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Applications of artificial intelligence in ship berthing: A review

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Ship berthing operations in restricted waters such as ports requires the accurate use of onboard-vessel equipment such as rudder, thrusters, and main propulsions. For big ships, the assistance of exterior supports such as tugboats are necessary, however with the advancement of technology, we may hypothesize that the use of artificial intelligence to support ship berthing safely at ports without the dependency on the tugboats may be a reality. In this paper we comprehensively assessed and analyzed several literatures regarding this topic. Through this review, we seek out to present a better understanding of the use of artificial intelligence in ship berthing especially neural networks and collision avoidance algorithms. We discovered that the use of global and local path planning combined with Artificial Neural Network (ANN) may help to achieve collision avoidance while completing ship berthing operations.

[**Keyword**s: Artificial intelligence, Berthing, Collision avoidance, Ship design, Ship maneuvering]

Introduction

Safe ship berthing requires complicated maneuvers within several zones: outer zone of the water channel, the water channel, the turning zone and finally mooring zone. The process of a ship entering in port can be separated into two stages, declaration stage and berthing stage. The speed of the ship should be in a certain level and maintained on the scheduled route by adjusting the rudder angle and the engine inputs. At the speed of 2-3 knots within the berthing area, the use of thrusters and tugboat assistance are required to complete the maneuvering. Such process is repetitive, tedious, and time-consuming, however necessary to complete a safe berthing operation.

With the advent of technology, an elegant artificial intelligence may play its roles via the use of sensors and positioning systems. This can be combined with the automatic piloting control of the vessel. Ship's motion, distance from obstacles and environment data are able to assist the algorithms to effectively control of the berthing-unberthing process of the vessel[1].

The aim of this paper is to provide a review on the use of artificial intelligence for ship berthing operation within the period of 1999 to 2020. We have organized our review corresponding to the review protocol demonstrated in Table 1. A search of the chosen databases followed by curating a list of literatures has resulted in a total of 269 prominent works in this topic. These studies were analyzed within the research scope where 53 studies were chosen to be elaborated in this work.

The discussion in this paper is divided into two sections. The first section discusses the use of Artificial Neural Network (ANN) in ship berthing and secondly collision avoidance (especially global path planning and local path planning) algorithms. In brief, various neural networks have been developed for ship berthing such as, classical ANN, ANN with two parallel structures, and ANN with auxiliary devices and head-up coordinate system. These neural networks have shown satisfactory effectiveness to support ship berthing. In the second part of the paper, collision avoidance algorithm (especially path planning) has been highlighted to show its importance to avoid collision and grounding. The discussion on path planning shall be focusing on the global path planning which is for static well-known environment, and local dynamic path planning for unknown environment (obstacle is unknown and dynamic).

Neural networks

Neural network is a mathematical concept inspired by how human brains work[2,3]. In ship berthing, the use of ANN starts with the training of ship data (sensors as input, and ship's responses *e.g.* desired thruster, rudder angle and engine output. Within the field of ship

Table 1 — Description of scope of studies within the body of literatures

Subject	Description
Database	Scopus & IEEE
Keywords	Artificial intelligence, Neural network, ship, navigation
Search field	Title, abstract, keywords
Publication type	Journal and conference paper.
Publication language	English
Time interval	1990 - 2021

maneuvering research, the application strategy of ANN was described in many ways, such as:

a) ANN contains of several interconnected simple non-linear system assisted by transfer function, consequently, has the ability to imitate human brains and execute the act that a human performs in several situation[4].
b) Shuai *et al*.[5] explained that the ANN is capable to learn from maneuvering data, hence able to perform automatic ship docking.
c) Borkowski[6] iterated that an ANN has the capability of producing desired output even though there is lack of information. ANN takes intelligent decisions when they encounter similar problems and can perform multiple tasks simultaneously. It is trained through trial-and-error method since there are no specific rules for the structure.

The discussions above can be summarized as, ANN is a mathematical model or machine learning algorithm based on human's brain biological function or neural structure of human brain, able to provide response and decision automatically in particular situation, capable to accomplish tasks even in different conditions from the training data, can be trained through trial-and-error method, and it is capable to provide decision even lack of information which ultimately can be applied in rudder, propeller control and thruster for an autonomous ship.

