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Ant Colony Optimization based navigational decision support system

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Abstract

This paper presents a Swarm Intelligence (SI) application using Ant Colony Optimization (ACO) techniques in a navigational Decision Support System (DSS). The problem-solving capability of the system includes path planning and collision avoidance of a ship in the open sea as well as in restricted waters. The developed system enhances automation of the safe ship control process. It can also be employed in Unmanned Surface Vehicles (USVs) control system, what will contribute to enhancement of their autonomy. The following issues are introduced in this paper: the developed navigational DSS architecture and the path planning and collision avoidance problem definition. This paper will also present ACO principle and ACO based algorithm implemented in navigational DSS. Exemplary results, conclusions and plans for further investigations are also included.

Keywords: Ant Colony Optimization; Artificial Intelligence; Automation; Decision Support System; Safe Ship Control; Ship Navigation; Swarm Intelligence.

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1. Introduction

Dynamical development of soft computing techniques encourages researches to apply these methods, such as Genetic Algorithms (GA) or Ant Colony Optimization (ACO) in intelligent Decision Support System (DSS). An example application of DSS concerns ship navigation process. Currently the process of ship collision avoidance at sea is performed by the system operator, in ship navigation it is an officer on watch. The system, which aids navigators in decision making process, consists of a radar with Automatic Radar Plotting Aid (ARPA), Automatic Identification System (AIS) and Electronic Chart Display and Information System (ECDIS). These devices support the decision making process by supplying information about the navigational environment with its constraints such as shorelines, shallows, canals, fairways and target ships. The ARPA system provides a possibility to check the effect of a planned collision avoidance manoeuvre, but it does not propose solutions. Therefore many researchers constantly develop new methods to enhance the functionality of applied safe ship control systems. Development of DSS would increase

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automation of ship navigation process and would also enhance the autonomy of safe ship control. In the expanded version it could constitute a part of the control system for Unmanned Surface Vehicles (USVs).

Among many navigational decision making support methods developed through the years, approaches based on Artificial Intelligence (AI) can also be distinguished. One of such methods is introduced by Smierzchalski[1], who proposed the application of Evolutionary Algorithms (EA) to ship path planning. This method has recently been developed by Smierzchalski & Kuczkowski[2] by application of the multi-population approach and the migration of individuals between populations. Similar approach, based on GA, was introduced by Tam & Bucknall[3]. Application of GA was also presented by Tsou et al.[4]. Other approach based on AI was developed by Tsou & Hsueh[5], who introduced a method based on ACO. This paper also presents application of ACO based method for navigational DSS. However these two approaches differ significantly. The differences between these two methods are stated in the following part of the paper. Further analysis of collision avoidance and path planning methods applied to the ship navigation process was presented by Tam et al.[6] and Statheros et al.[7]. State of art concerning collision avoidance systems for improving the autonomy of USVs was described by Campbell et al.[8].

Nomenclature

m	number of ants
u	control signal - course alteration of OS
wp	waypoint
x	longitude of OS position
y	latitude of OS position
D_j	the distance of the j-th TS from OS
D_j^{min}	the distance of the Closest Point of Approach of TS
D_s	the safe distance of the TS from OS
I	index of control quality
M	number of line segments composing the OS trajectory
N	true north
N_j	the bearing of the j-th TS
OS	the own ship - the ship with DSS system
P	probability of choosing the next waypoint by the ant
TS	the target ship - the ship that need to be avoided
U	control space of ship collision avoidance process
V	the speed of the OS
V_j	the speed of the j-th TS
X	state space of ship collision avoidance process
α	coefficient defining the importance of τ
β	coefficient defining the importance of η
η	visibility
ρ	pheromone evaporation rate
τ	pheromone trail
Ψ	the course of the OS
Ψ_j	the course of the j-th TS

Based upon the review of literature conducted by analyzing the above mentioned works, the following limitations of the existing methods have been distinguished:

- the capability of solving only collision situations in the open sea;
- the capability of solving only two ships encounters;
- solutions not fulfilling the COLREGs, especially the rule 8b of COLREGS stating that the manoeuvres should be large enough to be obvious for other vessels;

- not handling of static obstacles (e.g. coastlines, shoals, canals, fairways);
- not considering the dynamical properties of the OS;
- determination of only one manoeuvre, not a sequence of manoeuvres;
- long computational time, what causes that the method is not applicable in real navigational DSS onboard a ship; and
- limited ability to return identical solution for every repetition of calculations performed with the use of the same input data.

