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Ship Collision Avoidance by Distributed Tabu Search

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ABSTRACT: More than 90% of world trade is transported by sea. The size and speed of ships is rapidly increasing in order to boost economic efficiency. If ships collide, the damage and cost can be astronomical. It is very difficult for officers to ascertain routes that will avoid collisions, especially when multiple ships travel the same waters. There are several ways to prevent ship collisions, such as lookouts, radar, and VHF radio. More advanced methodologies, such as ship domain, fuzzy theory, and genetic algorithm, have been proposed. These methods work well in one-on-one situations, but are more difficult to apply in multiple-ship situations. Therefore, we proposed the Distributed Local Search Algorithm (DLSA) to avoid ship collisions as a precedent study. DLSA is a distributed algorithm in which multiple ships communicate with each other within a certain area. DLSA computes collision risk based on the information received from neighboring ships. However, DLSA suffers from Quasi-Local Minimum (QLM), which prevents a ship from changing course even when a collision risk arises. In our study, we developed the Distributed Tabu Search Algorithm (DTSA). DTSA uses a tabu list to escape from QLM that also exploits a modified cost function and enlarged domain of next-intended courses to increase its efficiency. We conducted experiments to compare the performance of DLSA and DTSA. The results showed that DTSA outperformed DLSA.

1 INTRODUCTION

Several methods are used to prevent ship collisions, such as lookouts, radar, and VHF radio. More advanced methodologies, such as ship domain, fuzzy theory, and genetic algorithm, have been proposed (Szlapczynski 2006, 2007, Goodwin 1975, Fujii & Tanaka 1971, Hasegawa, Kouzuki, Muramatsu, Komine, & Watabe 1989, Wang, Meng Xu, & Wang 2009, Lee, Kwon, & Joh 2004, Kim, Kang, & Kim 2001). However, in reality, collisions between ships frequently occur. This is partly due to the ever-increasing size and speed of ships each year. A primary cause of ship collisions is officer error. Officers generally have some expertise in finding safe routes that will avoid ship collisions; however, particularly when shipping lanes are crowded and many ships encounter each other simultaneously, finding such routes is especially difficult for officers. The need to repeat this task throughout the voyage multiplies the risk of human error. To support the need to find safe routes for ship travel in crowded waters, we proposed the Distributed Local Search Algorithm (DLSA) as a precedent study (Kim, Hirayama, & Park 2014). In DLSA, we assume that ships can exchange information with each other (using a communication device such as the Automatic Identification System (AIS)) to cooperatively establish routes to avoid collisions. More specifically, when multiple ships meet, the ship that can reduce collision risk most significantly has the right to choose its next course. Where there is a tie in the maximum risk reduction, the one with the highest priority has the right to choose its next course. These choices are then relayed to their neighboring ships as their current courses. Each individual ship computes its collision risk based on the information on current courses that it receives from the neighboring ships. This process is repeated until the collision risk disappears. DLSA works well empirically, but, according to our recent study, it is sometimes trapped in Quasi Local Minimum (QLM) that prevents a ship from changing course even when at risk of collision.

To deal with this issue, we developed a new distributed algorithm called the Distributed Tabu Search Algorithm (DTSA). DTSA enables a ship to search for a new course compulsorily when trapped in QLM, to allow it to escape. Furthermore, DTSA exploits a modified cost function and enlarged domain of next-intended courses to increase its efficiency. The cost function, which computes the collision risk of the current course in DLSA, is modified so that it includes the notion of efficiency. More specifically, we add the relative bearing of the current course to the destination. In this way, DTSA enables ships to find shorter paths to their destinations while avoiding collisions.

Our paper is organized as follows: in Section 2, we outline the background of this work. We then describe DLSA and DTSA in Section 3 and explain how DTSA is applied to ship collision avoidance in Section 4. We present our experimental analysis in Section 5 and our conclusions in Section 6.