In the following section, the implementation of various types of neural network in ship berthing is reviewed.

Background studies of ANN for ship berthing (1990-2019)

A study on the application of ANN as a ship controller for ship berthing control was presented by Yamato *et al*.[7] in 1990. One year later Fujii & Ura[8] provided deeper insights on the efficacy of ANN as a controller for both supervised learning and non-supervised learning system demonstrated using Autonomous Surface Vehicle. While this approach achieved excellent results. Yamato *et al.*[9] has extended the combination of human factor or called 'expert system' in 1992. Zhang *et al.*[10] proposed the use of a multivariable neural network controller which have the inputs of desired states, ship states and the control signal at earlier stages and the parameters which could be modified by an online training process. Gruau[11] proposed 'cellular encoding' which is the first effective indirect encoding of ANN. In his method, every neuron was represented by a cell which was linked with other cells. Each cell was capable to replicate in series or parallel connection of its two offspring. In that method the neural networks can produced and modified with modularity. Such modular structures are constructed of numerous subnetworks, organized in a hierarchical way but according to Łącky[12] in some situation the subnetwork may be repeated.

Later in 2001, Namakyun[13], demonstrated a control rudder and ship thrust RPM control using NN-Base, which has parallel structure in a hidden layer to achieve improved results than a centralized network. Consequently, the research results showed, proposed controller able to reduce the effect of current and slight wind but unsuccessful to maneuver the vessel to the target during rough environment. In 2003, ANN-based nonlinear model prediction was proposed to generate the optimal berthing, but greater computational resources are necessary to obtain the maneuver path[13].

In 2007, ANN controller presented by Im *et al*.[15] for ship maneuvering considered the case of a ship berthing that began from any point across the berthing region. Alternatively, Nguyen & Jung[16], used predetermined berthing route and adaptive interaction learning method to developed two ANN controllers to control ship speed and the ship heading simultaneously. Additionally, Mizuno *et al.*[17] presented a Nonlinear Programming Method (NPM) to produce minimum time ship maneuvering data[18]. In 2013, Adnan & Hasegawa[19], attempted to utilize Nonlinear Programming Language (NPL) in order to generate ship berthing data with confined conditions in which stern tugboat and bow thruster were included concurrently into the ANN controllers as new-found outputs, this work was also extended by Tran & Im[20].

In 2018, Im & Nguyen[21] recommended an adaptive backstepping controller to pulling or pushing cruise ship under the wind; but this approach requires few specific caveats; the vessel is close the pier of the berth, and the lateral force should be controlled to transport the vessel into a berth in a crabbing motion.

To train the NN controller ship data from captain who has experience of successful berthing the ship was used. Shuai *et al.*[5] has iterated where generally, such docking operation method was not suitable because it's too complicated to collect real ship docking data which is very large under various cases. Recently in 2019, Feng *et al.*[22] proposed the use of a robust adaptive NN method using navigation dynamic deep-rooted information to recreate the lumped uncertainties produced by exterior disturbances and unidentified ship dynamics.

ANN models for autonomous berthing operations

In the literature, there are various neural networks strategies that are capable to conduct safe ship berthing operation. In this section, such neural network models reported in the literature are discussed.

Two-parallel structures ANN

An efficient parallel artificial neural network (as shown in Fig. 1) was presented by Shuai *et al.*[5] that demonstrated and examined autonomous low speed navigation under environmental disturbance. The process consisted of manual maneuvering using joystick within the simulation to collect reliable and sufficient data from successful maneuvers. An artificial neural network with parallel structures was used for different subsystem control such as ship's rudder and thrust, respectively. The system was tested within a dynamic environment such as wind interference, which shows poor performance however managed to steer the vessel into dock.

