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Intelligent Autonomous Ship Navigation using Multi-Sensor Modalities

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ABSTRACT: This paper explores the use of machine learning and deep learning artificial intelligence (AI) techniques as a means to integrate multiple sensor modalities into a cohesive approach to navigation for autonomous ships. Considered is the case of a fully autonomous ship capable of making decisions and determining actions by itself without active supervision on the part of onboard crew or remote human operators. These techniques, when combined with advanced sensor capabilities, have been touted as a means to overcome existing technical and human limitations as unmanned and autonomous ships become operational presently and in upcoming years. Promises of the extraordinary capabilities of these technologies that may even exceed those of crewmembers for decision making under comparable conditions must be tempered with realistic expectations as to their ultimate technical potential, their use in the maritime domain, vulnerabilities that may preclude their safe operation; and methods for development, integration and test. The results of research performed by the author in specific applications of machine learning and AI to shipping are presented citing key factors that must be achieved for certification of these technologies as being suitable for their intended purpose. Recommendations are made for strategies to surmount present limitations in the development, evaluation and deployment of intelligent maritime systems that may accommodate future technological advances. Lessons learned that may be applied to improve safety of navigation for conventional shipping are also provided.

1 INTRODUCTION

The motivation for autonomous commercial ships stems from a desire to enhance safety, reduce costs and decrease environmental risk associated with shipping operations. Human error is estimated to be responsible for between 76%-94% of marine casualties.[Allianz 2012] Seafarers and human support can account for 30%-44% of ships costs in terms of salaries, crew quarters, bridge space, human interfaces and controls, and environmental systems (heating and air conditioning, food, water, lighting, plumbing, etc.).[Minter 2017, CBI 2018] Maritime shipping is a significant contributor of greenhouse gasses into the environment, accounting for between 2.8%-3.1% of annual emissions.[IMO 2015]

Much can be said about how and when unmanned and autonomous ships may be realized in the future. A classic perception of how a remotely controlled vessel may operate is characterized as follows:

The captain with a giant screen which overlays the environment around his vessel with an augmented reality view can navigate confidently using the computer-enhanced vision of the world, with artificial intelligence spotting and labeling every other water user, the shore, and navigation markers.[Stewart 2018].

Expanding this concept to autonomous ships merely requires replacing the captain with an automaton. While this may be well stated as a goal, such a bold level of self-assurance, confidence and trust in the capability and correctness of sensor and reasoning systems and their proper integration on which the captain must rely should be considered premature as the safe and reliable performance of such systems has yet to be proven. Furthermore, in this scenario there is no consideration of situational awareness below the waterline.

Machine learning and deep learning artificial intelligence (AI) technologies form the core decision making capability to navigate Maritime Autonomous Surface Ships (MASS). The results of research presented focuses on the specific requirements of vessel navigation in terms of the sensors needed to survey the immediate vicinity to achieve situational awareness for tactical decision making in response to immediate threats and conditions. However, also considered is the larger context of Maritime Domain Awareness (MDA) as relates to the successful completion of a voyage by extending shipboard capabilities using external sensors and information resources. The nature and characteristics of sensor data is also considered in terms of the information to be conveyed and limitations of the data taking into account completeness, accuracy and latency.

Having considered the scope of the information that is available, an assessment of the processes, methods and framework used in the development, testing and deployment of decision making products is made. Issues considered include the proper use of machine learning and deep learning AI, verification of implementation as being correct and suitable for their intended purpose, and ultimately to determine whether their scope is sufficient to ensure safety of navigation. Key factors influencing the probabilities of achieving the goals of enhanced safety, reduced costs and decreased environmental risk are discussed based upon the results of experiments performed.

Conclusions are provided regarding critical gaps in sensor coverage and capabilities as well as shortfalls in MASS-enabling technologies that are presently not considered by industry, regulatory authorities and academia. Recommendations are also given to address these deficiencies to help advance MASS goals and objectives.