2 BACKGROUND

2.1 *Existing methods for Collision Avoidance*

There are many methods for preventing ship collisions at sea. From a regulation point of view, the 1972 Convention on the International Regulations for Preventing Collisions at Sea (COLREGs) (IMO 1972) compels or recommends that ships follow specific regulations, for example, navigational lights, traffic laws of the waterways, and the buoyage system. From a technological point of view, several algorithms are used in ship collision avoidance, such as ship domain (Fujii & Tanaka 1971, Goodwin 1975), fuzzy theory (Hasegawa, Kouzuki, Muramatsu, Komine, & Watabe 1989), and genetic algorithm (GA) (Tsou, Kao, & Su 2010). The ship domain algorithm computes collision risk depending on whether the ship's safety domain is penetrated. The fuzzy theory computes the membership function for collision risk. To compute collision risk, several parameters - Variation of Compass Degree (VCD), Time to the Closest Point of Approach (TCPA), and Distance to the Closest Point of Approach (DCPA) -are used. The GA is based on the principle of evolution, that is, survival of the fittest. Tsou, Kao, & Su (2010) used GA to find the safest and shortest path that also complied with COLREGs. The fitness function is defined as the distance from the turning point to the original route. As chromosome constitution, there are four parameters - avoidance time, turning angle, restoration time and limited angle. They found optimum routes under three situations in which a ship can encounter a target ship. Fan & Ajit (2014) suggested collision avoidance without mutual communication. They were inspired by nature, such as the behavior of humans in crowded areas. In their study, however, individual agents can stop at anytime, which is impossible for ships. As mentioned previously, these works well in one-on-one situations, but, with multiple ships collisions may be difficult to avoid. To solve this problem, we suggest DLSA as a precedent study.

2.2 *Distributed Local Search Algorithm*

Local Search Algorithm (LSA) is a metaheuristic method to solve the optimization problem and an incomplete algorithm. Examples are hill-climbing, simulated annealing, and the tabu search algorithm. A solution may or may not be found for a certain problem. LSA has been used for the nurse scheduling and travelling sales-man problems. LSA is a centralized system based on a computer or server. If the system is broken, it is impossible to maintain it. In comparison, DLSA does not have a server or a computer (Russell & Norvig 2003, Yokoo, Durfee, Ishida, & Kuwabara 1998, Yokoo & Hirayama 1996). An individual agent solves a certain problem by exchanging information with other agents locally. DLSA is flexible during a system failure. DLSA is easily applied to ship collision avoidance in multiple-ships situations. All ships can chart their course freely. They prefer a course that will allow them to reach their destination safely and quickly. A certain sea area, such as an entry port, crossing area, or narrow area has no option but to be crowded because all ships will travel in a similar pattern. In addition, each individual ship must find a solution by itself using local information. Therefore, we applied DLSA to avoid ship collisions as precedent study.

2.3 *Tabu Search Algorithm*

Tabu Search (TS) is a heuristic method proposed by Glover (Glover 1989). Tabu means prohibited. By using memory to prohibit certain moves, TS searches for global optimization rather than local optimization. There are several kinds of memory structures, such as, short, intermediate, and long-term memory. The short-term memory prohibits a solution (move) from being selected in the tabu list. The intermediate-term memory may lead to bias moves toward promising areas. The long-term memory guides to new search areas for diversity. TS is being used in integer programming, scheduling, routing, and the traveling sales-man problem. In conventional problems, application of the short-term memory only is sufficient. In our paper, we use TS to escape QLM, which prevents a ship in risk of collision from changing course. In this paper, we describe the new method with DTSA and the use of DLSA as a precedent study for ship collision avoidance.

3 ALGORITHM FOR SHIP COLLISION AVOIDANCE

3.1 *Ship Collision Avoidance by Distributed Local Search*

We propose DLSA to prevent ship collisions as a precedent study. The variables used are:

- Time Step: estimated position in a specific time.
- Detection of Range: distance to recognized neighboring ships.
- Neighboring Ships: ships located in the detection range and able to exchange information.
- Safety Domain: distance that must be maintained from neighboring ships. Ships entering this domain are considered to have collided.
- Number of Collisions: expected number of collisions with neighboring ships.
- Remaining Time: time remaining for the soonest expected collision expected most rapidly.
- Collision Risk: sum of the number of collisions and remaining time.
- Ok? Message: includes information on position, speed, and course.
- Improvement Message: includes the number indicating how much collision risk is reduced.
- ID: identification given at an initial state and used when improvement is the same as that for a neighboring ship. A ship with a higher priority ID has the right to choose the next course.