The research problem stated in this work was the development of an innovative method based on soft computing technique for solving the ships path planning problem in collision situation at sea, eliminating the above mentioned limitation of the existing approaches. The method developed would constitute a core of the navigational DSS capable of determining automatically the safe ship manoeuvres. This solution will innovate automation of navigational DSS, because commercial solutions currently applied onboard a ship are only capable of checking the manoeuvre planned by the navigator, but does not provide the possibility to propose solutions. ACO metaheuristic has been chosen to be applied to the considered problem due to its encouraging application to other issues, such as vehicle routing problem or robot path planning problem presented by other researchers.

2. Navigational DSS based on ACO

The ships path planning and collision avoidance problem is briefly described in this section. The developed navigational DSS architecture is presented. A short description of ACO fundamentals followed by the specification of the ACO based algorithm developed for path planning and collision avoidance at sea is also reported in this part.

2.1. Description of the navigational DSS

The main task of the navigational DSS is the determination of safe control signals, that is a safe course and/or speed alteration or a sequence of safe course and/or speed changes, which constitute a safe trajectory of the ship. This objective is accomplished by the application of an appropriate control algorithm. Input data of the algorithm describe the current state of the process. The current state of the safe ship control process is defined with the use of information describing actual navigational situation. These data include:

- course and speed of OS;
- course and speed of the j-th TS;
- bearing of the j-th TS;
- distance of the j-th TS from OS; and
- data related to static navigational obstacles (shoals, shorelines, buoys).

These data are received from electro-navigational equipment constituting elements of navigational DSS, such as log to measure the speed of OS, gyrocompass for measuring the course of OS, radar with ARPA to calculate motion and approach parameters of TS. AIS is also used for identifying and locating TS. The information received from AIS is displayed in ECDIS, which integrates data from GPS, echosounder, log, gyrocompass, AIS and ARPA. The GPS determines the geographical position of OS, while the echosounder is used for determination of the actual depth. An example of navigational situation is shown in Fig 1.

The goal of the safe ship control is therefore to determine such control signals, that do not exceed the static constraints such as lands or shoals and also avoid moving obstacles. Dynamic constraints can rely on the designation of such controls, that the distance of the Closest Point of Approach (CPA) is higher than the safe distance, specified by the system operator. This relationship is described by Equation (1).

$$D_j^{min} = \min(D_j(t)) > D_s \tag{1}$$

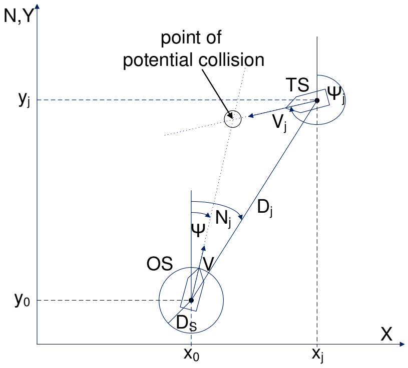

Fig. 1. An exemplary navigational situation.

Dynamic constraints can also be taken into account in the safe ship control process with the use of a domain. The ship domain, as defined by Goodwin[9], is the area around the OS, which the navigator wants to keep free from the TS and static obstacles. The shape and size of the ship domain can be specified by the system operator.

Depending on the final condition, two types of the safe ship control tasks are distinguished, for which the aim is to:

- avoid collision and return to the given final course, for the situation at open sea; and
- avoid collision and return to the given final point of the trajectory, for the situation in restricted waters.