2 REGULATORY ISSUES

For many decades the International Regulations for Preventing Collisions at Sea (COLREGS) have required that "every vessel shall at all times maintain a proper look-out by sight and hearing as well as by all available means appropriate in the prevailing circumstances and conditions so as to make a full appraisal of the situation and the risk of collision." [COLREGS rule 5]. Vessels are further required to make proper use of radar equipment to obtain early warning of risk of collision, to use radar plotting or equivalent systematic observation of detected objects; and are warned that assumptions shall not be made on the basis of scanty information.[COLREGS rule 7b,c] Such regulations were written for vessels staffed by seafarers who rely on their human senses and interpretation of environmental conditions, navigation charts and instruments based upon knowledge and experience to execute a safe voyage. The present regulatory framework is limited to human vision and hearing, echosounder, radar, Automatic Radar Plotting Aid (ARPA), Automated Identification System (AIS), Electronic Chart Display Information System (ECDIS) and Global Satellite Navigation System (GNSS) to fulfill these requirements. However, these technologies fall far short of ensuring safety of navigation by remotely controlled or autonomous vessels. The International Maritime Organization (IMO) is now conducting a regulatory scoping exercise to amend the regulatory framework to enable the safe, secure and environmentally friendly operation of partly or entirely unmanned MASS and their interaction and co-existence with manned ships within the existing IMO instruments.[MSC 98/20/2] In view of these present international regulations MASS research and development is currently limited to within national waters and between adjacent countries.

3 ENVIRONMENTAL SENSING

Sensor systems dedicated to monitoring the surface ship maritime environment, illustrated in Figure 1, are available from three perspectives: the water's surface, below sea level and from space. Surface and subsea systems generally provide real time ship-centric, line of sight data and imagery while space-based systems provide access to data, information and imagery available worldwide from a wide variety of sources external to the vessel.

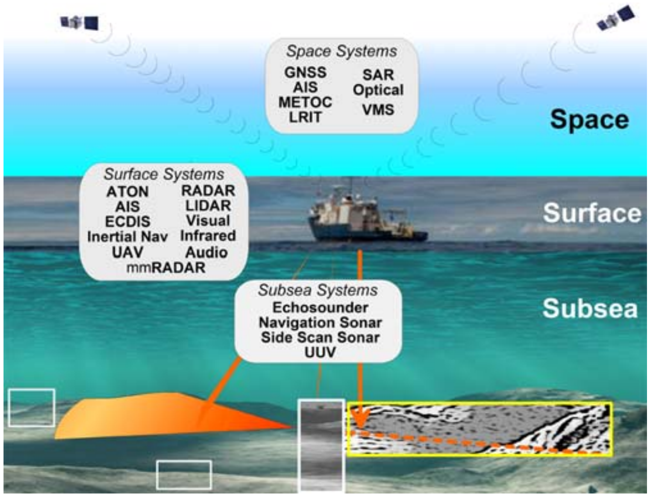

Figure 1. Maritime Environment Sensor System Perspectives.

The scope of sensors needed to safely navigate MASS along long stretches of relatively low traffic, deep ocean routes does not differ much from navigation in shallow, coastal waters amongst archipelagos crowded with both working and recreational vessels. More significant is the ability to properly integrate multiple sensor modalities with reasoning about vast amounts of data and imagery to create the information needed to make and explain observations, critically assess their significance regarding potential threats, vessel capability and performance; and to react to these observations to minimize risk, ensure the voyage is completed safely, recover from dangerous situations and, in the event recovery is not possible, to effectively preserve life, property and the environment. The scope of maritime sensors (beyond presently mandated equipment) available from all perspectives and the fusion of sensor data and imagery to create information for use by automated reasoning processes on board vessels and land-based operators are described in this paragraph. The methods and techniques used to analyze this information and take all appropriate action is covered in paragraph 4.

3.1 *Shipboard Sensors*

Sensor capabilities needed on board both remotely controlled and autonomous ships must not merely replicate the sight and hearing of seafarers, but must exceed their abilities by enabling constant vision through 360° around the vessel in four dimensions (x,y,z,time) at higher resolution and greater accuracy than is humanly possible. This includes the ability to see in the dark in all weather conditions including heavy rain, snow and through fog over the water's surface and to hear sounds associated with ships, aids to navigation (ATON) and in the environment such as sound signals and waves crashing on rocks. Also needed is the ability to see underwater ahead and around the vessel to detect and respond to threats not charted and to avoid groundings and allision. MASS must then reason with this information over extended periods of time in a manner that is consistent, correct and verifiable.

Shipboard sensors required under IMO vessel carriage requirements include human sight and hearing, often augmented with binoculars and hailer listening capabilities. This is supplemented with radar to help detect and avoid other vessels, ATON and land masses. An echosounder is also needed to maintain constant vigilance of water depth below the keel. ECDIS displays electronic navigation chart (ENC) information that should represent the most recent hydrographic surveys of the areas sailed, the locations of channels and ATON, and known hazards to navigation likely to be encountered along the route. AIS provides a wealth of information on nearby vessels related to position, speed and identity, and routing. GNSS provides context for all of the above information in terms of vessel geographic position, speed and direction of transit.