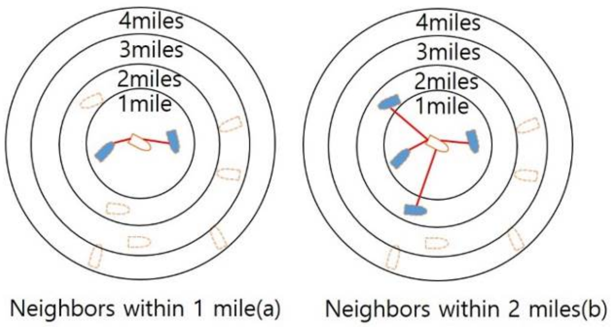

Figure 1. Contactable neighboring by DoR

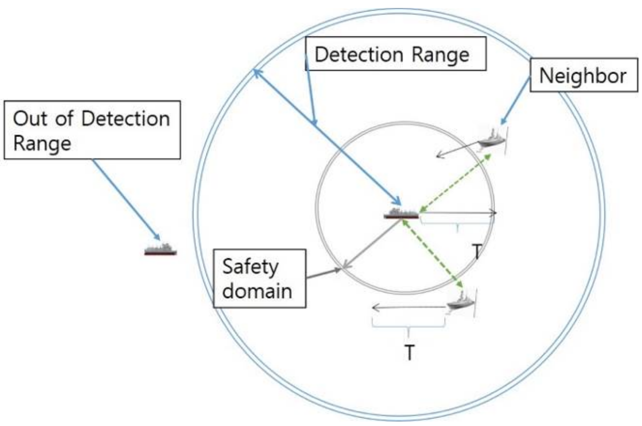

Figure 2. Variables

The procedures for preventing ship collisions are shown in Figure 3. Each ship searches its vicinity to find a target ship. If a target ship exists, it is registered in the neighboring ships list. Individual ships exchange an ok? Message and compute cost function. If a collision risk exists, individual ships exchange improvement messages. The ship with the largest improvement has the right to choose the next possible course. A ship with higher priority has the right to select the next course if the improvement for several ships is same. If the collision risk disappears, the ships move to the next position. This process is repeated until all ships arrive at the destination. Simultaneously altering the course of neighboring ships is restricted because of the possibility of entering into an infinite loop. The ships all have four types of variables – Time Step (T), Ship Domain (D), Detection of Range (DoR), and Course (C). Figure 1 shows the difference based on DoR. Using DoR, the number of recognizable neighboring ships changes. The variable definitions are provided in Figure 2. Any ship can prevent a target ship from penetrating their safety domain. Figure 4 shows the simulation with six ships. All ships arrived at their destination without collision.

while ship does not arrive at destination **do**
Search a vicinity with Detection of Range
if ship exists **then**
Add ship to list of neighboring ships
end if
Send ok? Message to ship registered in the list of neighboring ships
Add ok? Message of neighboring ship to list of ok? Message
Calculate collision risk for each course
if collision risk **then**
Calculate improvement for each course
$improvement_{max} \leftarrow max(improvement)$
Send $improvement_{max}$ to neighboring ships
Add $improvement_{max}$ to list of neighboring ships
Compare $improvement_{max}$ with neighboring ship's $improvement_{max}$
if $improvement_{max} > improvement_{max}$ of neighbors **then**
$Course_{new} \leftarrow$ course with $improvement_{max}$
else if $improvement_{max} < improvement_{max}$ of neighbors **then**
Hold current course
else
if $ID > ID$ of neighobrs **then**
$Course_{new} \leftarrow$ course with $improvement_{max}$
else
Hold current course
end if
end if
end if
Update Course
if $Course_{current} \neq course_{new}$ **then**
$Course_{current} \leftarrow course_{new}$
else
Hold $Course_{currrent}$
end if
if no collision risk **then**
Proceed to next poisition based on $course_{current}$
end if
end while

