Navigational Intelligence at River: A Laser-Based Imaging Approach for Nocturnal Vessel Detection

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Declaration

It is hereby declared that

1. The thesis submitted is our original work while completing a degree at Brac University.

2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.

3. The thesis does not contain material that has been accepted, or submitted, for any other degree or diploma at a university or other institution.

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Ethics Statement

This note is a disclaimer to indicate that the research paper in question has not violated the preservation of human rights, welfare, or dignity. The honesty and integrity of the research participants are incorporated into the work, which also includes highlighted citations from various reliable sources. No discrimination or disparity has been made in the data collection, and the results have not been manipulated for any prejudiced reasons. Rest assured, we hope our work reflects our respect for all intellectual property and is useful for the long-term welfare of humanity.

Abstract

In this 21st century, maritime routes are crucial for geographical and financial reasons in riverine countries which include passenger traveling, cargo vessels, fishing, etc., and play an equally imperative role in the economy. To fulfill all the maritime-based needs, current developing countries in the world do not have proper surveillance and monitoring systems in the local water vessels to tackle any possible disaster such as vessel collision. Despite being involved in trading through the maritime silk roads from 500 BC, the navigation system remains rudimentary in these developing countries and one of the worst outcomes of this architecture is regular death by launch accidents. Considering this paramount issue, we attempted to develop a secure, optimized, and effective system to make river traveling safe and secure, and in this paper, our focus was on Bangladesh's inland waterway transportation, particularly at night. We proposed a system with the help of laser technology that tracks both the host ship and its surrounding vessels and provides real-time tracking position. Cameras such as CCTV or IP-based ones will be used to monitor the face vessel's movement in real-time application. The diameter of the laser beam sphere was the primary source of data to work on for our proposed model, which was later annotated using image processing. The control room will be monitoring data continuously and since it is an AIS, the data will be updated automatically after the system is implemented on a vessel. This proposal was presented through modeling and simulations based on laser detection and identification.

Keywords: Laser, Vessel, Collision, Image Processing, Simulation.

Dedication

This thesis work has been dedicated to those who perished in the unforgiving embrace of the river. We devote our work to the lives lost in tragic launch collision accidents. May their souls find eternal peace, and may their memory serve as a poignant reminder of the fragility of life on the vast and unpredictable waters.
Also, we dedicate our work to all students of science who often fall into dilemma wondering how they can contribute back into society and make a few lives easier in this world. As the depths of these water bodies remind us how vast and deep the world is around, a student can similarly flow past and reach up to their greatest potential and into the depths of science by solely believing in oneself and maintaining perseverance at times of predicaments.

