Autonomous Ship Navigation Methods: A Review

Abraham Noel, Shreyanka K, Kaja Gowtham Satya Kumar, Undergraduate Student(s)
Academy of Maritime Education and Training (AMET deemed to be University)
Chennai, India
abrahamnoel3099@gmail.com
krishanka2@gmail.com
kaja.gowthamsatyakumar@gmail.com

Shameem B.M, Patel Akshar, Assistant Professor(s)
Academy of Maritime Education and Training (AMET deemed to be University)
Chennai, India
shameem.bm@ametuniv.ac.in
aksharpatel@ametuniv.ac.in

Synopsis

Autonomous navigation is achieved by training or programming the ship with the stored data about the vessel behavior in various sailing environment. The autonomous behaviour relies on intelligent analytics based on machine learning algorithms. As a major advance in machine learning, the deep learning approach is becoming a powerful technique for autonomy. The deep learning methodologies are applied in various fields in the maritime industry such as detecting anomalies, ship classification, collision avoidance, risk detection of cyber-attacks, navigation in ports and so on. The present paper reviews on various methods available in the literature for vessel autonomy and their applications in ship navigation. The focus of the work is to illustrate the advantages of deep learning approach over the machine learning and other traditional methods.

Keywords —Autonomous navigation; intelligent analytics; anomaly detection; collision avoidance; ship classification

1. Introduction

Machine learning and artificial intelligence are in fact, two significant factors in the digitalization of industries. These technologies have become noticeable and continued to be the foreground in the successful implementation of the fourth industrial revolution (i4.0). Machine learning techniques are widely used in many applications such as, speech recognition, autonomous detection and navigation, computer vision, object classification, virtual assistants, security and surveillance etc. Being capable of taking intelligent decisions and handling large scale of data are among the vital challenges for their successful implementation. Most of the traditional approaches in machine learning techniques are not capable of accomplishing these challenges. For instance, the concept of an autonomous ship is highly driven by the trending technologies, machine learning and deep learning. The method of deep learning is an advanced algorithm which has become an integral part of many engineering applications due to its "end-to-end learning" approach and the ability to draw independent knowledge from experience. Also, deep learning is predicted to shape the future of the maritime industry like any other industries due to its capability to take advantage of an increasing amount of available ship operational and performance data.

The dataset presenting the amount of research reported on deep learning methods reveal a steep rise in the number of articles published in the varied domain of autonomous navigation such as collision avoidance, anomaly detection and ship classification during the period 2015 to 2018. The statistics showing the progress of deep learning for autonomous ship navigation is shown from Fig 1 to 4. Mainly, this indicates that the use of deep learning has brought thoughtful change in improvising the fourth industrial revolution.

 http://doi.org/10.24868/icmet.oman.2019.028

All learning techniques require small to large amount of data in sophisticated format. Later, vivid algorithms infused to generate the working models. Hence data plays a crucial role in the proper functioning of these techniques that are used for autonomous navigation. The process of collecting and managing the data, particularly for learning techniques is called *data engineering* and the same is discussed in following section.

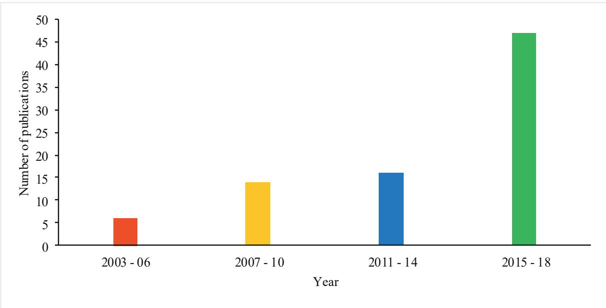

Fig 1: Deep learning in autonomous ship navigation

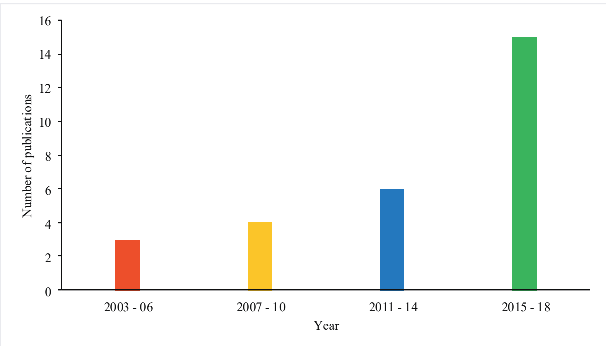

Fig 2: Deep learning in ship collision avoidance

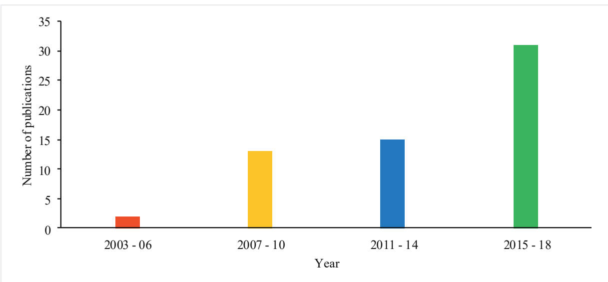

Fig 3: Deep learning in anomaly detection

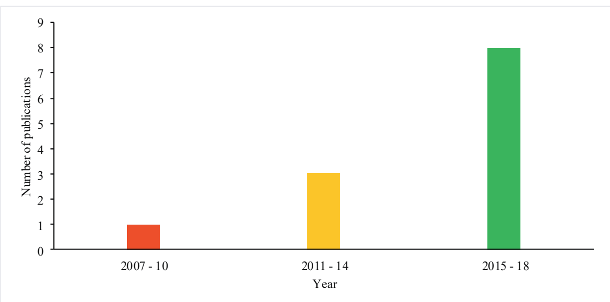

Fig 4: Deep learning in classification of ships

Another major factor in the smooth functioning of learning techniques is the method used to achieve it. Over the years, a greater number of methods have been proposed. Each of these methods possess both advantages and disadvantages. A brief about various methods and how they can contribute to autonomous navigation, particularly for ships is discussed in this paper. Autonomous vessel's vital objective is to possess safe navigation and avoid collisions in the open sea. In order to fabricate and design, some of the challenges offered to the successful deployment of these methods are presented.

2. Data Engineering

Although an umbrella word, 'Industry 4.0' covers heterogeneous components, they all share a common feature which is 'Data'. Data engineering is a systematic multifaceted process which converts the raw data into the desired format required for the processing.

Peculiarly in the field of ship automation, considering the varied scenario under which ship is exposed to, the amount of data to be engineered could escalate the so- called phenomenon 'Big Data'. On the contrary, a large amount of data offers more flexibility to test and train the model. However, a claim that a higher number of data offers a more efficient model could be the statement from a layman since, chances of hidden flaws with an increased amount of data could influence the diverse effect while training the model. In addition, the quality of data could eventually hinder the performance of a model if it is not being handled during the pre-processing stage, mainly for the machine learning algorithm. For instance, if outliers are not processed either from domain or stat knowledge, it could provide the wrong inference while performing the statistical study. In the case of deep learning, if the system is initialized based on the existing data set, one with missing and unsophisticated values, it could increase the processing time to counter the new situation. So, data cleansing plays a vital role at this juncture.