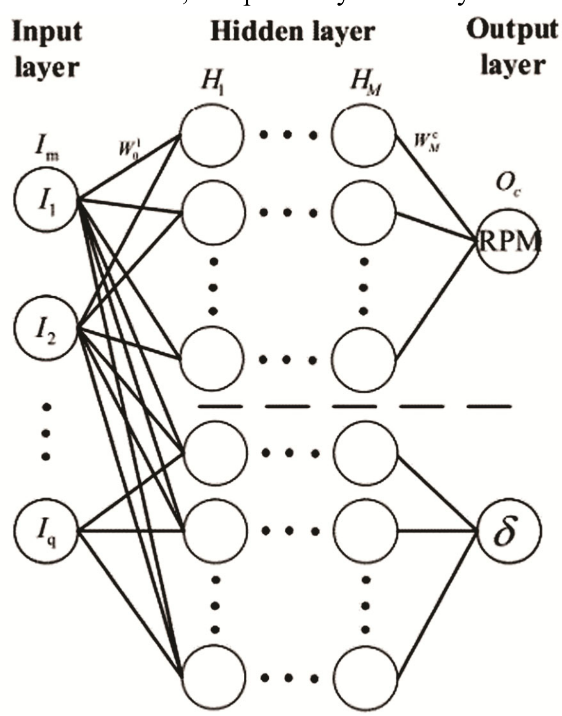

Fig. 1 — Multi-layer ANN with two parallel architectures

ANN with auxiliary support system

Tran & Im[23] presented an ANN model for automatic ship maneuvering with the assistance of auxiliary support system such as thruster and tugboat. The ANN was trained using four input variables (such as tug, rudder, thruster, propeller revolution) against the motion and location as the output values and demonstrated well within the simulation data.

The head-up coordinate system

Im & Nguyen[24], introduced the head-up coordinate system, which contains the comparative bearing and distance from the ship to the berth. In theory, an existing ANN controller may be able to berth a vessel in a different port if the data input of ANN is similar, at the risk of reduced accuracy. Therefore, ideally an ANN should be retrained in various ports; however that may be costly and time consuming. Therefore, a novel ANN introduced by Im & Nguyen[24], via the head-up coordinate system, which demonstrated excellent performance of ship berthing in different ports.

Feed-forward neural network

Ahmed *et al.*[25], demonstrated the use of feed-forward neural network and investigated the efficiency such ANN to operate within the known and unknown situation. They have observed that ANN is able to reproduce the improved trajectories even if in unknown situation. They claim that the proposed Feed-forward neural network controller is able to provide more advantage in the voyage of the vessel as it can reduce the time by proposing the ship to adjust its course in minimum time.

Static neural network and PID neural network

Skulstad *et al.*[26] used a Static Neural Network (SNN) for the control of an over-actuated ship. For the ANN training the thruster force and input instructions throughout a trail run of the simulated ship are recorded. After that the ANN is trained and used to convert virtual force instruction for a motion controller into thruster commands. Later, the network is trained and used to convert the virtual force commands from a motion controller into individual thruster commands. A PID (Proportional Integral & Derivative) controller, applying heading measurements and wave filtered positions, executed as motion controller for each Degree of Freedom (DOF) on the vessel.

Ratio[3] demonstrated the ANN controller trained using the optimal steering motions data. The training data represented a minimum-time course-changing from a fixed start point to an ordered terminal point. Through the combination of the feedback PD control, the controller performs successful automatic berthing even in case of untrained initial conditions, while having the ability to cope with steady wind disturbances.

Scheduled-route ANN

Qiang & Bi-guang[1] utilized the ANN algorithm based on schedule route to develop an automatic berthing model. This model can be applied in different port with various berth layouts after the ANN is trained in any port, opening the possibility to have a versatile ANN model. Additionally, it can be employed in complex system such as, turning berthing of a vessel. Ultimately this model used for the simulation of turning berthing and direct berthing in different ports.

Neuroevolution

Neuroevolution is a combination of Evolutionary Algorithms (EA) and ANNs. Neuroevolutionary techniques are incorporated to discover solutions to complicated tasks by means of ANN developing from evolution[12].

Stanley *et al.*[27] iterated that neuroevolutionary algorithms are effective to improve the neural network topology, particularly in dynamic constant reinforcement learning task. The great benefits of neuroevolution are its capability to adapt to network topologies modification with its corresponding linked weights and biases. Such robustness allows for the robust computational structures throughout dynamic ship maneuvering missions. Neuroevolution is also applied in many other disciplines of science, including, automation process[28], robotics[29,30], multi-agent system designing and diagnostics[28,31] and many others.