In the process of the safe ship control in addition to information about static and dynamic restrictions, also the following limitations are included:

- the International Regulations for Preventing Collisions at Sea (COLREGs); and
- dynamic characteristics of the OS (the time of manoeuvre).

The block diagram of the navigational DSS, inspired by the work of Lisowski[10], is shown in Fig 2. Detailed definition of assumptions, which have to be fulfilled by navigational DSS, have been described by Lazarowska in[11].

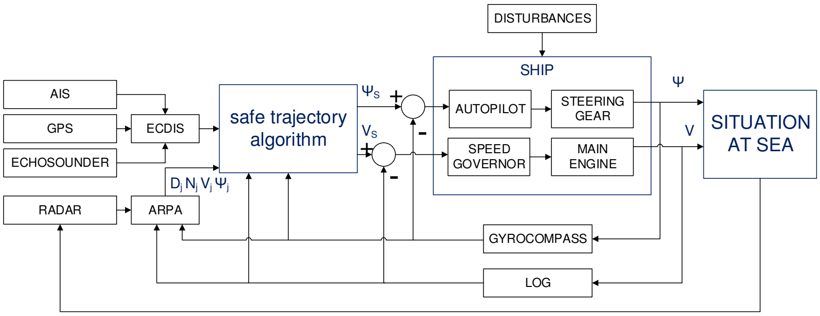

Fig. 2. The block diagram of the navigational DSS.

Safe ship control systems are also applied on USVs. Technologies and solutions for USVs currently constitute a dynamically developing area of research. Research conducted in the field of USVs led to the development of the control system for this type of vehicles, known as the Navigation, Guidance and Control (NGC) system. NGC system consists of the Obstacle Detection and Avoidance (ODA) subsystem, which is an equivalent to the safe ship control system of a seagoing vessel. The purpose of the ODA system is to identify obstacles and to determine appropriate collision avoidance manoeuvres. The ODA system consists of two parts:

- the module of deliberative ODA (global path planning); and
- the module of reflexive ODA (local path re-planning).

The module for the determination of the global path takes into account the environment with known static obstacles such as islands, buoys, shallows. The module of the local path re-planning starts its operation when an obstacle is detected with the use of sensors installed on the USV. The local path re-planning module does not contain information about the environment and the mission. Therefore, the most effective solution is the use of a hybrid system, combining tasks of both modules.

In the hybrid structure, local path re-planning module receives information about the entire environment and the final point of the trajectory from the global path planning module. The block diagram of the hybrid ODA system for USVs, inspired by the work of Campbell et al.[8], is shown in Fig 3(a).

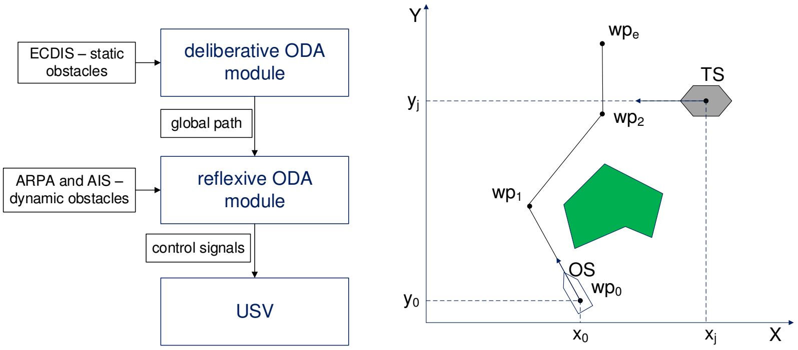

Fig. 3. (a) The block diagram of the hybrid ODA system for USVs; (b) an exemplary trajectory of OS.