On the other hand, data source and storage are other key components on which the total process of ship automation is based. More precisely, during the data acquisition stage, the quality of data relies on various factors to achieve better adeptness, see Fig 5. In a similar vein, considering the diverse type of data being loaded through sensors, experiments, simulation or calculation could intensify the problem of effective storage for the later stage of data cleansing and data transformation. At times, data warehousing alone could ask for months to neutralize the defects and making it suitable for the test and train process. For instance, categorical and numerical data could be stored and filtered easily, and at the later stage for analysis, categorical data will be easily framed into numerical data by performing either label encoding or one-hot encoding, whereas, the remaining data-set like audio-video files and time series need to be managed separately which could demand relatively more time (McKinney 2013).

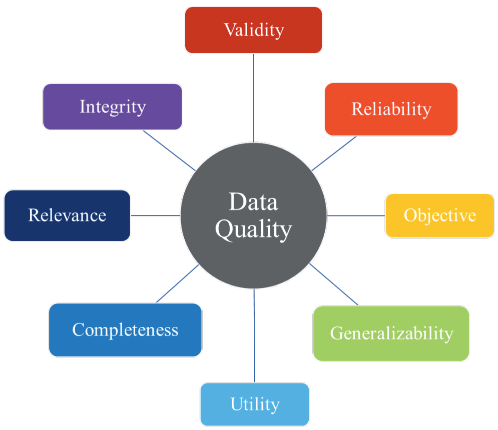

Fig 5: Factors affecting quality of data

In short, data engineering is the basis for what is expected for a model to perform in terms of the anticipated outcome. In this case, for a ship to navigate without pilot assistance, machine learning and deep learning algorithms required to perform effectively under predefined and new inputs where data acquisition, data pre-processing and data transformation could influence the model outcomes.

3. Autonomous Navigation

Autonomy is applied to many fields such as space exploration, ships, logistics, self-driving cars etc., to reduce human errors and improve precision (Zhao and Wang 2012). Autonomous navigation of ship consists of various sensors to detect the navigating path and environmental and vessel properties to determine safe travel (Fefilatyev 2008). The successful implementation of autonomy of vessels would occur with intelligent decisions at various operational conditions. For more than three decades, many methods have evolved from remotely operated to autonomous operations of machines, robots and other vehicles. In this paper, the traditional methods are presented in two categories - classical and reactive methods. The improvement in these methods has brought development in machine learning algorithms, further evolved to advanced intelligent decision algorithm - Deep learning method.

3.1 Classical Methods

3.1.1 Road Map Building

The Road map building mainly involves movement of a machine, a robot or any device to all possible ways, by which it can reach its destination. The device or the vessel scans the given paths and collects navigational data. This data is used as input for the development of its algorithm for path planning. Path planning is done using two road map approaches, Visibility graph and Voronoi diagram, see Fig 6. In visibility graph approach, the path of the vessel is very close to the obstacle that results in finding the minimum path distance, however in voronoi diagram, the path of the vessel would stay away from the obstacle (Parhi and Mohanty 2012). This path is later learnt by the vessel and used to generate the path planning algorithm (Ishii et al. 2010).

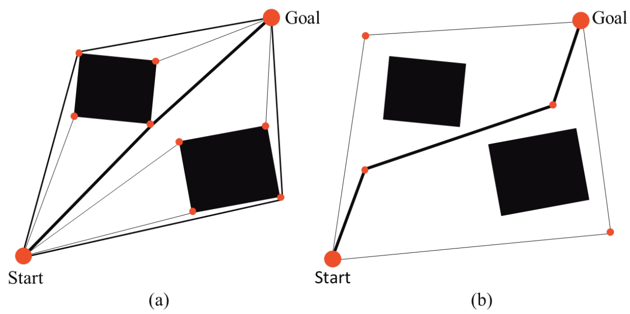

Fig 6: Path planning - (a) Visibility graph method (b) Voronoi method

The road map building method fails if the scanned path is changed or blocked, which is a disadvantage. The device must scan the whole map again to compute another route. This method can only be used for small scale mapping since it is tedious to scan the whole record again and compute results for large-scale mapping.

3.1.2 Cell Decomposition

In this method, the given space is divided or decomposed into several blocks called as cells. They are mainly of two types, exact cell decomposition and approximate cell decomposition method. The cells are analysed to obtain a possible path with the help of adjacent cells. A line is then drawn through the centre of each geometry, which reveals a well-defined path for the object to follow and reach the destination (Chen and Teng 1995). A typical approach in exact cell decomposition is shown in Fig 7. This method also has similar limitations as that of road map building method.

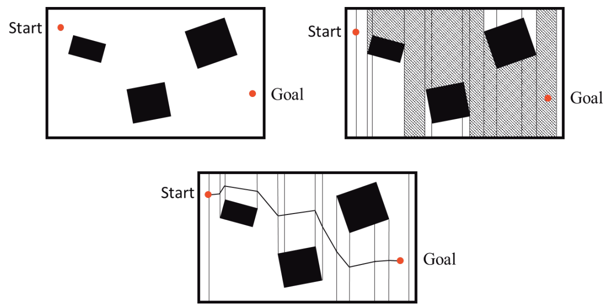

Fig 7: Path Planning done using exact cell decomposition method

3.1.3 Artificial Potential Field

In Artificial potential field method, the destination or goal is considered as an attractive force and any obstacle in the path as a repulsive force (Li et al. 2012). Any obstacle in the path would be detected by the vehicle or robot, and as a result the vehicle is pushed away to avoid collision with the obstacle to reach the destination, see Fig 8 (Pomerleau 1989; Cosfo and Castai 2004; Pêtrès et al. 2012). Multiple obstacles in the same region at close vicinity may lead this method to a failure. This may cause the robot to follow the same path repeatedly, repelling itself from the same obstacles, which makes it impossible to reach the goal.

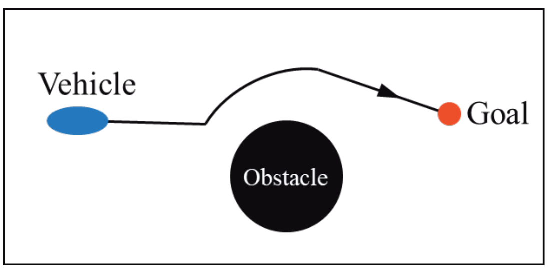

Fig 8: Artificial potential field method

3.2 Reactive Methods

3.2.1 Fuzzy Logic Controller

Fuzzy logic controller technique is used in devices for controlling certain tasks (Arney 2007; Isizoh et al. 2012). This technique is mainly used in machine controls, as it provides better decision- making statements such as “almost true” or “partially false” instead of simply stating “true” or “false”. The advantage of this technique is that it allows the implementation of “if then” logic rather than using complicated differential equations. It also allows use of graphical user interface which makes it easy to implement (Hasegawa et al. 1989; Tsourveloudis et al. 2001; Kao et al. 2007; Perera and Carvalho 2012).