These required sensors perform very well in extending the sight of seafarers at sea to accomplish traditional navigation functions. However, the IMO regulatory framework has failed to keep up with new technologies that can also enhance safety of navigation for conventional ships. With the advent of remotely controlled and MASS, new sensor capabilities are now being considered that hopefully may be applied to both staffed and autonomous ships. Several of these technologies extend the functionality of existing systems by providing new features, while others provide entirely new abilities that have not been possible in the past. Further, the integration of shipboard sensor data with external data and information resources available from space-based sensors and broadband communication channels provide the fundamental building blocks for cooperative decision making between vessels and shoreside operators, and locally between vessels using a wide area network (WAN) that is established amongst the vessels themselves.

Many such technologies are illustrated in Table 1. A discussion of their characteristics, the types of data they can produce and their application to enhance vessel situational awareness is provided in the paragraphs that follow.

3.1.1 *Surface Sensors*

Augmentation of present IMO-mandated vessel environmental sensor systems with further capability is essential to achieve situational awareness for MASS and to ensure proper supervision and traceability of decision making. These sensor systems can expand upon existing capabilities as well as provide new capabilities not presently available which, through the fusion of diverse data sources, can provide unprecedented levels of vessel situational awareness. Examples of shipboard surface sensing systems that can provide new and redundant precision navigation, timing, vision and acoustic capabilities include:

- Inertial Navigation Systems (INS)
- Laser Imaging (LiDAR)
- Millimeter Radar (mmRADAR)
- Video and Infrared (IR) Cameras, and
- Microphones.

Supplemental capability at and above sea level can be achieved using Unmanned Aerial Vehicles (UAVs) equipped with similar sensors to extend the vessel's vision. A basic complement of weather instruments integrated into the overall vessel sensor fusion architecture can provide real time data on wind speed and direction, temperature, barometric pressure, humidity and sea temperature that is vital for onboard reasoning capabilities to detect and compensate for the effects of wind, currents and other phenomena on MASS throughout the voyage.

Specific attention is given to ATON such as landmarks, buoys and other devices or systems external to vessels designed and operated to enhance the safe and efficient navigation of vessels and/or vessel traffic.[IALA 2014] Vision sensors on board an autonomous vessel must be capable of imaging ATON with sufficient resolution to detect their characteristics, make a positive identification and determine their position through the use of GNSS and ECDIS. Visual sensors may be supplemented with radar and forward looking navigation sonar to confirm ATON positioning on ECDIS with real time observations. ATON transmitted using AIS (AIS-ATON) may be co-located with physical ATON and viewable on AIS receivers on board the vessel provide another means for determining position. Virtual ATON (VATON) that require no physical infrastructure can also aid in determining position through coordinated use with GNSS, ECDIS and the vessel echosounder used to provide navigation through contour tracking along the seabed.[Wright and Baldauf, 2016] VATON may be placed at locations where physical and AIS-ATON are not possible due to harsh environmental conditions and/or remote location. Note that both AIS-ATON and VATON also adhere to the IALA definition in that they are external to the vessel. However, unlike physical ATON reliance upon the visible spectrum, AIS-ATON and VATON rely upon radio and sonar signals external to the vessel that are present in the electromagnetic spectrum.

3.1.2 *Subsea Sensors*

Seafarers develop skills and techniques over years of experience to assess changes to the environment which can indicate hazardous sea states and bottom conditions that compromise safety of navigation. Visual clues include changes in sea color during an approach towards a shoal, water temperature change, and breaking waves or areas of calm amongst rough seas without obvious cause. Without anything more than an echosounder to provide direct information of the depth of water directly blow the keel, seafarers today are expected to operate using second hand information of the depths, hazards and obstructions along their routes of transit provided by navigation charts that may contain obsolete survey data that is years, decades or even centuries old.

Remote and autonomous vessel operations must compensate for lack of human knowledge and expertise as well as deficient charts by providing sensor capabilities to directly assess bottom configurations and conditions in real time. Examples of shipboard subsurface sensing systems to provide new and redundant precision navigation and vision capabilities include echosounders and sidescan sonar, either separately or integrated together in one unit, to provide terrain tracking capabilities and high resolution imaging of seabed landmarks to aid in navigation.[Wright and Baldauf, 2016a] Navigation sonar with forward looking capabilities can provide high-resolution bathymetry that may be compared to electronic navigation charts (ENCs) displayed on ECDIS for backup navigation, detection of hazards to navigation and obstacles, and avoidance of large marine mammals.[Wright and Russell. 2017] These data are also sufficient to crowdsource bathymetry for navigation chart development.[FarSounder 2018] Also, much like UAVs, the use of Unmanned Underwater Vehicles (UUVs) can extend MASS vision ahead of and in the local vicinity of the vessel below the waterline.