2.2. *Definition of the collision avoidance process*

The trajectory of the ship is defined as a sequence of waypoints as shown in Fig 3(b). Every waypoint describes the position of the OS in the form of geographical coordinates (longitude and latitude).The safe trajectory of the OS from the current position of the OS to the next waypoint constitutes the solution of collision avoidance problem. The determined trajectory need to be characterized by the smallest possible loss of way for safe passage, avoiding moving and static obstacles. The optimization of the collision avoidance process is to find such control signals, so that the index of the control quality will have the minimum value, while fulfilling constraints. Equation (2) defines the criterion for assessing the quality of control.

$$I = min \int_{t_0}^{t_e} f[x(t), u(t), t]dt \tag{2}$$

The collision avoidance process is described with the use of a kinematic model of the ship motion. The state equations of the OS and the TS movement is defined by Equation (3), where j=1, ... , n and n is the number of moving obstacles identified in the environment. The dynamic characteristics of the OS are taken into account at the stage of the safe trajectory evaluation in the form of the manoeuvre time.

$$\begin{aligned} \dot{x}_1 &= V \cdot \sin\Psi(t) \\ \dot{x}_2 &= V \cdot \cos\Psi(t) \\ \dot{x}_{2j+1} &= V_j \cdot \sin\Psi_j(t) \\ \dot{x}_{2j+2} &= V_j \cdot \cos\Psi_j(t) \end{aligned} \tag{3}$$

2.3. *Ant Colony Optimization principle*

ACO belongs to the class of Swarm Intelligence (SI), which constitutes a category of AI. The term SI was introduced by Beni & Wang[12] with respect to cellular robotic systems. In 1999 Bonabeau et al.[13] extended the definition of SI. They described this term as any attempt to build an algorithm inspired by the collective behaviour of the colony of insects or other animal communities. A colony of insects is a decentralized system for problem solving, composed of a number of relatively simple interacting individuals, characterized by:

- self-organization;
- flexibility; and
- robustness.

Flexibility of the colony of insects allows it to adapt to changing environments. Robustness means the operation of the colony, even if some individuals do not fulfill their tasks. Colonies of insects solve problems such as foraging, building or expanding their nest, effectively dividing the work among individuals. Many of these problems have their equivalent in engineering and computer science. Observation of the behaviour of the colony of insects and the discovery of the factors affecting their functioning allows to use this knowledge in intelligent system design.

ACO was introduced by Dorigo & Stutzle[14]. Its first application was the combinatorial optimization problem of finding the shortest path between a group of cities, where each city has been visited only once. After all cities have been visited, we have to return to the city, from which we have started our voyage. This issue is called the Traveling Salesman Problem.

The inspiration for the development of ACO was the observation of foraging behaviour of the colony of ants. It has been discovered that the colony of ants uses self-organization to select the shortest path between the food source and their nest. It has been found out that ants communicate with each other and with the environment by depositing a chemical substance on the ground, called pheromone. Ants with the use of the pheromone trail transfer information to other individuals in the colony. This kind of indirect communication, when the behaviour of an individual modifies the environment, which in turn affects the behaviour of another individual in the colony is called stigmergy.

ACO uses the positive feedback mechanism based on the analogy to the trail-lying and trail-following behaviour observed in colonies of real ants. This mechanism strengthens parts of good solutions, what affects the quality of these solutions or strengthens entire good solution. The virtual pheromone trail is used for this purpose. This mechanism enables to keep good solutions in the memory, so that they can be used to obtain even better solutions.

Care has to be taken when strengthening good, but not very good solutions, because this can lead to premature algorithm convergence to a local minimum. This situation is called stagnation. To prevent stagnation, a negative feedback is used, which rely on the pheromone evaporation.

2.4. *ACO based navigational DSS algorithm*

Input data to the algorithm include information about the position and motion of all moving objects and about static obstacles. The data transmission algorithm and transmission details are presented by Lisowski & Lazarowska[15]. Static limitations are modelled in the form of concave and convex polygons, while TS is represented by a hexagon domain. In Tsou & Hsueh approach static obstacles are not considered and a circle domain used around OS instead of a domain around TS. When input data are received, the relative course, speed and bearing of the TS with respect to the OS is calculated.