3.2.2 Neural Network

In case of Neural network, several conditions are formulated as a network (Zhao and Wang 2012). The input received to the device is checked for satisfaction against these conditions. If a condition is detected to be true, the method executes the output to achieve the target associated with that condition (Lee et al. 2004). If more than one conditions are satisfied, this may give a different output. As the number of conditions increase, the network becomes complicated and requires higher capabilities of processing power. In case of neural network for autonomous ship navigation, sensors can provide inputs such as distance of an obstacle, direction, weather conditions, GPS data, etc. Further, this can be validated through a set of conditions or networks to provide instructions for direction of movement, speed of travel and decision to avoid collision (Yiwei et al. 2019).

3.2.3 Neuro - Fuzzy

Neuro - Fuzzy is a combination of both neural network and fuzzy logic controller. They provide a large array of possibilities in making precise decisions for safe navigation (Lin and Lee 1991). Since this technique incorporates fuzzy logic, “if then” with neural networks, it offers better decision-capabilities for autonomous navigation.

3.2.4 Genetic Algorithm (GA)

GA algorithmic uses a fitness function approach. This fitness function helps the technique to obtain various solutions through an iterative process. From the obtained results, the technique analyses to produce the optimum design solution. The working principle of GA algorithm is shown in Fig 9. For autonomous ship navigation, the GA algorithm could propose an appropriate decision to avoid obstacles. The decisions include its movement for manoeuvring or stopping with suitable selected speed. The algorithm could be implemented through the results obtained from various experiments to achieve optimized output (Tsai et al. 2011; Tuncer and Yildirim 2012; Dobrkovic et al. 2015)

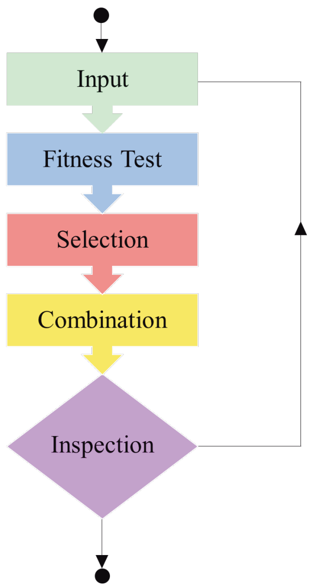

Fig 9: A flowchart for genetic algorithm

3.2.5 Ant Colony Optimization

Ant colony optimization is a direct adaptation of the movement of ants through a given space. The pheromone- based communication of biological ants is the basis of this technique i.e., the biological ants lay more pheromones along the best suitable path. In this manner, the simulation agents (called as artificial ants) record all possible solutions and choose the optimal path. In case of encountering an obstacle, ants move along the contour of the obstacle (Lazarowska 2015).

3.2.6 Particle Swarm Optimization

Particle swarm optimization technique consists of several algorithms, which are applied to the given problem to find best suited solution. This technique produces suitable results but may vary according to the chosen algorithm. The predicted paths that are similar in nature is selected as the best solution (Huh et al. 2002). The most important part of path planning in case of autonomous ship navigation is finding an optimal route that avoids collisions, congestions and deadlocks. In this case, use of particle swarm optimization algorithm can be beneficial for efficient path planning and avoiding such undesirable situations in the real-world environment.

3.2.7 Artificial Immune Network

Artificial immune network works based on human immune system (Inzartsev et al. 2016). In a human body, the immune system protects from several infections and viruses (Deepa et al. 2009; Enezi eta al. 2010). In case of Autonomous Navigation, an Artificial Immune System learns from previously encountered obstacles and anomalies. The trained data would be used to resolve the problems encountered during the voyage. This technique replicates the real environment and closely resembles modern day techniques such as machine learning and deep learning methods.

3.3 Machine Learning Methods

Machine learning is one of the most evolving procedures that solve problems pertaining to the data. It involves an algorithm that evaluates and segregates data and develops a logic. This section discusses the machine learning methods used for various applications, specifically autonomous ship navigation.

3.3.1 Transfer Learning

Transfer learning solves the problem through a learning process - a neural network model, from a set of structured data history. For the technique to perform in an effective manner, a set of undistorted data from the original network is necessary. This method even can compute complex situations in short duration of time. The model is initially trained with the previously obtained similar data and, one or more layers of this trained model is used for developing a new model. A typical flowchart representing the method of transfer learning is shown in Fig 10. In this technique, it is not feasible to inactivate or remove any layer to reduce the variables connected to the problem, since it affects the architecture and ends up in low level features.

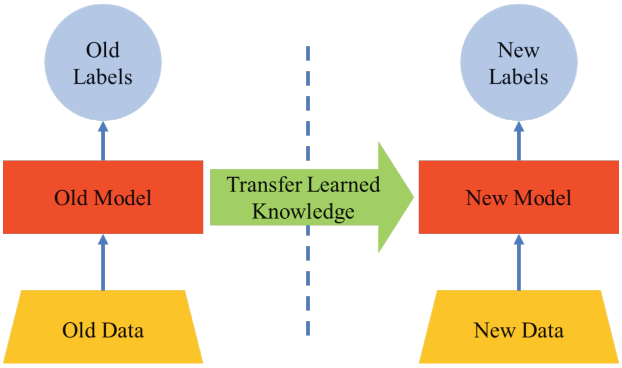

Fig 10: A flowchart showing working of transfer learning

The method of transfer learning is used in the shipping industry for identification and classification of different ships (Tweedale 2018). Other applications include text classification, text clustering, reinforcement learning, sentiment classification, collaborative filtering, sensor-based location estimation, logical action model learning for AI planning and page ranking, etc.

3.3.2 Artificial Neural Network

Artificial neural networks are a class of machine learning algorithms, based on mimicking the biological neural networks (Hwang et al. 2017). The structure of ANN is easily affected by the information that flows through the network however, the algorithm adapts to any changes based on its architecture - input, hidden layers and output, see Fig 11. The advantage of ANN is its 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 jobs simultaneously. It is trained through trial and error method, since there are no specific rules for the structure. In case of autonomous ship navigation, artificial neural networks are used for minimizing the errors in predicting the ship trajectory, weather forecasting and detection of targets (Borkowski 2017).