3.2 *Space-based Sensors*

As of 2018 there were approximately 4,600 satellites in Earth orbit, of which nearly 2,000 were operational.[UNOOSA 2018] One report shows the growth in satellite launches increasing three-fold over the next decade with 3,323 satellites with a mass over 50 kg. launched and to be launched between 2018-2027, compared to 1,019 satellites that were launched between 2008-2017.[Satnews 2019] Many of these satellites, when supplemented with terrestrial signals, can provide precise positioning and timing information with up to 1cm accuracy as part of the GNSS. Many other satellites are used in maritime operations to gather meteorological and oceanographic (METOC) and terrestrial imaging. However, much of the increase in satellite launches represent a new generation of small satellites sent to low earth orbit to create constellations of thousands that will provide ubiquitous global broadband access. This trend has already been noted with the announcement by Inmarsat that their worldwide Fleet Xpress service launched in March 2016 had by early 2017 passed the 10,000 ship milestone.[gCaptain 2017]

Table 1. Sensor Types and Data Classes amongst Maritime Surface, Subsea and Space Systems.

	Sensor Type	Data Class	Data Domain			Data Content				
Surface Systems (Shipboard)			Pixel	Time A	Freq. A	Unique ID	Position	Ground Track	Speed	Other
Aids to Navigation (ATON) - Physical	Receiver	Imagery	YES	NO	NO	YES	YES	NO	NO	light/sound
Aids to Navigation (AIS) - AIS	Receiver	Data	NO	YES	NO	YES	YES	NO	NO	
Aids to Navigation (VATON) - Virtual B,C	Data Object	Data	NO	NO	NO	YES	YES	NO	NO	
Automated Identification System (AIS)	Transceiver	Data/Imagery	YES	YES	NO	YES	YES	YES	YES	much data
Electronic Chart Display Info System (ECDIS)	Data Object	Data	YES	YES	YES	NO	YES	YES	NO	much data
Inertial Navigation C	Instrument	Data	NO	YES	YES	NO	YES	YES	YES	
Laser Imaging (LIDAR) C	Instrument	Imagery	YES	YES	NO	NO	YES	YES	YES	
Marine Radar (X/S band) with ARPA	Transceiver	Imagery/Signal	YES	YES	YES	YES	YES	YES	YES	
millimeter Radar C	Transceiver	Imagery/Signal	YES	YES	YES	NO	YES	NO	YES	
Visual (video) C	Receiver	Imagery	YES	YES	YES	Indirect	YES	Indirect	Indirect	much data
Infrared (IR) C	Receiver	Imagery	YES	YES	NO	Indirect	YES	Indirect	Indirect	much data
Audio (sound)	Receiver	Signal	NO	YES	YES	Indirect	YES	Indirect	Indirect	
Unmanned Aerial Vehicle (AUV) C	Receiver	Imagery	YES	YES	YES	Indirect	YES	Indirect	Indirect	much data
Subsea Systems (Shipboard)										
Echosounder	Transceiver	Imagery/Signal	Some	YES	YES	NO	YES	YES	NO	bottom
Navigation Sonar C	Transceiver	Imagery/Signal	YES	YES	YES	Indirect	YES	Indirect	Indirect	bathymetry
Side Scan Sonar C	Transceiver	Imagery/Signal	YES	YES	YES	Indirect	YES	Indirect	Indirect	water column
Unmanned Underwater Vehicle (UUV) C	Receiver	Imagery	YES	YES	YES	Indirect	YES	Indirect	Indirect	much data
Space Systems (Remote)										
Automatic Identification System (AIS) C	Receiver	Data/Imagery	YES	YES	NO	YES	YES	YES	YES	much data
Global Navigation Satellite System (GNSS)	Receiver	Data	YES	YES	YES	n/a	YES	YES	YES	much data
Meteorological and Ocenographic (METOC)	Receiver	Data/Imagery	YES	NO	NO	n/a	indirect	NO	NO	
Optical Imaging C (non-METOC)	Receiver	Imagery	YES	NO	NO	n/a	indirect	NO	NO	
Synthetic Aperature Radar (SAR) C	Receiver	Imagery	YES	NO	NO	n/a	indirect	NO	NO	

Notes: A. Time and Frequency domain data to supplement imagery. B. Experimental technology not yet in use. C. Not included in current IMO carriage requirements.

Broadband satellite connectivity is essential for communications to aid in the monitoring of MASS operations, the sharing of large volumes of sensor imagery, data and results of onboard decision making processes; and to help the implementation of blockchain technology and big data applications to ensure safe and secure operations. This includes space-based sensing of AIS, METOC imagery and numerical datasets, and other sensors including Synthetic Aperture Radar to aid in non-cooperative surface feature and object detection; and Long Range Identification and Tracking data for vessels.