In the next step the algorithm performs procedure of checking if any of TSs can be qualified as a dangerous object. A dangerous object is a moving object that intersects its course with the course of the OS. After that, a construction graph is created. At first, the OS trajectory from the current position to the next waypoint is divided into k steps. Next, on that basis, the construction graph is created, which consists of possible OS waypoints in the permissible state space. Admissible state space covers an area of at least five nautical miles to starboard and port side of the OS, one nautical mile astern the OS and a distance to the next waypoint before the bow of the OS. Possible waypoints are calculated taking into account all of moving and static restrictions. In Tsou & Hsueh solution the construction graph includes vector format data instead of grid format data representing OS waypoints. They use the following four parameters instead of the longitude and latitude of possible waypoints:

- the required time to the turning point;
- the required collision avoidance angle for passing the TS at safe distance;
- the time between the turning to collision avoidance and the turning to navigational restore; and
- the limited angle upon turning of navigational restore.

The next stage carries out the ACO procedure, which consists of three steps:

- ACO data initialization;
- solution construction; and
- pheromone trail update.

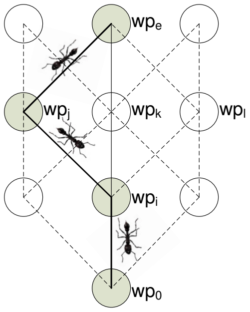

Fig. 4. An exemplary construction graph.

In the ACO data initialization procedure, the parameters of ACO calculations are defined such as α and β coefficients, initial pheromone trail amount at each of the possible waypoints, pheromone evaporation coefficient, number of ants, maximum number of steps to be made by an ant and number of iterations. The solution construction procedure performs the route construction from the current OS position to the next waypoint for each of the ants, as shown in Fig 4. Every ant builds its route until it achieves the end point , that is the next waypoint of OS trajectory or it reaches the maximum number of steps. At every step an ant has to choose the next waypoint with the use of so called action choice rule. This rule works similarly to the roulette wheel selection procedure used in EA. The probability of ant's next move, defined by Equation (4), depends on the pheromone trail amount deposited at each of the possible waypoints and some kind of heuristic information called visibility. The visibility in this approach is defined as the inverse of the distance between the current waypoint and each of the neighboring waypoints. If the route constructed by the ant is shorter than the shortest route found so far, then it becomes the shortest route.

$$P^{ant}_{wp_{ij}}(t) = \frac{[\tau_{wp_j}(t)]^{\alpha} \cdot [\eta_{wp_{ij}}]^{\beta}}{\sum_{l \in wp_i^{ant}} [\tau_{wp_l}(t)]^{\alpha} \cdot [\eta_{wp_{il}}]^{\beta}} \tag{4}$$

The pheromone trail update procedure, defined by Equation (5), consists of two stages:

- pheromone evaporation; and
- pheromone deposit.

$$\tau_{wp_j}(t+1) = (1-\rho) \cdot \tau_{wp_j}(t) + \sum_{ant=1}^{m} \Delta\tau^{ant}_{wp_j}(t) \tag{5}$$

The pheromone evaporation means reducing the pheromone trail amount for all of waypoints by a defined value. The pheromone deposit means adding a certain value to all of waypoints belonging to the routes constructed by ants at solution construction stage. After the pheromone trail update procedure, the best route found by ants in the current iteration is saved. When the maximum number of iterations is achieved or the maximum computation time is reached, the best solution, considering all of iterations, is found. The best solution is characterized by the shortest length of the determined trajectory. The fitness function, defined by Equation (6), is similar to the optimality criterion used by Tsou & Hsueh, who also used the minimization of the distance of the trajectory as the aim of the optimization process[5]. The block diagram of ACO based navigational DSS algorithm is shown in Fig 5.

$$I = \sum_{i=1}^{M-1} \sqrt{(x_{i+1} - x_i)^2 + y_{i+1} - y_i)^2} \rightarrow min \tag{6}$$

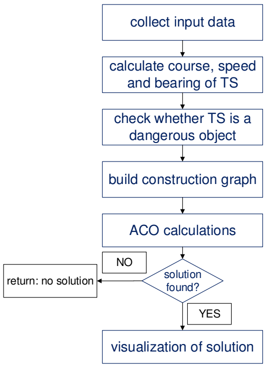

Fig. 5. The block diagram of ACO based navigational DSS algorithm.