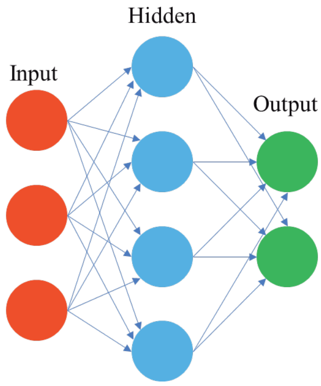

Fig 11: Networks and nodes in an artificial neural network

3.3.3 Active Learning

Active learning is a special case of machine learning that interacts with the user or source to obtain the desired outputs at new data points. It is based on the method of multiple learning classifiers (Mus´ılek et al. 2005; Silver et al. 2012) to take appropriate decisions. Based on data sampling methods such as entropy, active learning is used for multi classification problems such as ship classification in complex environments (Huang et al. 2016). Moreover, the active learning principles can be used for anomaly detection in autonomous ships (Pimentel et al. 2018).

3.3.4 Extreme Learning Machine

Extreme learning machine (ELM) is a single hidden layer feedforward network which is capable of training complex algorithms. ELMs are many times faster in executing the tasks compared to the traditional neural networks. ELM layers can combine to form multi-layer networks that is suitable for advanced methods such as deep learning. Extreme learning is used in autonomous ships for prediction of six degrees of freedom motions - roll, pitch, yaw, heave, sway and surge. For ship detection, the efficiency is improved by combining ELM with the additional features such as fusion and classification (Tang et al. 2015). Though ELMs can combine to form multi-layers, sometimes it may fail to encode more than one layer of abstraction. Further, ELMs are used in activity recognition for manoeuvrable devices, imbalance data processing, etc., (Demertzis et al. 2018; Gao et al. 2018).

3.3.5 Incremental learning

Incremental learning takes input data continuously to extend the existing model's knowledge. Algorithms that assist incremental learning are known as incremental machine learning algorithms. The method is mostly used in traffic route extraction process due to its ability to adapt evolving situations. Point-based incremental algorithms are used in maritime knowledge discovery and exploitation (Vespe et al. 2012). Applying incremental learning to big data aims to produce faster classification or forecasting times. Hence it is used for the automatic classification of objects and complex environments to assist autonomous navigation (Chenadec et al. 2019).

3.3.6 Feature Learning

Feature learning is a collection of techniques that can automatically differentiate the illustrations desirable for feature detection or classification from the existing data. These algorithms are often artificially designed based on the problems to be solved and the characteristics of data. Manual feature engineering is replaced, which in turn allows a machine to both learn the features and use them to perform a specific task. In case of autonomous ship navigation, this technique is used to classify objects from AIS data (HZye et al. 2007; Høye et al. 2008; Næss 2018).

3.4 Deep Learning Methods

Deep learning, a subset of machine learning, utilizes a hierarchical level of artificial neural networks to carry out the process of machine learning. The artificial neural networks are built like the human brain, with neuron nodes connected like a web. Deep learning is one of the promising methods in developing fully autonomous ships. Mimicking the helmsman behavior is featured to be one of the major areas of focus to capture the automation (Sato and Ishii 1998; Hasegawa 2009; Boogaard et al. 2016). A considerable section of ship intelligence will consist of a deep learning-based framework, i.e. deep neural network. The same framework will create the respective agent behavior within the autonomous vessels. Similar frameworks have been implemented by other transport systems, i.e. autonomous navigation systems of driverless cars (Mou et al. 2006; Chen and Wang 2014; Wilmanski et al. 2016; Perera 2018).

3.4.1 Deep Neural Network

A Deep neural network (DNN) is a complex neural network that constitutes more than two layers. Deep neural network is different from neural networks due to its depth in the model architecture. The sophisticated mathematical modelling in the deep layers allows the technique to solve many complex situations. DNN trains several hidden layers within the network which provides better performance with less parameters in each layer. With deep neural networks, advances are achieved towards complex computational problems for developing new classes of signal processing algorithms. In modern training, deep neural networks are applied to the SAR ATR problems (Margarit et al. 2009; Duc et al. 2015; Tang et al. 2015; Song et al. 2017). In maritime industry, DNN is used in identification of various ships, pattern recognition and collision avoidance.

3.4.2 Convolutional Neural Network

Convolutional neural network (CNN) is a deep neural network used in image recognition and processing, specifically designed to process data (Perera et al. 2012; Ødegaard et al. 2016; Kim et al. 2018). Here the data can be structured or unstructured. CNNs can learn complex representations from the input data, without the requirement of handcrafted features, and have been productively used in several image classification tasks (Bentes et al. 2016; Kim et al. 2017; Wang et al. 2017). It is designed to learn a set of features from the input in a supervised training that makes the method capable to differentiate various situations. To determine the network performance, the CNN structure is optimized by training error curves (Rødseth 2015; Wagner 2016; Zhanga et al. 2016). Even though CNN takes longer time to train the model, it learns important features from the situations and thus provides a more efficient model.

The CNN is used in maritime applications such as collision avoidance for autonomous ships, anomaly detection and to mimic the behaviour of helmsman to take intelligent decisions (Bhandare et al. 2016). Furthermore, convolutional neural network is used for image classification and ship- iceberg discrimination in high resolution TerraSAR-X strip map images (Bentes et al. 2016).

3.4.3 Deep Convolutional Auto-Encoders

The structure of an autoencoder constitutes three layers: an input layer, an encoding layer, and a decoding layer. The network is trained to rebuild its inputs, which forces the hidden layer to learn good representations of the inputs. A deep convolutional autoencoder (DCAE) is proposed to remove features and conduct classification involuntarily and designed for high-resolution SAR image classification. DCAE network also provides an automatic method to learn discriminative features from the images, and then extracts the efficient features to provide better classification results. Hence DCAE features are obviously better than other hand-crafted features (Jin and Xu 2013; Fan et al. 2015). DCAE is used in shipping industry for high detection accuracy and remove clutter in radar signals (Guo et al. 2017; Zhang et al. 2017).

4. Deep Learning in Autonomous Ship Navigation

4.1 Collision avoidance

Most of the ship collision accidents are due to human errors, which is a large threat in open sea (Hasegawa 1987; Hammer and Hara 1990; Chauvin and Lardjane 2008; Hinostroza and Soares 2018). Decision-making processes in autonomous vessels will play an important role under such ocean autonomy (Nagasawa et al. 1988; Mou et al. 2006; Perera et al. 2015; Perera and Soares 2017). Therefore, various technologies to assist the intelligent decisions are to be developed (Isshiki 1994; Johansen et al. 2016). Intelligent navigation is important in mitigating the overall risk due to collisions. Automatic collision avoidance system is designed to support decision-making to ensure safe navigation (Smeaton and Coenen 1987; Statheros et al. 2008; Garg et al. 2013; Sun et al. 2018).