Spanning throughout the 20 years, the landscape of research that concerns about ship maneuvering and berthing remains progressive and evolving. Presented in Table 2 are rich content of summaries that are focused on the methods and its corresponding outcomes.

Collision avoidance algorithms

Numerous collision avoidance method is available which may serve as a building block for autonomous ship berthing, such as the improved APF (Artificial Potential Field)[47], modified Model Predictive Control (MPC)[48] and Dynamic Window (DW)[49]. In recent years, ANN training method based on deep reinforcement learning have become popular[50-52]. Another collision avoidance algorithm such, Velocity

Table 2 — Other available neural network method in ship berthing

Year	Name of the method	Description
1995	Proportional Integral & Derivative (PID) control algorithms	**Author**: Burns[32] **Purpose**: To implement single ANN that can adapt its limitations so that it delivers optimal performance over a variety of conditions, without acquiring a significant computational penalty via the use of PID. **Findings**: A single network has similar performance to a set of optimal guidance control laws, calculated for a set of various forward speeds.
1996	Feed-forward neural network	**Author**: Djouani & Hamam[33] **Purpose**: Feed forward neural network for optical ship berthing. **Findings**: Feed-forward neural networks is a reliable approach for real-time control of non-linear systems.
2003	Neural network based optimal solution generator	**Author**: Mizuno *et al.*[34] **Purpose**: To examine the effectiveness of this method in a feasible ship's minimum-time maneuvering. **Findings**: Neural network-based optimal solution generator is capable to perform minimum-time maneuvering of ships.
2007	Novel minimum time ship maneuvering method with NN and Nonlinear model predictive compensator	**Authors**: Mizuno *et al.*[17] **Purpose**: To perform minimum time control maneuvering using ANN and nonlinear model predictive compensator. **Findings**: The system provides approximate solution in good tracking performance and short computing time in real situations.
2008	Nonparametric system identification application	**Authors**: Rajesh & Bhattacharyya[35], Rajesh *et al.*[36] **Purpose**: Using ANN to perform maneuvering of larger tankers that are regulated by a well-recognized set of nonlinear equations of motion. **Findings**: Nonlinear equations of motion that defines large tankers can be paired with ANN for successful and safe maneuvering.

(*Contd.*)

Table 2 — Other available neural network method in ship berthing (*Contd.*)

