the phase (exploration, exploitation) in which it is most beneficial.

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