The International Maritime Organization (IMO) in 1972 by the Convention on the International Regulations for Preventing Collisions at Sea (COLREGs) has introduced a legal framework to regulate ship encounter situations (Perera and Carvalho 2012). These regulations can be recognized through artificial intelligence for collision recognition. Building algorithms and flowcharts eases the understanding of AI to solve collision problems. Advances in deep learning has made the approaches towards replicating these complex situations and autonomous collision avoidance an easily achievable task (Yavin et al. 1995; Rhee and Lee 1996; Jin and Xu 2013). A schematic representation is drawn to explain the procedure for collision avoidance, see Fig 12. Deep learning framework manipulates the self- driven vessel characteristics into a data classification problem and helps solving it in a systematic approach. CNN approach can provide an elegant and effective mechanism to capture helmsman behavior (Perera 2018).

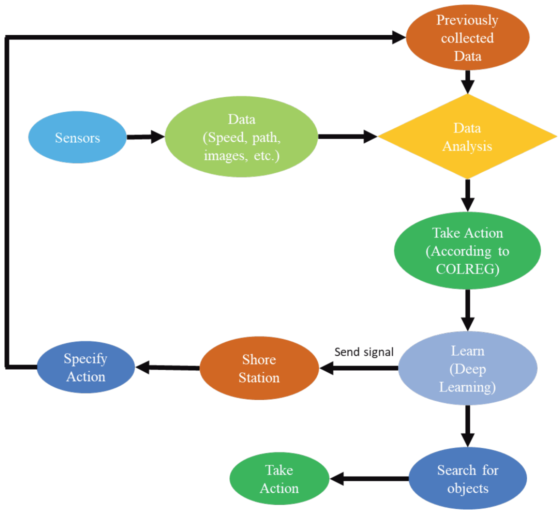

Fig 12: Schematic representation for autonomous collision avoidance

4.2 Anomaly Detection

A high level of recognition and situational awareness is necessary when AIS Data is combined with data from other sources (Carthel et al. 2007; Rhodes et al. 2009; Crassidis et al. 2011; Vespe et al. 2012). The methods used for recognition includes support vector machines, neural networks, Bayesian networks, Gaussian processes and Gaussian mixture model (Roy 2009; Cansado and Soto 2015; Guo et al. 2015a, 2015b). These methods identify anomalous behaviors, such as deviation from standard routes, unexpected AIS activity, unexpected port arrival, close approach, and zone entry. All these approaches can only be implemented with a minimum intervention of helmsman (Ristic et al. 2008; Laxhammar et al. 2009; Harguess and Rainey 2011;). To develop a fully autonomous anomaly detection system, it should be supported with the visuals of vessel interaction at various environments to take intelligent decisions (Laxhammar 2008; Baldacci et al. 2009; Li et al. 2009; Rainey and Stastny 2011; Obradovic et al. 2014; Rainey et al. 2014), which can be provided by the CNN algorithm.

4.3 Path planning

Path planning is one of the key parameters in Marine Autonomous System (MAS). Ship path planning can be categorized into two general groups, namely the deterministic and the heuristic approach. The deterministic approach follows a set of rigorously defined steps in order to determine the solution; whereas the heuristic approach only searches inside a subspace of the search space for an 'acceptable' solution rather than the best solution that satisfies the design requirements (Tam et al. 2009). Its essence is to avoid obstacles and reach the target point at optimum distance and time. At present, in the field of unmanned vehicles, mobile robots and drones, the effective path planning includes methods of artificial potential field, neural network, fuzzy logic and genetic algorithm. Most recent path planning algorithm, a deep learning approach, adopts a safety domain around each obstacle that serves to indicate the risk of collision. The algorithm uses deep reinforcement learning to reach the local target position successfully in unknown dynamic environment. Deep reinforcement learning solves the problem of dimensionality well and can process multidimensional inputs (Borkowski 2017; Lokukaluge and Carlos 2017; Xiaoyun et al. 2018).

4.4 Ship classification

Object recognition and classification algorithms for imagery are important for improving Automatic Target Recognition (ATR) and Maritime Domain Awareness (MDA). Recently, the deep learning approaches have achieved remarkable performance in object recognition (Phillip and Josh 2015). Deep architecture is said to have the ability to learn highly nonlinear irregularities in data with hardly any pre-processing. A Convolutional neural network (CNN) is one example of a deep architecture, provided it has enough layers. CNNs have recently been applied successfully in large scale image classification competitions for photographs found on the internet (Ødegaard et al. 2016). By using a CNN and the backpropagation algorithm, the neural network can learn to pick up on features in images that are characteristic for each class. However, the problem of classifying overhead satellite imagery of ships remains a challenging problem (Rainey and Stastny 2011). This challenge can be resolved using Statistical Convolutional Neural Network (S-CNN) along with specifically designed proposals and appropriate detection method. Experiment in (Zhanga et al. 2016) demonstrate that, proposed S-CNN-based method can provide enough proposals with a very high recall and improves the ship classification accuracy. A proposed schematic representation for ship classification, which can be implemented using CNN is given in Fig 13. The sensors or equipment installed on the ship capture the images of nearby vessels and objects. The CNN algorithm categorizes the input at each layer to identify the type of ship (Guo et al. 2014; Park et al. 2016; Leclerc et al. 2018).

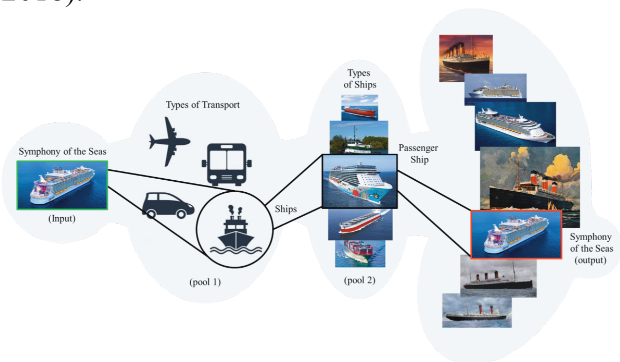

Fig 13: Convolutional neural network for ship classification

5. Conclusion

The paper reviewed various methods used for autonomous navigation, particularly the applications towards autonomy of ships. The traditional methods discussed here are used mainly to achieve supervised decisions, which is a disadvantage for the development of Industry 4.0. The intelligent decision making is a major requirement for establishing complete autonomy. More complex data is required to accomplish this goal and an efficient algorithm to execute. The machine learning algorithms are capable to accomplish intelligent decisions; however, this algorithm may become more complicated for unstructured data. These challenges can be handled by deep learning networks, where the complex situation is solved through a multi-layer hierarchical approach.

Deep learning is advancing towards very complex tasks to achieve complete autonomy in ship navigation. It is expected that the development in this deep reinforcement approach might progress in coming years and the complexity of achieving complete autonomy, which is not feasible today would be a routine in another ten years.