3.3 *Sensor Data Types and Characteristics*

Three classes of data are available from maritime sensors comprising the *pixel*, *time* and *frequency* domains which represent different perspectives of the environment.[Wright 2018] The *pixel* domain reflects a translation of a spatial quantity into a pixel representation. This occurs by capturing an image of a scene or object directly onto picture elements, or pixels, each of which contains an impression of the qualities of a small portion of the overall image. The original scene or object is reconstructed by means of reproducing the pixel impressions onto a display. This is the case for digital and infrared cameras and other visual sensors. Changes in imagery that occur as a function of time are reflected in the *time* domain. Different mathematical and statistical functions can be applied to pixel and time domain representations to extract data and correlate information regarding image content. Direct to pixel domain imagery is limited based upon the size and resolution of the sensor and can be enhanced using optical magnification and greater numbers of smaller pixels, as well as through the use of image filtering and software analytics.

Radar, sonar and LiDAR images are created using an entirely different process involving one or more transducers (antennas) that transmit and/or receive signals. These signals are subsequently converted into different domain representations. An example for radar is provided in Figure 2 where received waveforms are analyzed in the frequency and time domains (b,c) and processed to create a pixel domain representation (a).

Highly complex waveforms across many frequencies are projected onto a scene which are then modified through reflection and absorption based upon the physical and electrical characteristics of the objects within the scene. A portion of the transmitted signals are reflected back to and received by the transducer which are analyzed as a function of changes that occur over time as well as changes detected in the frequency of the signal. Analysis of time and frequency domain signals is performed to acquire the information necessary to subsequently create a pixel domain image for display in the manners customary to radar, sonar and LiDAR.

While this indirect approach has proven to be highly accurate and reliable, it can result in a great deal of variability in how the targets and scene are displayed to the user based upon signal resolution and manufacturer user interface design preferences. A target may be represented as a "blip" on a radar screen and navigation sonar can paint a 3D surface model of bottom terrain, while LiDAR systems can display a highly accurate model of the terrain and quayside environment.

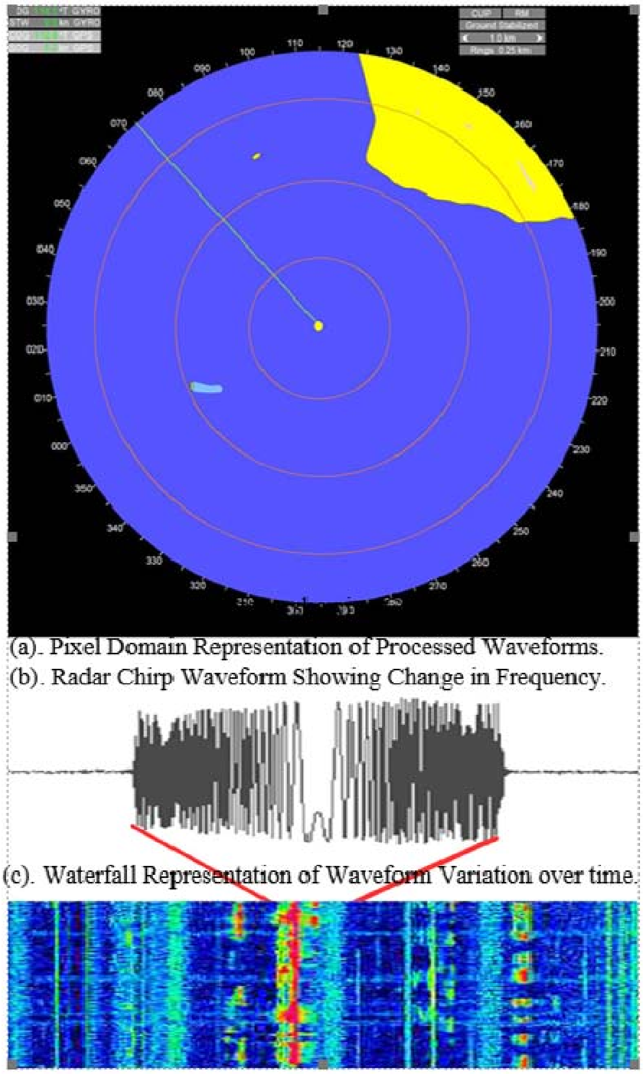

Figure 2. Chirp Waveform Variation over Time, with Resulting Pixel Domain Representation of the Local Environment.