Year	Name of the method	Description
2012	Generalized Ellipsoidal Function Based Fuzzy Neural Network (GEBF-FNN) method	**Authors**: Ning *et al.*[37] **Purpose**: To construct a novel vessel maneuvering model using ANN and Fuzzy concepts. **Findings**: GEBF-FNN is effective for maneuvering performance prediction.
2012	Convenient navigation systems	**Authors**: Shih *et al.*[38] **Purpose**: Design of optimal control of ship berthing patterns to avoid collision. **Findings**: Able to optimal turning maneuvering any particle situation and any type of ship.
2013	A PID control combined with Radial Basis Function (RBF) neural network	**Authors**: Li *et al.*[39] **Purpose**: Course control of ship steering. **Findings**: PID control combined with RBF-NN are able to trace the reference signal further effectively, so it can accomplish additional accurate control of the ship steering.
2013	Single-layer structure Neural Network	**Authors**: Pan *et al.*[40] **Purpose**: To perform tracking control of an ASV along with totally unknown vehicle dynamics and subject to significant uncertainties. **Findings**: Excellent performance through the on-line learning of the NN. Additionally, it can compensate bounded unknown disturbances.
2013	Artificial neural network trained by consistent teaching data using nonlinear programming method	**Authors** : Ahmed & Hasegawa[41] **Purpose**: Automatic ship berthing ANN training using non-linear programming method. **Findings**: The effectiveness is properly verified and able to perform safe navigation with different gust wind distributions.
2013	Novel feed-forward neural network	**Authors**: Zhang & Zou [42] **Purpose**: Ship maneuvering motion (Black-box modeling). **Findings**: The performance of feed forward NN with Chebyshev orthogonal is better than conventional back-propagation neural network to approximate non-linear functions of hydrodynamic model for ship maneuvering motion.
2013	Using back-propagation algorithm trained Artificial Neural Network	**Authors**: Tran & Im[20] **Purpose**: To perform automatic berthing of a ship. **Findings**: Excellent performance of berthing control system.
2015	A vision-based dual Feed-forward/ Feedback controller	**Authors**: Maravall *et al.*[43] **Purpose**: Indoor navigation UAV. **Findings**: Indoor autonomous navigation using performed well using vision-based ANN.
2019	Grey box framework via adaptive RM-SVM With minor rudder	**Authors**: Mei[44] **Purpose**: Ship maneuvering prediction using machine learning (RM-SVM). **Findings**: Firstly, prediction precision is extremely well compared to Computational Fluid Dynamics (CFD) and other technique. Secondly, RM-SVM needs a minor rudder and fewer data rather than other methods. which produces larger generalization capability. Thirdly, its shown approximation capability and delivers the base approximation for ship maneuvering.
2019	An efficient approach based on Artificial Neural Network (ANN)	**Authors**: Shuai *et al.*[14] **Purpose**: Automatic ship docking. **Findings**: The vessel is capable to reach the dock smoothly, which proves the efficacy of this method.
2020	An algorithm based on the artificial neural network	**Authors**: Bidenko *et al.*[45] **Purpose**: To assist safe maneuvering of the ship in restricted waters. **Findings**: The proposed method is able to avoid collision with hazardous objects or any other obstacles and perform safe maneuvering.
2020	Neuroevolutionary-based maneuvering	**Authors**: Ayob *et al.*[46] **Purpose**: To perform autonomous navigation in confined waters. **Finding**: ASV is able to avoid obstacles and navigate safely using neuroevolution.
2020	Artificial neural network algorithm for ship berthing	**Authors**: Qiang & Bi[1] **Purpose**: To perform automatic ship berthing using ANN. **Conclusions**: The artificial neural network provides safe berthing in different environments other than training environment.

Obstacle (VO)[53] is one of the well-performing methods for automated berthing. Later, several derivatives method were produced, such as GRVO (Generalized Reciprocal Velocity Obstacle)[54,55] and ORCA (Optimal Reciprocal Collision Avoidance)[56].

Path planning algorithm is one of the popular algorithms for obstacle avoidance. Path planning can be classified into two categories such as, global path planning methods (vessel navigate in the environment which have previously known static obstacle), and local path planning methods (vessel navigate in the environment which have unknown dynamic obstacle). Both methods are described in the following paragraphs.

Global path-planning methods

Shortest path length is one of the major objectives in ship path planning. The objective of the ship is the find the shortest path to the destination point. Majority of the time, a ship spends its journey within large body of water area, and therefore the global path planning can be used without considering obstacle avoidance. Alternatively, within an environment that is full of obstacles (fixed static obstacle such as buoys and lighthouse), global maps are incorporated. By using this global path planning method, the vessel selects her collision free path between starting and destination point. An illustration about few popular path planning is summarized in Table 3.

Local path planning methods

In dynamic obstacle environments, it is impossible acquire information of different obstacle before planning the path and this dynamic object is a safety concern for the ship. So, in this situation the ship required assistance from local path planning beside global path planning to avoid dynamic obstacle. Currently many local path planning methods are available such as Fuzzy Logic Algorithm (FLA), Artificial Potential Field (APF), Neural Network (NN), Random Trees (RT), Reinforcement Learning (RL) and Deep Learning (DL). The description about few local path planning methods is presented in Table 4.

Shaobo *et al.*[59] recommended DRL-based collision avoidance method for USV. They applied this method to the decision-making stage of collision avoidance which decides whether the avoidance is required, and if so, decide the path of the avoidance maneuver. The DRL method trained through frequent simulations of collision avoidance, and later applied in collision avoidance experiments. Such deep learning based collision avoidance is able to perform well within generalized environments, complex and ambiguous

Table 3 — Global path planning approaches for obstacle avoidance[57]