6. References

1. Hammer A, Hara K. Knowledge acquisition for collision avoidance maneuver by ship handling simulator. MARSIM & ICSM 90, Tokyo. 1990; 245-252.
2. Nagasawa A, Hara K, Inoue K. Simulation model to estimate a risk of marine traffic flow. Proceedings Techno-Ocean International Symposium, Kobe, Japan. 1988.
3. Baldacci A, Rolla S, Carthel C. Maritime traffic characterization with the Automatic Identification System. NATO Workshop on Data Fusion and Anomaly Detection for Maritime Situational Awareness, La Spezia, Italy. 2009.
4. Isizoh AN, Okide SO, Anazia AE, Ogu CD. Temperature Control System Using Fuzzy Logic Technique. (IJARAI) International Journal of Advanced Research in Artificial Intelligence. 2012;1(3).
5. Dean A Pomerleau. ALVINN: An Autonomous Land Vehicle in a Neural Network. Advances in neural information processing systems. 1989;305-313.
6. Patrick André Næss. Investigation of Multivariate Freight Rate Prediction Using Machine Learning and AIS Data. Thesis for: Master of Science. 2018.
7. Timothy Arney. An Efficient Solution to Autonomous Path Planning by Approximate Cell Decomposition. IEEE. 2007.
8. Ristic B, La Scala B, Morelande M, Gordon N. Statistical Analysis of Motion Patterns in AIS Data: Anomaly Detection and Motion Prediction. 2008 11th International Conference on Information Fusion, Cologne, Germany. 2008.
9. Deepa BBVL, Alok Kumar Jha, Dayal R Parhi. Path Planning of an Autonomous Mobile Robot Using Artificial Immune System. International Journal of Computer & Mathematical Sciences IJCMS. 2009.
10. Ashwin Bhandare, Maithili Bhide, Pranav Gokhale, Rohan Chandavarkar. Applications of Convolutional Neural Networks. (IJCSIT) International Journal of Computer Science and Information Technologies. 2016;7.
11. Piotr Borkowski. The Ship Movement Trajectory Prediction Algorithm Using Navigational Data Fusion. Sensors. 2017.
12. Pêtrès C, Romero Ramirez MA, Plumet. A potential field approach for reactive navigation of autonomous sailboats. Robotics and Autonomous Systems 60. 2012;1520–1527.
13. Chauvin C, Lardjane S. Decision making and strategies in an interaction situation: Collision avoidance at sea. Transportation Research. 2008;259-262.
14. Bentes C, Frost A, Velotto D, Tings B. Ship-iceberg discrimination with convolutional neural networks in high resolution SAR images, 11th European Conference on Synthetic Aperture Radar, Hamburg, Germany. 2016.
15. Carthel C, Coraluppi S, Grignan P. Multisensor tracking and fusion for maritime surveillance. Int. Conf. Information Fusion, Qu´ebec, Canada. 2007.
16. Nikos C Tsourveloudis, Kimon P Valavanis, Timothy Hebert. Autonomous Vehicle Navigation Utilizing Electrostatic Potential Fields and Fuzzy Logic. IEEE transactions on robotics and automation. 2001;17(4).
17. Antonio Cansado, Alvaro Soto. Unsupervised Anomaly Detection in Large Databases Using Bayesian Networks. Pontificia Universidad Católica de Chile, Santiago, Chile. 2015.
18. Yie Chien Chen, Ching Cheng Teng. A model reference control structure using a fuzzy neural network. Fuzzy Sets and Systems. 1995;73:291-312.
19. Ching Chih Tsai, Hsu Chih Huang Cheng Kai Chan. Parallel Elite Genetic Algorithm and Its Application to Global Path Planning for Autonomous Robot Navigation. IEEE transactions on industrial electronics. 2011;58(10).
20. Arambula Cosfo F, Padilla Castai Eda MA. Autonomous Robot Navigation using Adaptive Potential Fields. Mathematical and Computer Modelling. 2004;40:1141-1156.
21. Garagic D, Rhodes BJ, Bomberger NA, Zandipour M. Adaptive Mixture-Based Neural Network Approach for Higher-Level Fusion and Automated Behavior Monitoring. NATO

Workshop on Data Fusion and Anomaly Detection for Maritime Situational Awareness, La Spezia, Italy. 2009.

22. Konstantinos Demertzis, Lazaros S Iliadis, Vardis Dimitris Anezakis. Extreme deep learning in biosecurity: the case of machine hearing for marine species identification. Journal of Information and Telecommunication. 2018.

23. Andrej Dobrkovic, Maria Eugenia Iacob, Jos Van Hillegersberg. Using Machine Learning for Unsupervised Maritime Waypoint Discovery from Streaming AIS Data. i-KNOW '15 Proceedings of the 15th International Conference on Knowledge Technologies and Data-driven Business, Graz, Austria. 2015.

24. Dao Duc C, Xiaohui H, Mor`ere O. Maritime vessel images classification using deep convolutional neural networks. SoICT. 2015.

25. Yiwei Fu, Devesh K Jha, Zeyu Zhang, Zhenyuan Yuan, Asok Ray. Neural Network-Based Learning from Demonstration of an Autonomous Ground Robot. Machines. 2019.

26. Margarit G, Milanes J, Tabasco A. Operational ship monitoring system based on synthetic aperture Radar processing. Remote Sens. 2009;1:375-392.

27. Høye GK, Eriksen T, Meland BJ, Narheim B.T. Space-based AIS for global maritime traffic Monitoring. Acta Astronaut. 2008;62:240–245.

28. Smeaton GP, Coenen FP. Developing an intelligent marine navigation system. Computing & Control Engineering Journal. 1987;95–103.

29. Miao Gao, Guoyou Shi, Shuang Li. Online Prediction of Ship Behavior with Automatic Identification System Sensor Data Using Bidirectional Long Short-Term Memory Recurrent Neural Network. Sensors. 2018.

30. Shashank Garg, Rohit Kumar Singh, Rajiv Kapoor. Autonomous Ship Navigation System. Texas Instruments India Educators' Conference. 2013.

31. Isshiki H. Algorithm for collision avoidance of a ship. Journal of Kansai Society of Naval Architecture. 1994.

32. Alexander Inzartsev, Alexander Pavin, Alexander Kleschev, Valeria Gribova, Grigory Eliseenko. Application of Artificial Intelligence Techniques for Fault Diagnostics of Autonomous Underwater Vehicles. IEEE. 2016.

33. Eriko Ishii, Eiichi Kobayashi, Takashi Mizunoe, Atsuo Maki1. Proposal of New-Generation Route Optimization Technique for an Oceangoing Vessel. Oceans'10 IEEE Sydney. 2010.

34. Roy J. Automated Reasoning for Maritime Anomaly Detection. NATO Workshop on Data Fusion and Anomaly Detection for Maritime Situational Awareness. 2009

35. Tang J, Deng C, Huang GB, Zhao B. Compressed-domain ship detection on spaceborne optical image using deep neural network and extreme learning machine. IEEE Transactions on Geoscience and Remote Sensing. 2015;53:1174-1185.