Unlike imaging sensors, information contained within the received signal in the time and frequency domains are used to create the resulting pixel domain image based upon the properties of the waveforms being transmitted, the gain and resolution of the transducer elements, the sensitivity of the receiver and the capabilities of the software to analyze the reflected signals. The ability to actively interrogate targets using a wide range of waveforms provides greater flexibility to analyze their reflected signal properties across all data classes. Dynamic adjustment of waveform signal characteristics in real time based upon target properties and greater capabilities in analyzing time and frequency domain datasets continue to result in the retrieval of much greater information content than was previously possible. Recent examples in the case of sonar data include the acquisition of swath bathymetry from navigation sonar and other scientific data from high resolution side scan sonar imagery.[FarSounder 2018, Wright 2017]. Similar advances have also occurred in other maritime applications that include improvements in solid state Doppler radars.

4 EXPERIMENT PARAMETERS

Experiments performed using a combination of machine learning and deep learning AI techniques resulted in the acquisition, assessment and characterization of pixel, time and frequency domain representations of several different types of sensor data to enhance situational awareness for MASS operations. Specific examples illustrate the detection, identification and correlation of other ship and small vessel traffic and ATON to support safe navigation along a well surveyed route according to modern standards of navigation. Efforts included the fusion of shipboard sensor data with information contained within navigation charts, local notices to mariners, tide and currents, and other information applicable to the voyages. The scope of experiments performed as part of continuing research was limited to a subset of the complete vessel sensor suite needed to develop, refine and evaluate shipboard data acquisition methods, data analytics and resulting information processes for autonomous navigation in preparation for future full scale implementation on a research vessel test bed.

4.1 *Experimental Setting and Conditions*

The location of these experiments is in the Mid-Atlantic region on the east coast of the United States within the Chesapeake Bay and its tributaries near Annapolis, Maryland. This area is frequented by cargo, freighter, passenger ship, special craft and other large vessels in transit to and from the Atlantic Ocean and the Port of Baltimore. There are also many small recreational vessels present in the area, especially during the summer months.

The transit route is approximately 11 nm long beginning between buoys 87 and 88 on the eastern side of Chesapeake Bay 1 nm off of Kent Island, proceeding westward with Tolly Point Shoal (buoy 1AH) to starboard and the Naval Anchorage to port (buoy 2), then northwest up the Severn River past the city of Annapolis and the U.S. Naval Academy to a point ½ nm to the east of St. Helena Island in Little Round Bay.[NOAA 12282] This route ranges in depth from 31 meters in the east to 5 meters in the west, with an average depth of 8 meters along the final 9 nm of the route. Along the route are 26 buoys and fixed ATON, two bridges and several prominent landmarks in terms of buildings, domes and natural features that serve as ATON.

4.2 *Vessel and Sensor Configurations*

Participating in these experiments serving as a test bed for sensor integration and fusion is a 10-meter research vessel with 1-meter draft equipped with the following sensors:

- Furuno GP-37 WAAS/DGPS receiver,
- Furuno 1954C 4ft. 48 rpm radar with ARPA,
- Furuno GD-1920C color video plotter,
- ICOM MA-500T class B AIS,
- EchoPilot 3D forward looking sonar,
- Lowrance HDS5 echosounder/fish finder,
- FLIR MD-625 thermal imaging camera, and
- Hikivision 8MP ultra low light imaging camera.

Data communications are accomplished under the NMEA 0183 data bus architecture with direct image capture to video data recorder, all under the control of a Dell Inspiron quad core laptop, 2.3 GHz with NVidia GT 650M GPU, 8GB RAM, 1TB hard drive.

4.3 *Reasoning Systems*

A combination of machine learning and AI techniques were used to acquire, assess and characterize pixel domain imagery of vessels and ATON including buoys, bridges and prominent landmarks. Directed learning focusing on feature detection and classification was used to train a neural network to recognize various types of vessels and ATON. Optical character recognition (OCR) was used to positively identify individual buoys and fixed marks from video and infrared imagery with a 60 degree field of view that may be zoomed to 17 degrees for precise identification. Radar waveforms were analyzed using deep learning AI to help discern information beyond that available in the pixel domain radar image. This included analyzing changes in frequency, amplitude, phase and/or polarization. Lacking a direct interface to the radar system, many of these waveforms were simulated in the performance of this experiment. Imagery representative of basic signals and their many possible variations along with metadata obtained from other sensors were used in training neural networks to distinguish between targets.

Essential to the analysis of various images and signals is the creation of large datasets that are representative of potential objects and waveforms. These datasets consist of two parts, a *comprehensive* dataset and a *limited* dataset, with the former being a subset of the latter. The comprehensive dataset is shared for use in supervised learning in the development and refinement of statistical processes and for unsupervised learning in the development of neural network processes. It includes complete numerical data providing imagery and description of imagery components encompassing scale, range, units and other factors. The limited dataset contains only objects and waveforms and is used for unsupervised learning during neural network development. This training dataset consists of thousands of representative objects and signal waveforms of various resolutions, frequencies, bandwidths, sample rates and complexity.