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Nomenclature

AIS Automatic Identification System

ALC Automatic Location Communicators

BJT Bipolar Junction Transistor

CR Code Rate

DBSCAN Density Based Spatial Clustering of Applications with Noise

DHC Destination Handling Charge

DNN Deep Neural Network

DP Douglas Peucker algorithm

DSC Digital Selective Calling

FEC Forward Error Correction

FOV Field Of View

GAN Generative Adversarial Network

GIS Geographic Information System

GPRS General Packet Radio Service

GPS Global Positioning System

GRU Gated Recurrent Units

GSM Global System for Mobile communication

HADOOP High Availability Distributed Object Oriented Platform

IoT Internet of Things

IVSS Intelligent Vessel Scheduling System

KML Keyhole Markup Language

LDR Light Dependent Resistor

LED Light Emitting Diode

LIDAR Light Detection and Ranging

LoRa Long Range

LPWAN Low Power Wide Area Network

LSTM Long Short Term Memory

LSVM Least Squares Support Vector Machine

ML Machine Learning

MMSI Maritime Mobile Service Identities

MQTT Message Queuing Telemetry Transport

OSI Optical Satellite Imaging

R-CNN Region-based Convolutional Neural Networks

RADAR Radio Detection and Ranging

RFID Radio Frequency Identification

RIS River Information Service

RMSE Root Mean Square Error

SAR Synthetic Aperture Radar

SMS Short Message Service

SSD Single Shot multi-box Detector

SVM Support Vector Machine

TCP Transmission Control Protocol

UART Universal Asynchronous Receiver-Transmitter

USV Unmanned Surface Vehicle

VDES VHF Data Exchange System

VHF Very High Frequency

VTS Vessel Traffic Services

WiFi Wireless Fidelity

WSN Wireless Sensor Network

YoLov3 You only Look once version 3

1 Introduction

1.1 Motivation and Problem Statement

Bangladesh is considered a riverine country and around 700 [26] rivers flow through it. The most traffic-congested river is the 'Buriganga' which resides at the 'Sadarghat' departure terminal and hence was the center of study in this paper, more specifically inland waterway accidents. Around 300 passenger vessels service every day at this terminal [26] mainly towards the Southern parts of Bangladesh, consisting of Barisal division (majorly), Patuakhali, Chandpur, etc. The reason supporting this claim is the geographical positioning of these regions, which can only be accessed by water and hence are always heavily crowded by passenger vessels. The launch accidents have increased in recent years where the highest number of accidents had ascended to over 35 cases in a single year, 2019. Overall, these waterway calamities have increased by 7.5%, and consequently, so has the death count as it has risen by 23.2% over the years. Approximately 21000 people have gone down to watery graves and hundreds of Bangladeshis are missing, as stated by Mia et al [26]. Previously, these launch accidents had declined due to the precautious disposition of BIWTA (Bangladesh Inland Water Transport Authority), however, a sudden uprising had put the management into a dilemma. The main cause is discovered to be collisions and covers over 60.3% of all the cases, proving how severe yet avoidable this is.

Figure 1.1: 32 people dead from boat capsizing [40]

Collisions simply cannot be blamed on poor lighting and speed control as there have been numerous cases where unhealthy competition between vessel masters has been observed and where a poor culture of overtaking exists, even in the waterway. This leads to eminent collisions and the loss of hundreds of lives. Mia et al. [25] take notes on specific hours of accidents and it was midnight, more appropriately from 11 pm-1 am, when most accidents took place. This may infer poor environmental measures taken up by these vessels at night which portrays the absence of basic infrastructural systems within these vessels. Mia et al. [25] insinuate further small yet crucial lacking in the system by pointing out how there are no water markings in the routes which usually helps in navigation. Weather can act as an enemy at times of excessive waves and cyclones, leading to more capsizing of the vessels and this has been mentioned as how the weather forecasting system in Bangladesh is alarmingly subpar.

The second major reason was overcrowding during the festivities, which stands out as a persistent problem. Vessel owners, greedy for more profits, allow the masters to take on as many passengers as can fit in every corner of the vessel and then set on their journey. In addition, Mia et al. [26] identify unregistered vessels that are solely privatized and are under no educated supervision. Passengers traveling by these vessels are at extreme risk in this manner. Such illegal acts have led to the presence of an insufficient accident database which makes it difficult to study accidents in depth whenever such mishaps take place. More causes of accidents include stability failure which covers 3.91% of all accidents and next in line is grounding, which covers 7.81%. Stability failure can be linked back to weather conditions and hence it shows how one reason, in particular, cannot be colored as the whole management system is questionable and poorly conducted.

Figure 1.2: Collision between cargo ship and ferry [24]

Followingly, the objective of the paper by BSMRMU [36], is to investigate the safety condition of launch operations in Bangladesh that have been carrying passengers daily for decades, and generate ways for ensuring safety. Secondary research showed that usual casualty investigations end when a governing body or labor force can be accused of carelessness. Through an interview of around 40 officials of BIWTA and DoS (Department of Shipping), authorities responsible for the operations, it was found that inland passenger launches are operated without due attention to the safety of people, resulting from multiple shortcomings. Data collection was done

through surveys with passengers and professionals in the shipping industry, and also from KIIs (Key Informants Interviews) and FGDs (Focused Group Discussions) of government officials and other highly qualified personnel such as engineers, naval architects, etc. The main subcategories where issues were found are governance, technical security, and human resource elements. Under governance, it was found through strongly structured surveys and interviews that the laws regarding safety breaches and infrastructure building violations are too weak.