3. Results

Problem solving capability of the developed navigational DSS algorithm has been tested on a number of real navigational situations. Data concerning these test cases have been registered with the use of [1]. The following ACO algorithm parameters were used for these calculations: $\tau_0 = 0.01$, $\rho = 0.5$, $\alpha = 1$, $\beta = 2$, iterations = 20 and m = 10. The pheromone trail amount is limited to the following range: from $\tau_{min} = 0.01$ to $\tau_{max} = 1$. Graphical solution, based on the exemplary real navigational situation registered in the English Channel, is shown in Fig 6. Table 1 presents input data to the algorithm for this exemplary situation. Graphical solution of an exemplary situation with a static obstacle and two TSs is shown in Fig 7. Input data describing that situation are placed in Table 2.

Table 1. Data of navigational situation registered in the English Channel.

Ship/Setting	Course [°]	Speed [kn]	Bearing [°]	Distance [nm]
0	170	18.3	–	–
1	71	13.4	181	3.91
2	76	4.8	187	5.9
3	71	11.4	232	6.34
4	71	14.3	112	4.37

The method developed has also been compared with the approach based on Dynamic Programming (DP) introduced by Lisowski[16]. The comparison of the trajectories determined by these two approaches for an exemplary navigational situation from Table 2 is shown in Fig 8. The following conclusions have been formulated based upon the comparative analysis of these two methods:

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[1] http://www.marinetraffic.com/

Table 2. Data of an exemplary navigational situation - a landmass in the environment.

Ship/Setting	Course [°]	Speed [kn]	Bearing [°]	Distance [nm]
0	0	19	–	–
1	90	12.5	315	5.5
2	256	16	35	10

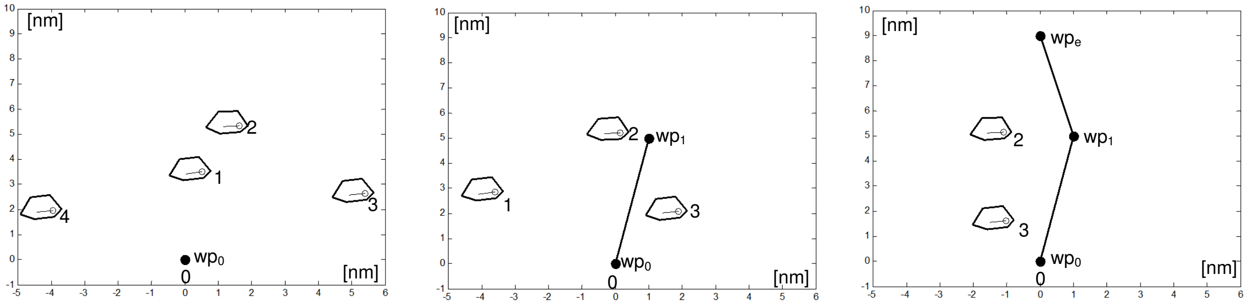

Fig. 6. Graphical solution of an exemplary situation using ACO based algorithm - Ψ: 181°, 156°; (a) OS at wp_0; (b) OS at wp_1; (c) OS at wp_e.