5 EXPERIMENT RESULTS

Our initial neural network configuration consisted of the ResNet-50 architecture with which we achieved ATON object and signal identification rates of between 93.22% and 97.55% accuracy rates. Subsequent use of a Convolutional Neural Network (CNN) resulted in enhanced results ranging from 98.34% to 99.97% accuracy. Further improvements were achieved through adjustments to existing CNN layers and adding new layers tailored specifically to features and attributes associated with vessels and ATON. Adjustments of learning rates, weight factors and other CNN characteristics also improved training speed and accuracy. The primary CNN architecture for the pixel domain was an AlexNet design consisting of 27 different layers tailored to and adjusted for object recognition. The primary CNN architecture for the time and frequency domains was an AlexNet design consisting of 29 different layers tailored to and adjusted for signal recognition in the time and frequency domains.

All ATON along the route were detected and identified by the CNN as being of the appropriate type (nun, can, fixed mark, dome, building, etc.) and having proper characteristics (red, green, numbers, letters, etc.). ATON position correlation was made using visual imagery, electronic navigation chart and radar target display for all ATON within visual range, and within sonar range using forward looking navigation sonar as an additional sensor. Positive identification of specific buoy or aid number occurred for 18 of the 27 occurrences; and for two bridges, one dome and three buildings. Positive identification occurred for three vessels and one AIS-ATON, with correct position correlation made using radar. Radar waveform variations correspond to vessel sizes and configurations were observed, along with ARPA correlation of heading and speed vectors.

Route selection by best waters considering vessel draft and route directness was confirmed by forward looking navigation sonar bottom topography, with temporary deviation from planned course necessary for vessel avoidance on three occasions. Variation of live echosounder depth measurements over the tracked course was within expectations,[Wright and Baldauf. 2016a] with notable shoaling evident on the navigation sonar near two bars.

6 DISCUSSION

CNN performance in ATON, landmark and vessel detection and identification was demonstrated in combination with radar and AIS target correlation and echosounder bottom terrain tracking over a transit route with complex features including large and small vessel traffic and land masses. Forward looking navigation sonar provided ATON position verification when they were within its effective range of 45 to 200 meters, which changes depending upon water depth. All ATON appear to be in their assigned positions considering variation within their proper watch circle due to the effect of wind and tides.

OCR was found to be an effective method for positive ATON identification during daylight hours and during nighttime with video, low-light and IR sensing when buoy designations were within camera field of view and not obscured by other vessels, heavy rain and other factors. Positive identification was reinforced through consistency within multiple hundreds of video frames. The primary factor in the failure of this method was in cases where the buoy identification was oriented away from the camera and not viewable due to buoy rotation.

The combination of video, IR, radar and ARPA, and navigation sonar sensing, in decreasing levels of resolution, provided nearly 100% detection of marine targets relevant to the vessel's route of transit and in determining vessel speed adjustments and alternate routes for collision avoidance. Significant exceptions occurred in cases of small vessels and watercraft demonstrating erratic behavior along with unpredictable changes in course and speed. ENC and navigation sonar provided below the waterline awareness of expected and actual environmental conditions to aid in alternate route determination.

7 CONCLUSIONS

The use of CNN for visual ATON, landmark and vessel detection and identification, when combined with radar target correlation and navigation sonar/ echosounder bottom terrain tracking, appeared sufficient for safe and reliable navigation under limited experimental conditions. Consideration should be given to ATON design enhancements that may better facilitate machine recognition of their characteristics and positive identification of individual buoys. A combination of multi-sensing modalities to achieve comprehensive situational awareness both above and below the waterline appeared to be effective in real-time alternative course planning, especially in the case of shoaling conditions not evidenced on the ENC.

The use of multiple redundant sensor system to overcome the limitations and vulnerabilities of individual sensor systems were evaluated in simulations performed using data recorded during the experiment. Use of a single beam echosounder for bottom terrain tracking provided effective to overcome loss of GNSS capability, but was limited to the resolution and placement of the soundings in the ENC. High-resolution bathymetry contained within ENC acquired using multibeam echosounders and/or navigation sonar has already been shown to be an effective remedy to this problem.[Wright and Baldauf. 2016b]

The results of this experiment were achieved with sensors having limited field of view. Significant improvements in safety and reliability can be achieved through 360 degree detection of ATON and potential hazards and threats, augmented with identification using high resolution video and IR sensing that may be directed at specific objects and features of interest.

