

Conversion Timing of Seafarer's Decision-making for Unmanned Ship Navigation

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ABSTRACT: The aim of this study is to construct an unmanned ship swarms monitoring model to improve autonomous decision-making efficiency and safety performance of unmanned ship navigation. A framework is proposed to determine the relationship between on-board decision-making and shore side monitoring, the process of ship data detection, tracking, analysis and loss, and the application of decision-making algorithm, to discuss the different risk responses of specific unmanned ship types under various latent hazard environments, particularly in terms of precise conversion timing in switching over to remote control and full manual monitoring, to ensure safe navigation when the capability of automatic risk response inadequate. This framework makes it easier to train data and the adjustment for machine learning based on Bayesian risk prediction. It can be concluded that the automation level can be increased and the workload of shore-based seafarers can be reduced easily.

1 INTRODUCTION

The study of autopilot aircraft and vehicles has entered a period of vigorous development in the aviation and land transportation industries. Artificial Intelligence (AI) has begun to play a major role in these industries (Prashanth et al., 2013). The re-search trend has been moving toward the conception of robotic vehicles capable of making spontaneous and effective decisions in demanding or uncertain situations. Considering the depression of the current shipping industry, optimizing and adjusting the industrial structure is crucial, in cases where the overhead of seafarer's expenditure and crew company management account for a large part of the payment. Unlike unmanned aerial vehicles (UAVs) and unmanned vehicles, unmanned ship swarms may have a higher superiority for certain ship types such as regular container ships for certain voyages (Gudelj and Krcum, 2012).

The real demanding circumstance of vehicle to everything (V2X) scenarios demands the need of handling fully automatic driving, remote management personnel in the state of surveillance, as well as any latent hazard requiring the car (where there is the possibility of the driver being involved) to take their own effective action at the critical instant. Undoubtedly, the current technical and legal aspects are still facing enormous changes. Many difficulties must be overcome for including fully automatic navigation in unmanned ship swarms, remote multi-agent monitoring, and efficient transportation of goods. On the other hand, in specific transport areas, under remote monitoring and perception, multi-agent transportation is technically advanced (Ren, Wei, 2007). Therefore, Autonomous Ship Swarms Transportation is a very promising field of research for unmanned ships (Sarda et al., 2016).

The study object of this paper is unmanned container ship swarms. Container ships, especially regular container ships, have characteristics such as standardized operations schedule, high level of automation in the process of loading and unloading of containers, and easy remote monitoring of goods condition. Upon removal of the bridge, an unmanned container ship can expand its packing capacity, improve enterprise business income, and reduce seafarer costs, in order to facilitate the shipping of large-scale company cargo dispatch, resulting in significantly improved efficiency (Dubrovsky, 2010). Yang and Wang designed a fully automated loading and unloading platform specifically for an unmanned container ship. When in a specific terminal wharf, both sides of the ship can load and unload simultaneously, thus improving ship loading and unloading efficiency, increasing wharf benefits and reducing the stagnation time of ships in the anchorage. It also allows the optimization of the port traffic flow (Yang and Wang, 2011). Nonetheless, market factors determine the research prospects of unmanned container ships. The container ship traffic is a huge business, even considering that a tiny accident may cause immeasurable disaster and loss. Therefore, it is necessary to construct the Autonomous Ship Swarms monitoring model before proceeding with the technical details. The ship itself has a limited ability to resist risks, especially under demanding or uncertain environment. Therefore, the decision-making cycle by itself may not have adequate capacity to avoid hazards. However, frequently invoking decision-making resources from the expert system of shore station may cause remote monitoring capacity insufficient, and shore-based monitoring seafarers may lead to more human errors or other latent failures. Therefore, it is necessary to maintain the resource balance between the decision-making cycle and the remote monitoring of unmanned ships, thereby optimizing the structure of the decision model.

Autonomous risk prediction and autonomous decision-making are genuine and significant parts of the unmanned ship swarms monitoring model (Kirsch, 2016). They are effective ways to diminish the workload of shore-based seafarers, reduce human error and improve commercial interests, by maximizing the risk prediction ability and risk avoidance decision-making of unmanned ships.

Even if the relationship between decision and maneuvering automation has already been proposed, if high automation is selected for the action part, then designers should resist the temptation of high automation levels of decision-making (Parasuraman, 2000). Even the real "noisiness" world always have some kind of unexpected situation emerged (Endsley and Kiris, 1995).