Besides, the court orders take too long to proceed. Proper safety administration of vessels does not take place as there is no one in the administrative body is answerable. Fund allocation in the transport system is lower than what is theoretically written in papers. Differences in water level during different times of the year are also not taken into proper consideration as shown in this paper. When interviewing passengers and operators on board, it was evident that both parties had minimal survival knowledge if the vessel faced any emergency, whether in terms of available life jackets or ways to evacuate the vessel. Interviews showed that the operators had no official training record, given the fact that they were not paid enough to go through the hassles. The investigation clearly shows the critical condition of the launches at present around Dhaka that travel to neighboring districts with a huge number of passengers at death risk.

Saving the lives of civilians is the primary motivation of this research. As discussed previously, in these papers by Mia et al. [26] & [25], the number of accidents occurring every year in the inland waterways of Bangladesh is alarmingly high and this is the main problem encircling this paper. Collisions, and natural hazards are common causes of such accidents. There is minimal to no communication between the authorities and drivers during routine travels with hundreds of passengers on board waiting to reach home. The weather forecast is extremely unreliable; basic lighting and safety measures are missing, resulting in more collisions in the dark hours. Low maintenance of ship infrastructure is yet another grave issue.

Figure 1.3: Vessel fire kills 38 people [33]

A person who wants to go back home after months of toiling in poor working conditions should be given a full guarantee of safe passage, discarding the weather uncertainty, in the sea, as a citizen of Bangladesh. However, this basic human right is being denied in the most heedless manner. The success we are aiming to achieve here is to eradicate the occurrences of accidents to the maximum extent by developing this intelligent system which integrates all aspects of maritime travel such as loading, speed control, and weather predictability.

1.2 Research Objectives

Our goals for this research work include the following objectives:

1. The core objective of our work is to automatically detect a potential collision between vessels and consequently, provide an early collision detection architecture.

2. To build a feasible and cost-effective intelligent system that will require minimal manual handling, which will be able to prevent artificial accidents, which are caused by technical ignorance and hence consequent negligence of water vessels, such as collisions of vessels due to zero monitoring, overloading vessels for financial benefits and also use image analysis to avoid traveling in close range.

3. To include real-time tracking of the neighboring ships, based on laser width detection.

4. To what extent does the strategic placement and integration of light lasers and specific cameras on ships improve collision avoidance and navigation safety in diverse maritime environments?

5. How does this implementation of a laser-based object detection model impact accident rates and operational efficiency?

6. How can this integration contribute to the development of safer and more efficient autonomous maritime operations?

Figure 1.4: Capsizing due to cargo ship and vessel collision

1.3 Contribution & Outcome

In this section, we will discuss the contributions made in our thesis work. Our core objective was to build a system for automatic collision probability detection and, in the process, include real-time tracking of nearby ships. Our approach utilizes laser light models for the system architecture, alongside budget-friendly camera specifications and safety measurements, which helps us to stand out from previous research works as they do not focus on collision detection architecture in developing countries like Bangladesh.

The comparison analysis of previous research works shows how various factors contribute to choosing a technology for our system, including data output accuracy, complexity of the technology itself, etc. However, the major setback is the cost of technology implementation. We have introduced a minimalist physical system incorporating laser lights and cameras, focusing on the fact that our system is specifically designed for optimal efficiency during nighttime usage. A simple real-life prototype was used to replicate our proposed laser model.

Additionally, emphasizing on our primary focus, we have designed an algorithm for accurate collision probability detection. We have taken into account the exact measurements required to feed into our algorithm for computation, which led to multiple mathematical formulae derivation for ship size calculation, vessel distance from host vessel, etc.

To validate our algorithm, we have built a dummy scenario in an open space and collected necessary data to compare with the outcome from our image processing data, to ensure there is a certain acceptable accuracy level of our algorithm. The algorithm has also been fed with self-created dummy data before the above-mentioned real-time small-scale implementation, and both have shown remarkable accuracy.

A simulator has been built to imitate a real-time scenario between vessels, which has been designed in multiple steps to increase efficiency. The simulator displays on one side how the top view would look like when a vessel is nearing another vessel, and on the other side how this scenario would look from the host vessel's point of view.