Figure 3. Algorithm for Ship Collision Avoidance by DLSA

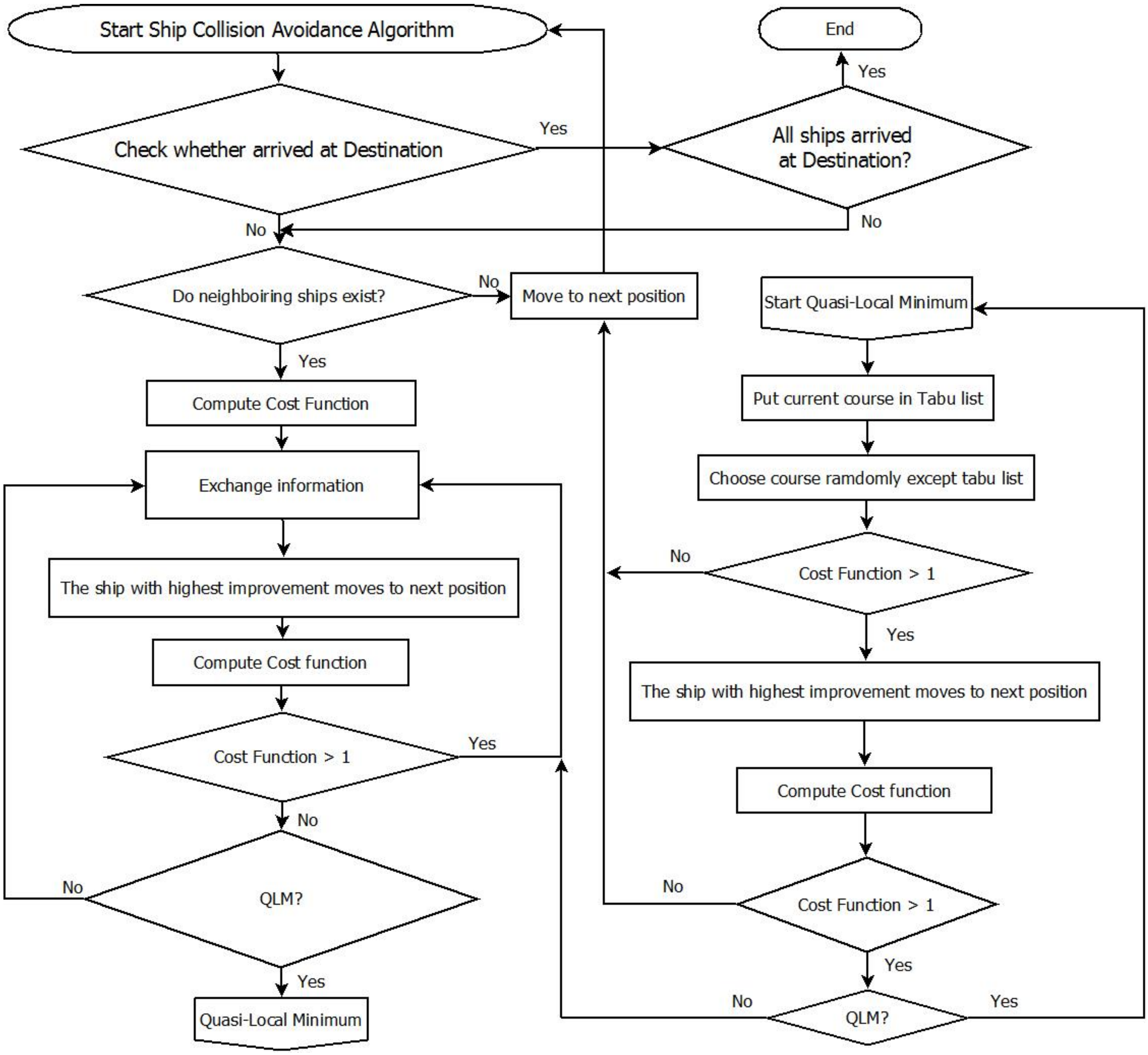

Figure 5. Procedure for DTSA

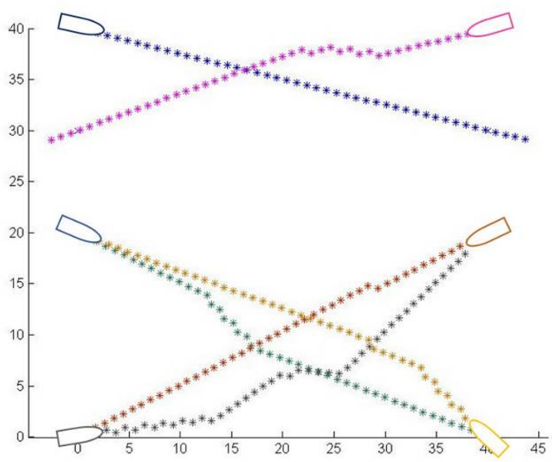

Figure 4. Simulated encounters among 6 ships by DLSA

3.2 *Ship Collision Avoidance by Distributed Tabu Search*

DLSA suffers from QLM, in which a ship cannot change its course even though a collision risk still exists. To solve this problem, we applied DTSA. DTSA enables individual ships to choose another course compulsorily. For efficiency and simplicity of the algorithm, we modified the cost function. To compute the cost function, the relative bearing from the ship's heading to the destination is added. The candidate courses are also modified. Table 1 shows the difference between DLSA and DTSA. Figure 5 illustrates the DTSA procedure. All ships repeat this process until they arrive at their destination. Each ship checks for whether it has arrived the destination. If not, the ship searches the vicinity to find a neighboring ship. The ship exchanges an ok? Message and improvement messages with its neighbors. The ship with the highest improvement chooses the next-intended course. If there is no collision, all individuals move to the next position. If not, the ship exchanges the exchanged information with its neighboring ship. If a QLM situation occurs, the current selected course is stored in the tabu list. The ship chooses the next-intended course randomly except for any course in the tabu list. If the collision risk has disappeared, all ships move to the next position. Figure 6 shows a simulation with five ships. All ships arrived at their destination without collision.

Table 1. Difference between DLSA and DTSA

Difference	DLSA	DTSA