36. Geng J, Wang H, Fan J, and Ma X. Deep supervised and contractive neural network for SAR image classification. IEEE Transactions on Geoscience and Remote Sensing. 2017;55(4):2442-2459.

37. Geng J, Fan J, Wang H, Ma X, Li B, Chen F. High-resolution SAR image classification via deep convolutional autoencoders. IEEE Geoscience and Remote Sensing Letters. 2015.

38. George J, Crassidis JL, Singh T, Fosbury AM. Anomaly Detection using Content-Aided Target Tracking. Journal of Advances in Information Fusion. 2011;6:39–56.

39. Harguess J, Rainey K Are face recognition methods useful for classifying ships? Applied Imagery Pattern Recognition Workshop, USA. 2011

40. Hwang JI, Chae SH, Kim D, Jung H.S. Application of Artificial Neural Networks to Ship Detection from X-Band Kompsat-5 Imagery. Appl. Sci. 2017.

41. Mou JM, Zou ZJ, Huang LW, Ji YQ. Ship maneuvering simulation-based safety analysis for vessel traffic environment. Proceedings MARSIM International Conference on Marine Simulation and Ship Maneuverability, Terschelling. 2006.

42. Al Enezi JR, MF Abbod, Alsharhan S. Artificial immune systems – models, algorithms and applications. IJRRAS. 2010;3(2).

43. Ørnulf Jan Rødseth. Maritime Unmanned Navigation through Intelligence in Networks (MUNIN). MESA Workshop on "The Connected Ship and Shipping". 2015.

44. Dei Jeung Huh, Jong Hun Park, Uk You1 Huh Hak Il Kim. Path Planning and

Navigation for Autonomous Mobile Robot. IEEE. 2002.

45. Hasegawa K. Automatic collision avoidance system for ships using fuzzy control. 8th Ship Control System Symposium, Hague. 1987.

46. Hasegawa K. Advanced marine traffic automation and management system for congested water and coastal areas. Conference in Ocean Engineering, ICOE, Chennai, India. 2009.

47. Hasegawa K, Kouzuki A, Muramatsu T, Komine H, Watabe Y. Ship auto-navigation fuzzy expert system (SAFES). J. of the Society of Naval Architecture of Japan. 1989;166.

48. Rainey K, Stastny J Object recognition in ocean imagery using feature selection and compressive sensing. IEEE Applied Imagery Pattern Recognition Workshop, San Diego, California. 2011.

49. Rainey K, Parameswaran S, Harguess J. Maritime vessel recognition in degraded satellite imagery. Conference Paper in Proceedings of SPIE - The International Society for Optical Engineering, San Diego, CA 92152, USA. 2014.

50. Kim KH, Hong SJ, Choi BH, Kim IH, Kim ET. Ship Detection Using Faster R-CNN in Maritime Scenarios. School of Electrical and Electronic Engineering, Yonsei University, Korea. 2017.

51. Gudrun K HZye, Torkild Eriksen, Bente J Meland, BjZrn T Narheim. Space-based AIS for global maritime traffic monitoring. Acta Astronautica. 2007;62(2–3):240-245.

52. Rhee KP, Lee HJ. Development of a collision avoidance system considering the navigation plan. MARSIM, Copenhagen. 1996;341-348.

53. Kwanghyun Kim, Sungjun Hong, Baehoon Choi, Euntai Kim. Probabilistic Ship Detection and Classification Using Deep Learning. Article, School of Electrical and Electronic Engineering, Yonsei University, Korea. 2018.

54. Chee Kuang Tam, Richard Bucknall, Alistair Greig. The Royal Institute of Navigation Review of Collision Avoidance and Path Planning Methods for Ships in Close Range Encounters. The journal of navigation. 2009;62:455–476.

55. Perera LP, Rodrigues JM, Pascoal R, Guedes Soares C. Development of an onboard decision support system for ship navigation under rough weather conditions. Taylor & Francis Group, London. 2012.

56. Perera LP, Carvalho JP. Intelligent Ocean Navigation and Fuzzy-Bayesian Decision/Action Formulation, IEEE Journal of Oceanic Engineering. 2012;37(2).

57. Perera LP, Guedes Soares C. Weather Routing and Safe Ship Handling in the Future of Shipping, Center of Marine Technology and Ocean Engineering. Instituto Superior Tecnico, Portugal. 2017.

58. Perera LP, Ferrari V, Santos FP, Hinostroza MA, Guedes Soares C. Experimental Evaluations on Ship Autonomous Navigation & Collision Avoidance by Intelligent Guidance. IEEE Journal of Oceanic Engineering. 2015.

59. Rikard Laxhammar. Anomaly detection for sea surveillance. Saab Systems, Saab AB, Järfälla, Sweden. 2008.

60. Agnieszka Lazarowska. Ship's Trajectory Planning for Collision Avoidance at Sea Based on Ant Colony Optimisation. The journal of navigation. 2015;68:291–307.

61. Gilles Le Chenadec, Quentin Olivau, Benoit Clement Panagiotis Papadakis, Karl Sammut. Incremental Learning for Classication of Objects of Interest. 2019.

62. Maxime Leclerc, Ratnasingham Tharmarasa, Mihai Cristian Florea, Anne Claire Boury Brisset, Thiagalingam Kirubarajan, Nicolas Duclos Hindie. Ship Classification using Deep Learning Techniques for Maritime Target Tracking. 21st International Conference on Information Fusion (FUSION), Cambridge, UK. 2018.

63. Guanghui Li, Atsushi Yamashita Hajime Asama Yusuke Tamura. An Efficient Improved Artificial Potential Field Based Regression Search Method for Robot Path Planning. Proceedings of 2012 IEEE International Conference on Mechatronics and Automation, Chengdu, China. 2012

64. Perera Lokukaluge, Guedes Soares, Carlos. Weather Routing and Safe Ship Handling in the Future of Shipping. Ocean Engineering. 2017.

65. Sheng Long Kao, Kuo Tien Lee, Ki Yin Chang, Min Der Ko A Fuzzy Logic Method for Collision Avoidance in Vessel Traffic Service. The journal of navigation. 2007;60:17–31.

66. Wilmanski M, Kreucher C, Lauer J. Modern approaches in deep learning for SAR ATR. Proc. SPIE 9843. 2016

67. Vespe M, Visentini I, Bryan K, Braca P. Unsupervised learning of maritime traffic patterns for anomaly detection. 9th IET Data Fusion Target Tracking Conference (DF TT 2012). Algorithms Applications. 2012;1 –5.

68. Hinostroza MA, Guedes Soares C. Collision avoidance, guidance and control system for Autonomous Surface Vehicles in complex navigation conditions. Progress in Maritime Technology and Engineering. 2018.

69. Wes McKinney. Python for Data Analysis. O'Reilly Media, Inc. 2013.

70. Sang Min Lee, Kyung Yub Kwon, Joongseon Joh. A Fuzzy Logic for Autonomous Navigation of Marine Vehicles Satisfying COLREG Guidelines, International Journal of Control. Automation, and Systems. 2004;2(2).