A real-time small-scale experiment was conducted in our research work to mimic the entire procedure of our system to provide an idea of how this architecture will function during waterway journeys. The experimental setup, the image processing and the algorithmic output data has been presented to bolster the efficacy of our work.

To summarise our work, we have done an in-depth analysis to build a system architecture for collision detection in a developing country at night time, which opens up further scopes of research required for the entire eradication of vessel collision issues from the busy river ways of developing countries like Bangladesh.

1.4 Thesis Structure

The subsequent parts of this thesis have been organized as follows:

1. In the first part of chapter 2, we have presented the literature review where we have discussed various sensors used in data collection in maritime routes, different approaches for vessel monitoring in multiple locations, and weather conditions. Lastly, networking models, protocols, and holistic approaches for ship detection and collision avoidance techniques have been explained in this chapter.

2. In chapter 3, a whole description of methodology has been provided. Firstly, we have discussed our system architecture and models. Next, the required image processing, ship detection algorithm, and its formulas have been illustrated in the later part.

3. In chapter 4, modelling and simulation in various cases are showcased.

4. In chapter 5, a brief comparison amongst current technologies has been reviewed at first. Later, dummy data were generated for algorithm testing with results at the end for validation.

5. Chapter 6 encompasses the main experiment of the thesis where the setup, data collection methods, and results have been portrayed. Later, the findings and discussions related to them have been shared.

6. In chapter 7, the potential of further research and more scope in improving the models and algorithm, have been discussed.

7. Chapter 8 encloses the conclusive part of the research where new limitations have been shared along with the efficacy of our work on the aforementioned research objectives.

2 Literature Review

The current cases of launch accidents in Bangladesh have been appalling to the extent that no measures have been taken to counter them and instead, as years pass by, the number of accidents is only rising. Waterway transportation has never been safe and no liable authority is eager to change it. The papers reviewed include an elaborate discussion on the negligence and immediate stakeholders in the accidents, safety measurements, and technological applications that can be executed to eradicate this problem. Most technologies applied in waterway transportation consist of sensor network models, the use of weather predicting systems, GPS technologies for location detection, and miscellaneous IoT-based infrastructures for data collection and security purposes. The below assessments contain the primary objective, methodology, and limitations of the following papers.

2.1 Sensor Based Data Collection and Maritime Application

2.1.1 Overweight and Overcrowding Detection

Shamrat et al. [35] target in this paper to solve the problem of overweight in passenger vessels by using various sensors and micro-controllers, embedded in the vessels, and the stations will have the corresponding receivers implemented in them, servers inherently. The mechanism is simple; Whenever vessels are overloaded, the automatic sensors detect it immediately and send, not only a signal but also the detailed location of the vessel to police the master if any rule is further broken. This helps the management to build communication and such technology is reliable throughout. Shamrat et al. [35] mainly use two sensors where the first sensor is GPS and the second is a water float switch sensor which will initiate the main signal of being overcrowded. The system has been divided into two modules: the loading module and the notification module. There is inter-connectivity between these three modules whenever the overweight module is triggered, an SMS, along with the GPS location, will be sent to the associated server of the notification modules. A Raspberry Pi microcontroller is embedded in the notification module. Shamrat et al. [35] suggest this technological conflation as the ultimate solution to the problem of overcrowding in Bangladeshi passenger vessels; however, the only limitation is the cost and the maintenance of the system.

Meanwhile, in this paper, Bondi et al. [7] discuss & implement different techniques of real-time people counting in an overcrowded area. Also, this paper tries to compare their method and other methods to create a more deeper understanding of the research. In the introductory part, they discuss some techniques by which people counting can be overcome, but not as efficiently as it should be. Therefore, they developed their technique of Localizing Heads using an algorithm defined by them as head localization and projecting the top head point onto the automatically-estimated ground plane. Also, their algorithm does not need any sort of training, plus it works in real-time scenarios. Next, they moved on to using a multi-target tracking system where people will be in motion. Later, they evaluate their system by conducting a series of experiments. So, while doing head localization they face problems in an overcrowded situation where all blobs got added up representing as one, so they process each blob in such a way that the problem is resolved. Multiple target tracking solves the problem of counting the exact number of people entering & exiting a controlled area of surveillance. Afterward, when experiments are conducted, they are done in three sequences, one is the flow sequence, the second is queue sequence, and lastly is the group sequence. They represent the results in tabular and graphical form for each sequence using their method, the Latent SVM, and the LSVM plus segmentation enhanced. Moving on, they prove that their method is the most precise at extracting heads compared to the other two methods. In conclusion, this paper significantly shows their improvised method to be precise and give accurate results while counting people from depth imagery of crowded environments in real-time.