Cost function	Number of expected collisions + remaining time	Number of expected collisions + remaining time + *relative bearing from heading to destination*
Candidate courses	3 kinds	User's needs
Remedy for QLM	None	Tabu Search

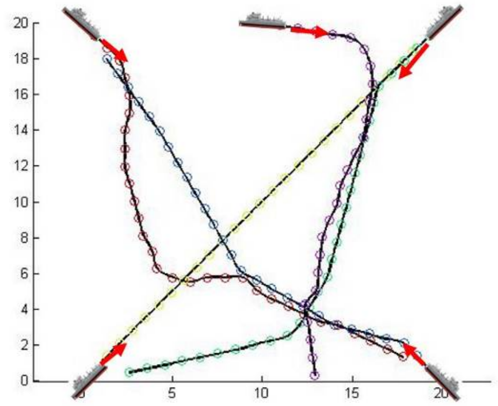

Figure 6. Simulated encounters among 5 ships by DTSA

4 EXPERIMENTS

Our experiment used six different situations depending on the number of ships and ship position to test the performance of DTSA as compared to DLSA. Each variable has the following given values: Safety Domain = {2, 3, 4} miles, Range of Detection = {10, 20} miles, and Speed = {1, 2, 3}. The minus and plus signs indicate the port and starboard, respectively. To evaluate the performance, we computed an average distance and the number of failures. We used MATLAB for the experiments. Table 2 shows the meaning of the index used in the experimental results.

4.1 *Experiment 1*

We experimented with six ships with three variables. Figure 7(left) illustrates the situation for experiment 1. Table 3 shows the neighboring ship list. Each ship records its neighboring ships in the list. That is, ship 1 recognizes ships 2 and 3. Ship 2 recognizes ships 1, 3, and 5. There is no collision risk for ships 1, 3, 4, and 6, but ships 2 and 5 are at risk of collision. All variables are used by exchanging their values in one situation. In total, forty-two experiments were conducted. Figure 10 shows the result for experiment 1. Compared with DLSA, DTSA has a better result. The average distance and the amount of failures had a tendency to decrease as the number of candidate courses increased. The cases of 45 and ALL DTSA showed the best results, which were no failures and low average distance. Table 4 shows the variables and values used in this experiment.