71. Petr Mus´ılek, Sa Li, Loren Wyard-Scott. Enhanced Learning Classifier System for Robot Navigation. Enhanced Learning Classifier System for Robot Navigation. 2005.

72. Ødegaard N, Knapskog AO, Cochin C, Louvigne JC. Classification of Ships Using Real and Simulated Data in a Convolutional Neural Network. 2016 13th IEEE International Conference on Advanced Video and Signal Based, Colorado Springs, Colorado. 2016.

73. Ines Obradovic, Krunoslav Zubrinic, Mario Milicevi. "Machine learning approaches to maritime anomaly detection". Article, NASE. 2014.

74. Verbancsics Phillip, Harguess Josh. Feature Learning HyperNEAT: Evolving Neural Networks to Extract Features for Classification of Maritime Satellite Imagery. 2015;9303:208-220.

75. Tiago Pimentel, Marianne Monteiro, Juliano Viana, Adriano Veloso, Nivio Ziviani. A Generalized Active Learning Approach for Unsupervised Anomaly Detection. 2018.

76. Lokukaluge Prasad Perera. Autonomous Ship Navigation Under Deep Learning and The Challenges In COLREGS. Proceedings of the 37th International Conference on Ocean, Offshore and Arctic Engineering, Madrid, Spain. 2018.

77. Song Q, Xu F and Jin YQ. A Deep Convolutional Generative Adversarial Networks (DCGANs)-Based Semi-Supervised Method for Object Recognition in Synthetic Aperture Radar (SAR) Images. Article, Remote Sens. 2018. 2017;10(6).

78. Laxhammar R, Falkman G, Sviestins E. Anomaly detection in sea traffic – a comparison of the Gaussian mixture model and kernel density estimators. 12th International Conference on Information Fusion, Seattle, WA, USA. 2009.

79. Dayal R Parhi, Prases K Mohanty. A study of various methodologies used for navigation of autonomous mobile robot. International Science Press: India. 2012.

80. Fefilatyev S. Detection of marine vehicles in images and video of open sea. Graduate Theses and Dissertations. 2008.

81. Park S, Cho CJ, Ku B, Lee S, Ko H. Simulation and ship detection using surface radial current observing compact HF radar. IEEE Journal of Oceanic Engineering, Korea. 2016.

82. Chen, S. and Wang, H. (2014): SAR target recognition based on deep learning. International Conference on Data Science and Advanced Analytics, Shanghai, China.

83. Huang S, Xu H, Xia X. Active deep belief networks for ship recognition based on BvSB. Optik - International Journal for Light and Electron Optics, Harbin, China. 2016.

84. Wagner SA. SAR ATR by a combination of convolutional neural network and support vector machines. IEEE Transactions on Aerospace and Electronic Systems. 2016;52(6).

85. Guo Sai, Zhang Qi, Shao Yuming, Chen Weidong. Sea Clutter and Target Detection with Deep Neural Networks. DEStech Transactions on Computer Science and Engineering. 2017.

86. David Silver, Andrew Bagnell J, Anthony Stentz. Active Learning from Demonstration for Robust Autonomous Navigation. IEEE International Conference on Robotics and Automation RiverCentre, Saint Paul, Minnesota, USA. 2012.

87. Statheros T, Howells G, Maier KM. Autonomous ship collision avoidance navigation concepts, technologies and techniques. Navig. 2008;61:129–142.

88. Johansen TA, Perez T, Cristofaro A. Ship collision avoidance and COLREGS compliance using simulation-based control behavior selection with predictive hazard assessment. IEEE Transactions on Intelligent Transportation Systems. (In Press). 2016.

89. Chin Teng Lin, George Lee CS. Neural-Network-Based Fuzzy Logic Control and Decision System. IEEE transactions on computers. 1991;40(12).

90. Adem Tuncer, Mehmet Yildirim. Dynamic path planning of mobile robots with improved genetic algorithm. Computers and Electrical Engineering. 2012.

91. Maurits Van Den Boogaard, Andreas Feys, Mike Overbeek, Joan Le Poole, Robert Hekkenberg. Control concepts for navigation of autonomous ships in ports. Proceedings of the 10th Symposium on High-Performance Marine Vehicles (HIPER 2016), Cortona, Italy. 2016.

92. Guo W, Xia X, Wang X. A remote sensing ship recognition method based on dynamic probability generative model, Article, Expert Systems with Applications 41. 2014;14:6446–6458.

93. Guo W, Xia X, Wang X. A remote sensing ship recognition method for entropy-based hierarchical discriminant regression. Optik - International Journal for Light and Electron Optics 126. 2015.

94. Guo W, Xia X, Wang X. Variational approximate inferential probability generative model for ship recognition using remote sensing data. Optik - International Journal for Light and Electron Optics 126. 2015.

95. Jeffrey W Tweedale. An Application of Transfer Learning for Maritime Vision Processing Using Machine Learning, Weapons and Combat Systems Division, Defence Science and Technology Group, Edinburgh, SA 5111, Australia. Intelligent Decision Technologies. 2018;87-97.

96. Sun X, Wang G, Fan Y, Mu D, Qiu B. An Automatic Navigation System for Unmanned Surface Vehicles in Realistic Sea Environments. Appl. Sci. 2018.

97. Li X, Han J, Kim S. Motion-alert: automatic anomaly detection in massive moving objects. Intelligence and Security Informatics. 2006;166-177.

98. Lei Xiaoyun, Zhang Zhian, Dong Peifang. Dynamic Path Planning of Unknown Environment Based on Deep Reinforcement Learning. Journal of Robotics. 2018.

99. Yavin Y, Frangos C, Zilman G, Miloh T. Computation of feasible command strategies for the navigation of a ship in a narrow zigzag channel. Computers Math. Applic. 1995;30(10):79-101.

100. Sato Y, Ishii H. Study of a collision avoidance system for ships. Control Engineering Practice. 1998;6:1141-1149.

101. Jin YQ, Xu F Polarimetric scattering and SAR information retrieval. Wiley-IEEE Press. 2013.

102. Qi Zhang, Yuming Shao, Sai Guo, Lin Sun, Weidong Chen. A Novel Method for Sea Clutter Suppression and Target Detection via Deep Convolutional Autoencoder. International Journal of Signal Processing. 2017.

103. Ruiqian Zhanga, Jian Yaoa, Kao Zhanga, Chen Fenga, Jiadong Zhangb. S-CNN-Based Ship Detection from High-Resolution Remote Sensing Images. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences. 2016.

104. Teng Zhao, Ying Wang. A Neural-Network Based Autonomous Navigation System Using Mobile Robots. 12th International Conference on Control Automation, Robotics & Vision, Guangzhou, China (ICARCV 2012). 2012.