2.1.2 Heterogeneous Sensor Networks

Zunair et al. [46] compiled this paper to make a star network intelligent system in the ships of Bangladesh. The system consists of a water level detector, communication between the crew and authority, a web application, and a GPS ship detector. Firstly, the water level detector is made using a laser diode and LDR that distinguish different water levels. The sensor that is activated, the laser diode recognizes that sensor, sending value to the microcontroller. The model is cost-effective and suitable for ships in Bangladesh, and they are easily replaceable as well. The communication module uses a star network topology for the shortest-distance communication between the individual ship database and the administrator. The system uses Raspberry Pi 3 as the central hub in the station, with suitable transceivers of short-range coverage since the system is built for overloading detection when the ships are at a dock close to the station. The GPS, consisting of an AI Thinker A6 GPS module, is used for emergency location notification to the nearest ship, provided in latitude and longitude. Lastly, the web application has an admin interface that shows present data of all ships, including their depth in real-time at sea, using a MySQL database connected to the app. Alarms are efficiently put to use when faults are detected. All these features have been implemented on a small-scale model. The limitations however are, that a large number of wires are needed for the star topology, which is not cost-effective for developing countries like Bangladesh. Also, if a ship gets lost in the sea with no ship within a few kilometers, the emergency signal may not reach other ships due to low area coverage. Prospects of this project include making an application for thorough monitoring, onboard alarms for emergencies, a mesh network installation between ships for intercommunication, etc.

Next, Dobbins et al. [13] take up a new approach to accumulate data from sensors automatically and then assess them for further analysis. Automatic Identification System, AIS, exists between vessel to vessel, vessel to stations, and between different stations as well. The communication is a multi-access one where companies, whoever wants to experience this system, may buy subscriptions and in return agree to share the location of their vessels with other subscribed entities. Vessels are communicated over VHF radio and throughout the entire journey of a vessel, a navigation picture is created onto a screen image and this will help in aiding navigation for the vessels. Tools required for AIS are a receiver, VHF antenna, computer, and internet connection. The methodology of this paper starts with assigning unique identification numbers to every subscribed vessel. 27 different types of distress or informative messages are transmitted. Messages are transcribed and stored as text files on servers. Among the collected data (messages), sampling is done to select the positions of the vessels, to create that navigation picture. Data is grouped and the creation of this navigation picture is aided by using data visualization tools which are widely available. The limitation of this system is that mostly since GIS software is being used here, GIS software cannot handle huge data sets and here, thousands of vessels may interchanging at a time, if required and hence this is a major drawback. There is a risk of security here as a vessel's current location's information is publicized and vulnerable. Overall, AIS is important for vessels that have less confidentiality to them such as passenger vessels in daily life.

Previously discussed papers' ideas can be broadened with technologies in the following paper. Ahmed et al. [2] propose an IoT technology-based watercraft system that makes use of multiple modules to make an efficient secure system for a water vehicle. They propose an underwater obstacle detection unit, an overweight monitoring system, a vehicle navigation system, a communication unit, and finally as an extra security measure, a door lock security system. In the obstacle detection system, an ultrasonic sensor is used along with servo motors for a front-facing horizontal 180-degree radar system for obstacle detection. BJT is connected to an Arduino with the collector and emitter terminals connected in such a way that an LED lights up when the vehicle crosses a certain weight threshold. For location monitoring, a GPS module with high precision has been used, connected to the server for constant surveillance. For sending emergency messages to nearby ships or the main server in surveillance, UART, MQTT, and TCP protocols have been used. UART connects all micro-controllers used in the project for information exchange to be possible. For data transmission to the server, MQTT has been used. For emergency messages in case of an accident, TCP protocol is used to send location information to nearby ships. Lastly, an RFID module has been implemented for security door installation, which will also turn on the buzzer if any unauthorized person tries to access it. The paper talks about a survey on the launch terminals of Dhaka, but no data has been provided. Also, the project uses modules that are costly to implement in reality in the launches in Bangladesh and suggests the use of GSM to reduce cost on the given project. Leakage detection is a future scope of work suggested by the paper, besides a more automated system of the project for ease of handling of under-skilled men in charge of ship management.