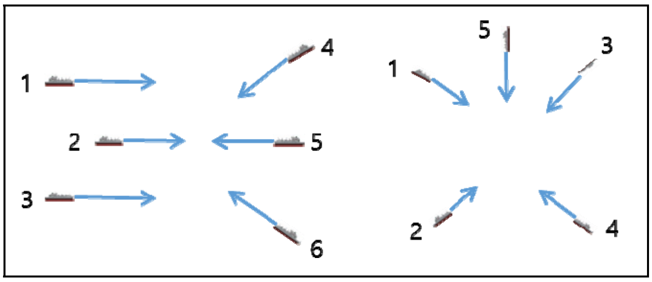

Figure 7. Situation for experiments 1 (left) & 2 (right)

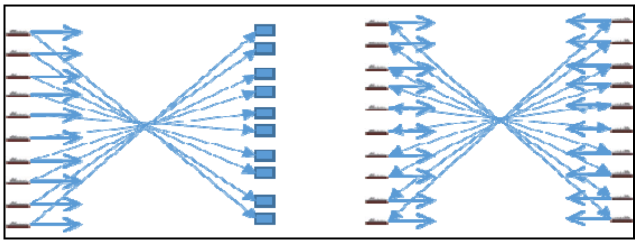

Figure 8. Situation for experiments 3 (left, 10 ships with same direction) & 4 (right, 20 ships with opposite direction)

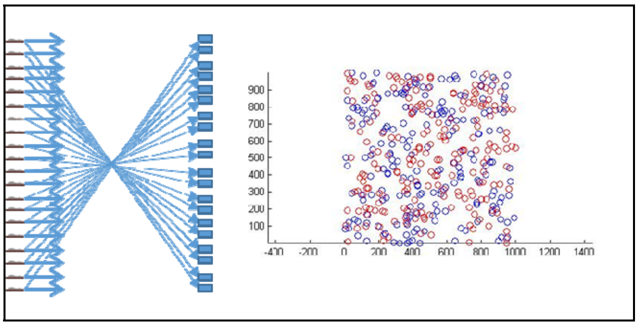

Figure 9. Situation for experiments 5 (left, 20 ship with same direction) & 6 (right, 100 ships initialized randomly)

Table 2. Candidate course by Index used in experiments

Index	Candidate course
15	-15°, 0°, +15°
30	-30°, 0°, +30°
45	-45°, 0°, +45°
ALL	-45°, -30°, -15°, 0°, +15°, +30°, +45°

Table 3. List of neighboring ships for experiment 1

Number of ships	1	2	3	4	5	6
1	x	o	o	x	x	x
2	o	x	o	x	o	x
3	o	o	x	x	x	x
4	x	x	x	x	o	o
5	x	o	x	o	x	o
6	x	x	x	o	o	x

Table 4. Variables and values for experiment 1

Variables	Values
Safety Domain	2, 3, 4(miles)
Range for Detection	10, 20(miles)
Speed	1(20 knots)

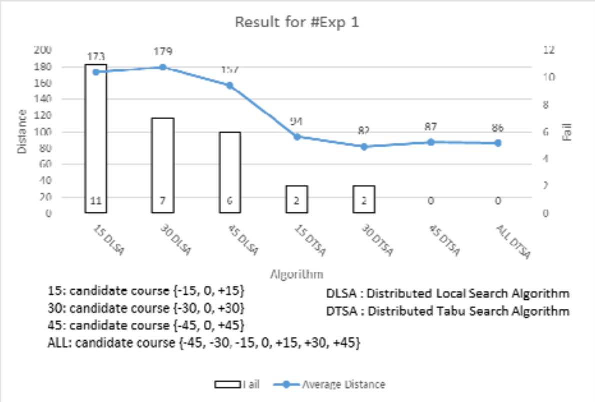

Figure 10. Result for experiment 1.