The purpose of this paper is to build an automatic decision cycle model to improve the decision-making efficiency and safety performance of unmanned ships. According to the previous assumptions, with unmanned container ship response to various hazards, calculated training data and parameter adjustment, the performance of automatic decision-making can be improved. The situation of remote human intervention will then become less significant. When a new uncertainty situation appears, original

data tracking and analysis and handling of data loss are required. In this case, the insufficient ability of automatically respond to facing hazards will cause the model to shift to manual monitoring and remote control to ensure safe navigation.

2 AUTONOMOUS DECISION-MAKING

Because the term "automation" has been used in many different ways, the British Dictionary defines automation as:

- 1 The use of methods for controlling industrial processes automatically, esp. by electronically controlled systems, often reducing manpower.
- 2 The extent to which a process is so controlled.

Autonomous decision-making should have a new implication, which the authors defined as automaticity between the different decision-making cycles. Although researchers have already described the conflict between high automation levels and the automation of decision-making (Parasuraman, 2000), their opinions are focused mainly on high levels of automation, and do not considered the decision-making aspect mistake. Moreover, "error-trapping" shows that lower link communication automation can allow more action errors. When high automation is selected for maneuvering, researchers should resist the temptation for high automation levels of decision-making. Therefore, high levels should be executed only for low-risk situation awareness; for all other situations, the level of automation decision should not exceed the level of the computer suggesting a preferred alternative to controller.

On the other hand, with the improvement of machine learning algorithms, more unlabeled data can be used, and more reliable automatic decision-making does not require human intervention, considering mainly the concept of "human-centered automation" re-understanding (Metzger, 2005). As there are two distinct centers (ship swarms and shore expert station) for the autonomous decision-making of unmanned container ship groups, and more decisions can be made by the cycle itself before the "human-centered" is involved (Zhang, 2016), the environment for automatic decision-making has become easier.

2.1 *The levels of autonomous decision-making*

The basis for automatic decision-making must be based on a good automaticity classification (see Table 1). From low to high, automated carry forward also shows the development of ship automation decision-making process, which proves that the direction towards automation is inevitable. It can be seen from the table that the lowest level, level 1, is completely comprised of manual operations; the second level of the decision-making system can provide all the decision options, but at this level, the system doesn't make its own decisions (data learning and training process); The third level can optimize the selection and reduce the possible decisions output (perception process); the fourth level can provide an optimal decision-making program, but still cannot take action (optimization process); The fifth level of decision-

making is a conversion point, in which the system usually needs to be agreed with the seafarer to take action, but this level of decision-making is able to provide a decision-making operation by itself, so any level of automaticity higher than this can be considered as completely autonomous decision-making. Note that the decision of the fifth level according to this table is important for this paper, as it is also a turning point for the ships own decision-making cycle and shore-based decision-making. For decisions taken at a level higher than this, such as the sixth level, the system can take action on its own, and only part of the uncertain data is sent to the shore-based seafarer for record; for seventh level and above decision-making, the system can recognize the timing of conversion by itself, and take action, without human involvement.

Automaticity Levels	High
	9 • Full decision making and take actions autonomously,
	8 • Informs the seafarers if interrogated, or
	7 • Conversion timing permitted automatically, take maneuvering, or
	6 • Autonomous decision making, data presented to the seafarers, and
	5 • Executes the optimal action if the seafarers approve, or
	4 • Present an optimal solution automatically but no action,
	3 • Optimization options, compression all results, or
	2 • The system offers a complete set of decision/action alternatives,
Low	1 • Seafarers take all decisions and Maneuvering

Table 1. Automaticity selection by on-board decision cycle and shore-based monitoring center

There is a problem that must be noted: when an unmanned container ship encounters a totally new situation, automaticity can transit from a high level to a lower level; thus, automaticity can change dynamically according to the ship navigation. The following discussion of the different target ships for the object of the decision-making will use this table 1 as standard to illustrate.