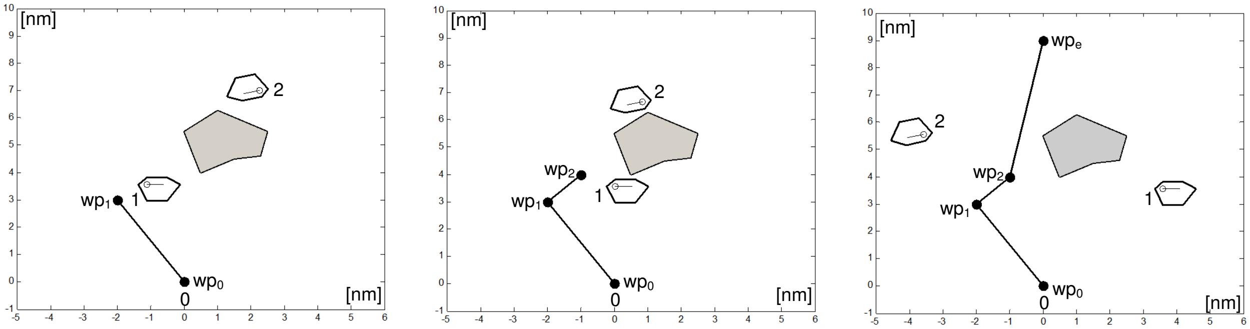

Fig. 7. Graphical solution of an exemplary situation with landmass using ACO based algorithm - Ψ: 326°, 45°, 11°; (a) OS at wp_1; (b) OS at wp_2; (c) OS at wp_e.

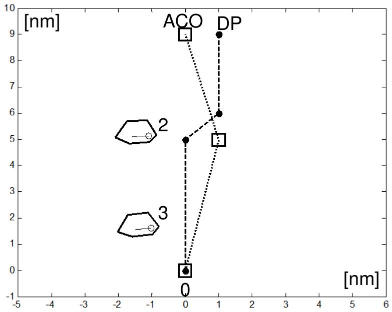

Fig. 8. Graphical solution of navigational situation registered in the English Channel: ACO - Ψ: 181°, 156°; DP - Ψ: 170°, 215°, 170°.

- the final condition of the ACO based navigational DSS algorithm is the return to the given final point of the trajectory, while the final state of the DP based navigational DSS approach is the return to the given final course.
- solution determined by ACO based algorithm is characterized by the manoeuvres starting at the beginning of the control process, while the safe ship manoeuvres determined by the DP based method are executed at the stage of the control process, where the state variables exceed the constraints.

4. Conclusions

The presented navigational DSS can be applied on a seagoing vessel as the safe ship control system, what will enhance the automation of this process. The developed path planning and collision avoidance algorithm is based on ACO. This SI method is inspired by the collective behaviour of the colony of ants. The colony of ants is characterized by self-organization, flexibility and robustness. These features are very desirable in intelligent DSS. ACO based navigational DSS benefits from these characteristics of real ants, which have been implemented to the group of agents called artificial ants. These agents influence each other by depositing values of some parameter on the construction graph, dependent on the quality of their solutions. It has been found out that such mechanism enables the development of an effective, innovative navigational DSS. This system is characterized by near-real time operation and COLREGs compliance, what is essential for this type of devices.

An approach based on ACO to ship collision avoidance process has also been introduced by Tsou & Hsueh. The solution construction presented in their work is different than that presented in this paper. In Tsou & Hsueh method, every multi-ship encounter situation is divided into situations of individual encounter between the OS and each of the TSs. The TS with the highest collision risk is first determined and the collision avoidance calculations are performed with regard to that TS. When the determined trajectory intersects with any of the other TSs, it has to be recomputed. In approach presented in this paper, multi-ship encounter situation, also taking into account static obstacles, are treated as a whole and the solution is calculated with the consideration of all of the restrictions.

The introduced navigational DSS can also be applied to USVs, in order to enhance their autonomy, because of the short time of calculations, not exceeding one minute and the possibility to adapt the fitness function in order to fit it to the type of mission. It is also possible to use other than hexagon shape domain of the TS, for example circle or elliptic, also the size of the domain can be variable, for example defined with the use of neural networks or set by the system operator.

Further works include addition of the speed alteration, in situations, when the course change does not solve the problem. After simulation tests and implementation in real navigational system onboard a ship, sea trials are planned to be performed.

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