4.2 *Experiment 2*

In experiment 2, we experimented with five ships that individual ships encounter, as shown in Figure 7(right). The tracks of ships 1, 2, 3, and 4 produced an X shape. Ship 5 cuts across the space simultaneously. Figure 11 shows the result for experiment 2. In the experimental result, except for 15 DLSA, the average distance showed similar figures. The cases of 30 and ALL DTSA recorded no failures and low average distance. 15 DLSA had the greatest drawback in terms of average distance. Table 5 shows the variables and the values for experiment 2.

Table 5. Variables and values for experiments 2-6

Variables	Values
Safety Domain	2, 3, 4(miles)
Range for Detection	10, 20(miles)
Speed	1, 2, 3(1 => 1 mile/3 min)

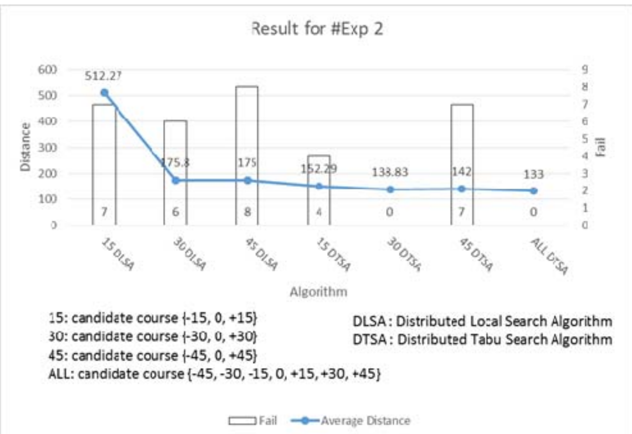

Figure 11. Result for experiment 2

4.3 *Experiment 3*

We experimented with ten ships traveling in the same direction toward the destination, as shown in Figure 8(left). Figure 12 shows the result for experiment 3. Compared with DLSA, DTSA demonstrated better performance overall. All DTSA showed low and uniform average distance. Among all DTSA, only 15 DTSA recorded a failure. Table 5 shows the variables and values used in experiment 3.

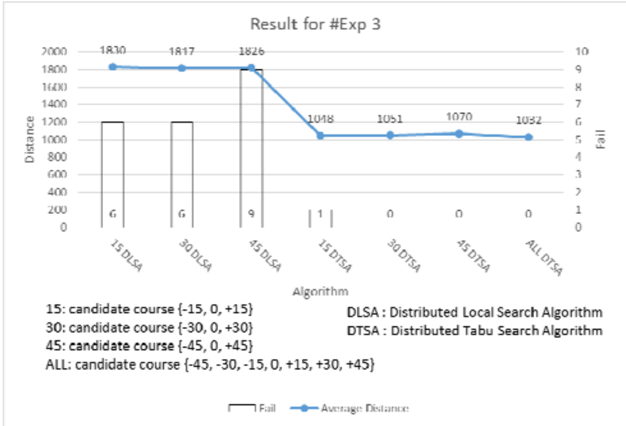

Figure 12. Result for experiment 3

4.4 *Experiment 4*

We experimented with twenty ships traveling in the opposite direction away from the destination, as shown in Figure 8(right). In this experiment, DLSA is unable to compute a situation involving more than twenty ships. We therefore used DTSA only in this experiment. Figure 13 shows the result for experiment 4: the larger the candidate course, the smaller the failure counts. ALL DTSA performed best in regard to average distance and 45 DTSA had the highest average distance. Only 15 DTSA recorded any failures (seven). Table 5 shows the variables and values used in experiment 4.

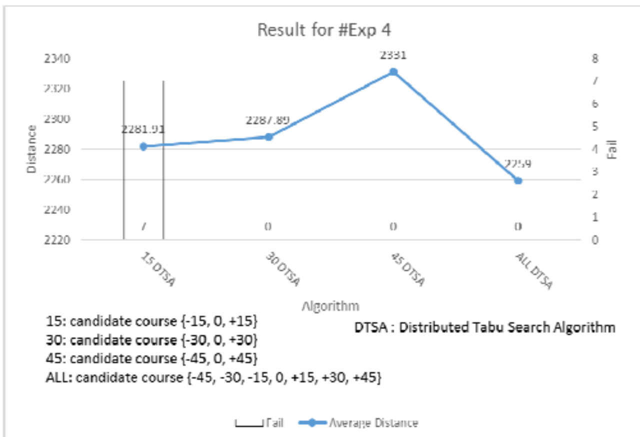

Figure 13. Result for experiment 4.