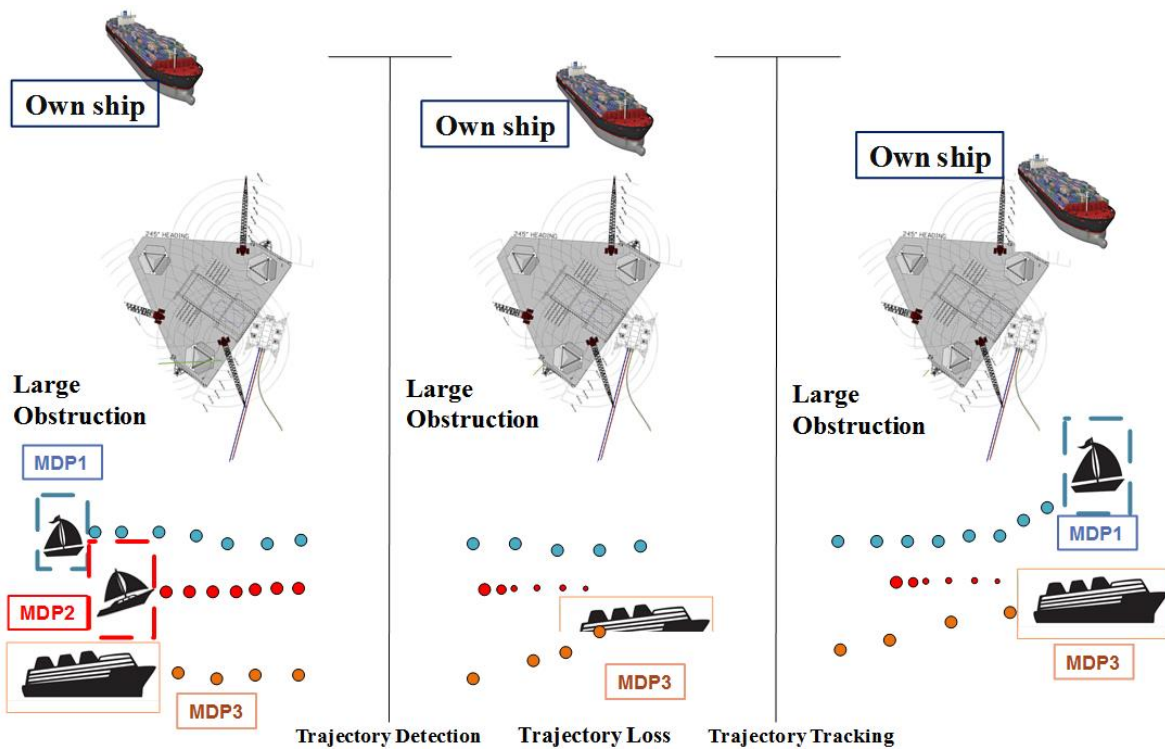


Figure 1. Different target detection, tracking, loss, and state analysis by Markov Decision Processes

Table 2. An example of Multiple Target Tracking in a Markov Decision Process

MDP1	Sailboat 1	Detection	➡ Tracking	➡ Loss	➡ Tracking
MDP2	Sailboat 2	Detection	➡ Tracking	➡ Loss	➡ Loss
MDP3	Ro-Ro Ship	Detection	➡ Tracking	➡ Tracking	➡ Tracking

2.2 Markov Decision Process for target perception

In prior research (Zhang, 2016), the authors used the Robot Operating System as a tool, extended the Markov Decision-making (MDM) and supported the decision-making methodologies based on Markov Decision Processes (MDPs). The aim of the MDPs is to provide an action set of decision-making for the on-board cycle. When an action is executed, marine areas whose state changes according to a known probability distribution, are converted to another state, and the probability distribution is related to the actions performed. As shown in Figure 1, three different target ships can be considered as three continuously changing MDPs by detecting, tracking, analyzing and losing. According to the data obtained from the sensors of the ship (unmanned container ship), in order to observe the navigational status of the target ships, the table 2 was obtained. MDP3 is a large-scale ship, and, as such, the course of navigation is always within the scope of the own ships control, and the target ship can be completely in accordance with the navigation rules and decision-making procedures for collision avoidance or other actions; MDP1 indicates the course of the sailboat 1. Although the tracking process is blocked by a large obstruction, the ship itself can be based on the heading course and speed before disappearance, in order to speculate the state of sailboat 1, and for the reappear to be verified; MDP2 illustrate the blockage of the sailboat by a large obstruction, for example, due to fishing work or other unpredictable factors, which led to the target disappearance from the control scope (loss state). In this situation, wherein the system cannot be based on past data training or experience to get more information, a shift to remote control to acquire the necessary expert support is the best choice.