A significant limitation of this experiment was the lack of direct availability of radar and sonar sensor signal data in the time and frequency domains. Future experiments will further explore the direct acquisition, analysis and use of these data in combination with other sensor modalities. This will include integrating sensor modalities to aid in object and threat detection with immediate route planning and maneuvering to avoid such occurrences.

Another limitation is in the bandwidth of existing NMEA data bus architectures to support very large numbers of sensors in terms of both data and imagery. This may be remedied in part by the proposed International Marine Electronics Association (IMEA) OneNet open standard based on Internet Version IPv6 and the IEEE 802.3 Ethernet Local Area Network. The results of a Radar Working Group within OneNet developing radar messages on the network will be of keen interest in determining its potential in this regard.

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REFERENCES

Allianz 2012. Safety and Shipping 1912-2012: From Titanic to Costs Concordia. Allianz Global Corporate & Specialty. March 2012. 3. www/agcs/allianz.com/PDFs/Reports.

CBI 2018. Digitizing the First Mile: Technology and Shipping. CBInsights. 2018. http://support.citrixonline.com/en_US/ Webinar

COLREGS Rule 5. International Regulations for Preventing Collisions at Sea. 1972. Rule 5 Look-out.

COLREGS Rule 7. Ibid. Rule 7 Risk of collision, (b) and (c).

FarSounder 2018. FarSounder Joins NOAA as a Trusted Node. Press Release. October 17, 2018. www/farsounder.com/ about/press_releases.

gCaptain 2017. Connected at Sea: Inmarsat's New High-Speed Broadband Service Hits 10,000-Ship Milestone. May 4, 2017, http://gcaptain.com/fleet-xpress-exceeds-10000-ship-milestone-first-anniversary/

IALA 2014. IALA International Dictionary of Aids to Marine Navigation, cited in IALA NAVGUIDE Aids to Navigation Manual. 2014. Seventh Edition. 30.

IMO 2015. Third International Maritime Organization Greenhouse Gas Study. Section 3: Scenarios for shipping emissions 2012-2050. 18.

Minter 2017. Adam Minter. Autonomous Ships Will Be Great. Bloomberg. May 16, 2017. https://wwwbloomberg.com/ opinion/articles/2017-05-16/autonomous-ships-will-be-great.

MSC 98/20/2. Work Programme. Maritime Autonomous Surface Ships Proposal for a Regulatory Scoping Exercise. Regulatory Scoping Exercise for the Use of Maritime Autonomous Surface Ships (MASS). MSC 98/20/2. 27 February 2017.

NOAA 12282. Chesapeake Bay, Severn and Magothy Rivers. NOAA Chart 12282.

Satnews 2018. Euroconsult Report Focuses on Satellites to be Built and Launched by 2027. Satnews Daily. January 26, 2019. http://satnews.com/story.php?number=2091711277

Stewart 2018. Stewart, J. paraphrase, Rolls Royce wants to Fill the Seas with Self-Sailing Ships. Wired. 15 October 2018. https://www.wired.com/story/rolls-royce-autonomous-ship/.

UNOOSA 2018. Annual Report 2017. United Nations Office for Outer Space Affairs. Vienna. March 2018. 5.

Wright 2017. Scientific Data Acquisition using Navigation Sonar. IEEE/MTS Oceans Conf. Anchorage AK. Sept. 2017.

Wright 2018. Signals Intelligence Automated Assessment of Test Capabilities. IEEE Automatic Testing Conference. Washington, DC. September 2018.

Wright and Baldauf, 2016. Wright, R. Glenn and Baldauf, Michael. Virtual Electronic Aids to Navigation for Remote and Ecologically Sensitive Regions. The Journal of Navigation. The Royal Institute of Navigation 2016. doi:10.1017/ S0373463316000527.

Wright and Baldauf. 2016a. Wright, R. Glenn and Baldauf, Michael. Correlation of Virtual Aids to Navigation to the Physical Environment. TransNav, the International Journal on Marine Navigation and Safety of Sea Transportation. Vol. 10, No. 2, 2016.

Wright and Baldauf. 2016b. Wright, R. Glenn and Baldauf, Michael. *Hydrographic Survey in Remote Regions: Using Vessels of Opportunity Equipped with 3-dimensional Forward-Looking Sonar*. Journal of Marine Geodesy. Vol. 39. No. 6. DOI 10.1080/01490419. 2016.1245266. 339-357.

Wright and Russell. 2017. Wright R. Glenn and Ian Russell. *Navigation Sonar use in Maritime Frontier Exploration*. Soundings. Hydrograph. Soc. of the UK. Sum. 2017. 33-36.