4.5 *Experiment 5*

We experimented with twenty ships moving in the same direction toward the destination, as shown in Figure 9(left). Table 5 shows the variables and values used in experiment 5 and Figure 14 shows the result. Failures occurred only in the 15 DTSA case (two). ALL DTSA showed the lowest average distance and 45 DTSA showed the highest average distance. The pattern of the experimental result was similar to that of experiment 4.

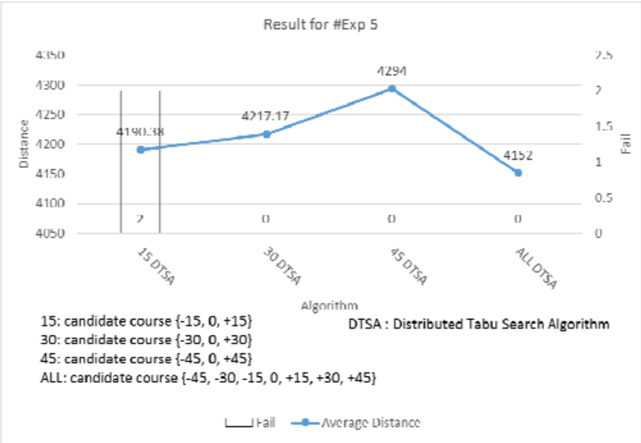

Figure 14. Result for experiment 5

4.6 *Experiment 6*

We used one hundred ships in experiment 6, as shown in Figure 9(right). The ship positions and headings were initialized randomly. The red and blue circles indicate the origin and destination for the individual ships. Table 5 shows the variables and values used in experiment 6 and Figure 15 shows the result. ALL DTSA had no failure and the lowest average distance. In addition, the pattern of the result showed a similar tendency to that of experiments 4 and 5.

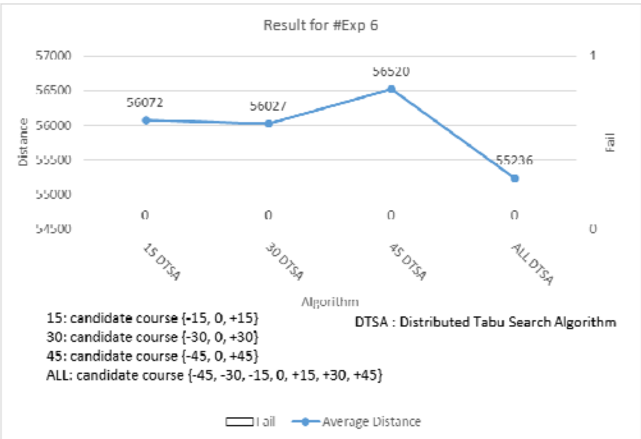

Figure 15. Result for experiment 6

5 CONCLUSION

We explained earlier that several algorithms work in specific situations, such as one-on-one situations. To avoid ship collisions in multiple-ship situations, we applied DTSA and DLSA as a precedent study. We used the tabu search algorithm to avoid the QLM problem. We improved cost function by adding the relative heading toward the destination and also increased the candidate courses as per the users' needs. Our experiments demonstrated how individual ships can avoid collisions in multiple-ship situations. In the experimental results, DTSA outperformed DLSA. Some experiments showed similar patterns: The more the number of candidate courses is increased, the shorter the average distance; the less the size of the degree of the candidate course, the greater the failure count. This is because a ship can bore off quickly if it drastically alters its course. In experiments 4, 5, and 6, the experimental results' patterns were similar. 45 DTSA recorded the highest average distance. In the case of 45 DTSA, the range of fluctuation for the candidate course was larger. ALL DTSA showed the lowest average distance in most cases. This means that the more candidate solutions, the better the performance.

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