Algorithm	Advantages and disadvantage	Improvements
A* Algorithm	-Direct search -No preprocessing required -Large amount of calculation -Optimal solution not guaranteed.	-The search process is more flexible Considering the anisotropy of current.
Genetic Algorithm	-Strong global searching ability -Slow convergence. -Inadequate local optimization. -Poor stability.	-Adjust the fitness function. -Add smoothing operator and node deletion operator. - add tangential operator and change initial population and -Enhance mutation rate and diversity evaluation criteria.
Differential Evolution	-Comparable to genetic algorithm. -Higher mutation probability.	-Improved cost function. -Utilizing current energy.
Nonlinear SQ algorithm	-Fast response. -Strong adaptability in different state.	-Improved battery power limitations. -Enhance underwater homing and docking of AUV[58]
Ant Colony Optimization	-Strong global searching ability. -High efficiency. -Higher convergence speed in later stage. -Slow convergence speed in early stage.	-Add cutting operator and insertion point operator. -Include penalty factor. -Pheromone elimination. -Add the reinforcement idea. - to reduce invalid searches utilized alarm pheromones. -Improved heuristic function. -Improved pheromone update rules. -Develop the initial pheromone.
Nature inspired optimizer	-Strong exploration ability. -Less error. -Maximum terminal velocity. - comparatively better performance than GA and PSO (Particle Swarming optimization).	-3D trajectory optimization is more effective than traditional 2D. -Cuckoo search algorithm[59]
Particle Swarm Optimization	-Quick search time. -Higher convergence velocity in early stage. -Slow convergence velocity in later stage. -Simple to fall into local optimum.	-Enhanced particle update strategy. -Solving the critical point problem. -Adaptive quantum particle swarm optimization. -Improved quantum particle swarm optimization. -Combining with differential evolution algorithm.

Table 4 — Local path planning algorithms[57]

Algorithm	Advantages	Disadvantages
Rapidly exploring Random Trees	Solve high dimensional space. Excellent ability to explore. The path is usually suboptimal.	Poor stability. Poor real-time performance.
Artificial Potential Field	Simple structure. Good real-time performance. Fast path planning speed.	Easy to fall into a local minimum. Oscillations near obstacles.
Fuzzy Logic algorithm	Strong flexibility. Good real-time performance. Small amount of calculation.	No precise mathematical models. Lack of systematic process. Rely on expert knowledge.
Reinforcement learning	High generalization ability. Strong robustness. Without prior obstacle information. Strong learning ability.	Dimensional disasters. Handcrafted state features.
Deep reinforcement learning	High generalization ability. Reduce dimensions. Automatic learning state features.	Training takes a long time

situations with multiple obstacles. In addition, it can empirically foresee future risk of collision when considering avoidance action candidates.

Zhao *et al.*[61] presented an autonomous ship framework under unknown environmental disturbances to adjust its heading in real time. A three-degree-of-freedom dynamic model for the autonomous ship was developed, and the Line-of-Sight (LOS) guidance system was used to guide the autonomous ship along the predefined path. Then, a Proximal Policy Optimization (PPO) algorithm was implemented for the problem. Through Reinforcement Learning (RL), autonomous ship can learn the safest and most economical avoidance behavior through repeated trials[62]. Nevertheless, the application of RL in the automation of ship maneuvering is still scarcely explored in scientific literature[63], and therefore may serve as an important future works for the autonomous maneuvering and berthing research.

Conclusion

In this paper, several literatures spanning throughout 20-years that relates to artificial intelligence in ship berthing has been reviewed. Various artificial intelligence methods are applied in ship piloting to achieve safe and collision avoidance navigation. It can be observed that within ship berthing theme, ANN was chosen by a large body of literatures because of its ability to mimic the human response, highly accurate prediction ability, and the ability to decide automatically in a generalized environment. Several interesting works have been reviewed, notably parallel ANN, head-up coordinate system ANN, neuroevolution, PID-ANN and finally global and local path planning. Based on the number of publications in this field of research, we can conclude that autonomous ship berthing and maneuvering still stands as a body of research that requires more work in the future. This therefore contributes to the safer sea and ports globally.

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Conflict of Interest

The authors would like to declare that there are no conflicts of interest to publish this review paper in the journal.

Author Contributions

Conceptualization and design of the work: AFA & SJ; data collection, analysis and interpretation, and software and writing – original draft: AFA & MMHI; and supervision and writing – review, editing and final approval: AFA, MMHI & SJ.

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