2.3 Target perception and decision-making

According to the previous scenario, the combination of the Table 1 and Figure 1 originates Figure 2. Because of the size, shape and speed different of the target ships, divergent detectors may also obtain different data reliability. The level of predictability varies, as the automaticity level is constantly unstable. According to the Table 1, it can be concluded that there are nine different automaticity levels, in different states, in which target ships have their own decision level. It can also be concluded that Markov Decision Processes can produce decision-making cycles of different automaticity levels decision-making under the closed ship itself, the fifth level can be seen as a timing conversion standard, lower than fifth level leads to the conversion to shore-based remote control, higher than fifth level belongs to the on-board decision cycle.

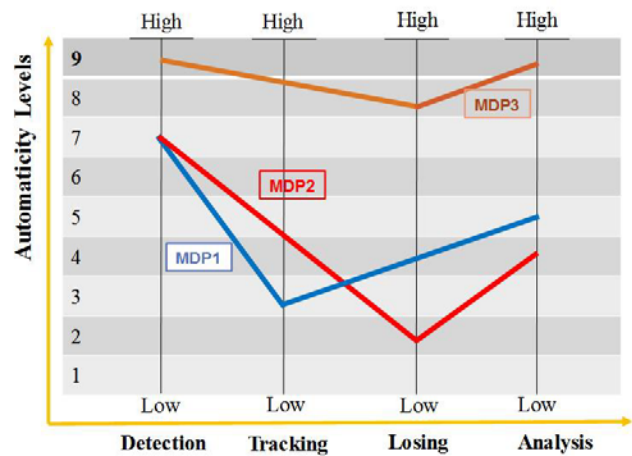


Figure 2. Levels of automaticity assessment for the decision of which MDPs should convert to shore-based monitoring or keep decision by on-board decision cycle itself.

3 ADVERSARIAL DECISION CYCLES

The mainstream technology of auto-driving prediction and decision-making is becoming clearer nowadays that machine learning is based on both deep learning and reinforcement learning. However, machine learning needs large data to achieve high performance and high reliability. It means that developers need to install an automatic driving equipment in a large number of automatic ships, so that the ships in the current operation can produce the required amount of data to enrich the decision-making cycle in order for the amount of data to lead to an improvement in the decision-making efficiency.

3.1 Unmanned ship decision cycles

Unmanned ship maneuvering cycle is generally divided into four main sections: sensory detection, tracking & perception, decision-making and optimal action. The model identifies the object from the environment, performs tracking and risk recognition, makes decisions and takes effective action, and the effect of the action is fed back into the environment to confirm the new position relationship. Consider a decision cycle as shown in Figure 3. The external environment also constitutes a part of the cycle, including the ships surrounding marine environment and the ships own hardware environment. The decision-making stage is the link to the shore-based remote control and ship swarms, so having decision-making as the end of the cycle (human decision center automation), it is possible to build the dependency relationship of the big decision-making cycle. It can be seen in Figure 4.

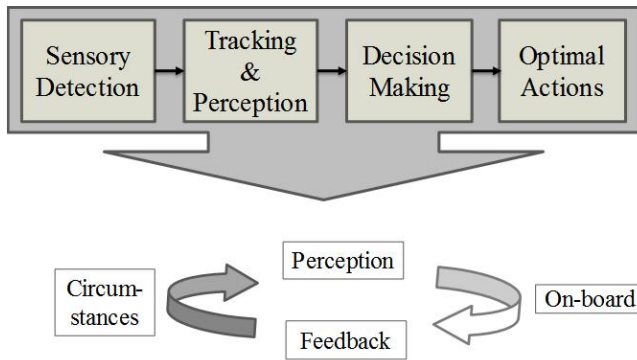


Figure 3. An example of unmanned ship maneuvering cycle based on the four-stage of human information processing

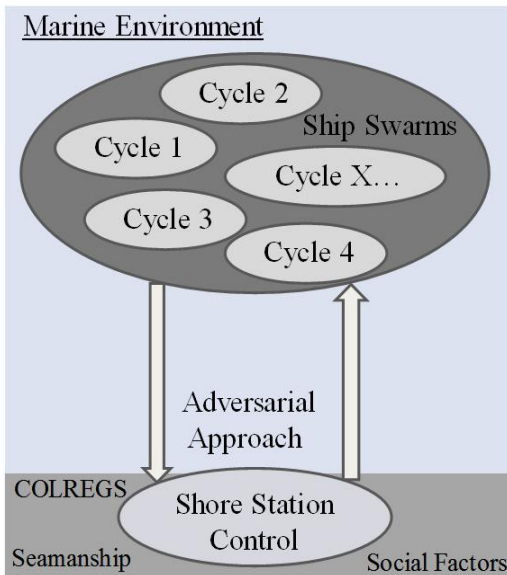


Figure 4. A flowchart of conversion timing optimization of decision-making between on-board decision cycle and shore side monitoring. An adversarial decision cycles approach has been presented.

3.2 Autonomous decision process training

There are two main decision-making cycles of the unmanned ship: the first one is on-board decision cycle, countless monomer decision-making cycle constitutes the ship swarms; the second is a large group of ships and shore-based cycle. The relationship between the two main sections is similar to the Generative Adversarial Nets (Goodfellow et al., 2014) in deep unsupervised learning. Ship swarms and shore station center belong to two main bodies of confrontation. At first, the decision-making cycle of a single ship is very small, and most of the decision-making cycle needs shore support to complete. However, as unmanned training data increases, due to the fact that the ships own decision-making capacity can be continuously enhanced, high quality decisions can finally be achieved, being as good as shore station seafarers would make. In this process, the workload of shore-based seafarers is gradually reduced, and the ship swarms automatic decision-making capacity is gradually increased.

4 APPLICATION EXAMPLE

This autonomous ship swarms transportation model of human-automation interaction can be applied to specific systems in conjunction with a consideration of evaluative criteria, which we have discussed in this paper – human workload and cost expenditure of the ship company, automaticity reliability and automatic level, the adversarial relationship between the on-board decision cycle and shore-based monitoring. To further demonstrate the application of this model, the authors briefly draw the outline of image for its use in the design of near future unmanned ship transportation system, based on the previously presented study and other researcher’s study conclusions.

Jansson proposed a vehicle collision avoidance framework based on statistical decision and stochastic numerical integration (Jansson, 2008). The main purpose of decision-making framework is to deal with the uncertainty of state estimation. Application of this model suggests the following recommendations for future swarm ship transportation automation. Jansson presented a probabilistic framework for designing and analyzing a collision avoidance algorithm, calculate risk for faulty intervention and the consequences of different maneuverings. Jansson’s work was based on Monte Carlo techniques, where sampling-resampling methods are used to convert sensor readings with stochastic errors to a Bayesian risk. The authors also proposed the construction of a reliable decision-support system for risk and accident predictions based on past experience and objective accident-probability statistics using Bayesian Network (Zhang, 2016). We discussed the prospects of an intelligent decision-support system to ensure reliable navigation safety. It included a case study which can provide a procedure for complete automatic decision-making based on experience probability.

For a simulation study (Łački, 2015), the author assesses the feasibility of this idea. Łački narrowed the study to a smaller scale. Forecasting the location of the target ships and assisting the own ships on making the maneuvering decision can be used as part of this framework. Łački using a neuroevolutionary method, presented a concept of the advanced ship action prediction system for the simulation of a learning process of an autonomous control unit. Data is provided to this system by the ship sensor, to make possible the completion of forecasting data training tasks as individuals in the population of artificial neural networks. The environmental sensing and the evolutionary algorithms learn to execute each given task efficiently. This mathematical model of maneuvering VLCC tank ships with the single-propeller and single-rudder was applied to test the prediction performance of the system (Łački, 2008). Artificial neural networks based on modified methods increase the complexity and performance of the considered model of ship maneuvering in restriction waters.

5 CONCLUSIONS

The scenario presented in this paper is an automatic decision-making solution in extreme cases where ships are rarely encountered in such complex situations when navigating in open waters. However, in order to improve the decision-making efficiency of the unmanned ship under remote control, it is needed to take into account this kind of situation in the beginning of the system design. The author first proposed automaticity stratification, with the data accumulation of the on-board decision cycle, floating up and down real-time assessment data training of the situation encountered. Between the on-board decision and shore side monitoring of the adversarial decision cycle model it is demonstrated that the conversion timing continuously changes and always tends to on-board if the decision cycle can make decisions similar to those of the seafarer's (expert system). This structural model is based on the Bayesian network machine learning, with the advantages of easier data train and parameter adjustment, easier improvement of the automation level. It can reduce the workload of shore-based crew significantly.

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