On the contrary, industries nowadays rely on machine-to-machine communication for maintaining a proactive management of the operating environment and equipment. Trillions of devices are persistently sensing, processing, and sending data over the interconnected network. However, often due to networking problems or hardware issues, there are many gaps in measurements. Malfunctioning sensors, packet losses over the network, uncertain interference in the communication channel, interceptions by attackers, etc. are the main causes behind missing data. This is a big problem when it is a high-frequency reception where even the smallest time lag in input is enough to cause big errors and system failure.

For industrial IoT deployments, new solution design needs to be optimum and lightweight at the same time. For intensively diverse data, developing new techniques is quite challenging. Dzaferagic et al. [14] focus on investigating the outcomes of missing data and use a framework for imputing the data. This framework uses GAN which finds patterns in input data and provides replacements based on that.

This framework involves three main phases: fault detection, fault classification, and missing data imputation. When there is no missing data fault detection is activated and in an event of anomaly fault classification phase follows. However, when some data is absent data-imputation module is first activated before running the fault detection and classification procedures. Fault detection uses RMSE for estimating an error in the inputs. The reference minimized RMSE is found on the non-faulty segment of data. The faulty data gives a larger RMSE thereby indicating the presence of an anomaly.

The fault classification phase uses DNN on the input measurements and is only activated if there is an anomaly. Missing data imputation is based on GAN, and the data model is fine-tuned with the help of DNN as well. This framework can ideally check for whether the components of an entire industrial process are working correctly by finding out if there are any faults in the data. In the presence of anomalies, the issues are classified and the errors are mitigated by the substitution of imputed data. By the use of the Tennessee Eastman Process data-set the framework is thoroughly evaluated and is proven to function well even in cases of persistent data loss.

2.1.3 Vessel Scheduling and Maritime Traffic Detection

Xie et al. [39] researched the waiting time of different kinds of water vessels in congested waterways in China, developing IVSS to reduce waiting times efficiently. This paper also focuses on the objective of providing an analysis of the data acquisition, transmission, and processing of the proposed scheduling system. Since manual decision-making is not enough in case of increasing ships entering or exiting the channel, a dynamic system is proposed as an efficient solution. Though ships waiting to cross are dealt with on a first come first serve basis, with safety being the utmost priority, certain kinds of ships may face extremely long waiting times leading to fuel wastage. The functions of the proposed system are real-time knowledge of watercraft navigational status, storage and analysis of previous navigation records of individual vehicles, and long-term speed and route prediction to avoid collisions. The scheduling system comprises three layers- the perception and execution layer consisting of the executing body and sensors used, the data transmission layer utilizing AIS base stations, VHF communication, WiFi, cellular networks, etc., and the control and application layer handling the storage and computation of the scheduling. Many factors are taken into account in the system discussed, including vessel type, route, navigation duration, etc., and prominent ones. The scheduling system was implemented in the middle and upper Yangtze River, which showed that the proposed system was successful in reducing the average waiting time of ships by 22 minutes compared to the traditional manual method. However, the limitation of the system is its instability in heterogeneous environments, and waterways will need advanced security and upgraded facilities to be able to accommodate the fairly new concept of the system suggested in this paper.

Lidar systems use laser light to create a detailed 3D map of the ship's surroundings.

They can detect objects on the water's surface as well as shoreline features. Lidar ranges can vary greatly, from tens of meters to a few kilometers. Lidar costs depend on the type (airborne, terrestrial, marine), range, and resolution. Marine Lidar systems can range from several thousand to tens of thousands of dollars. With this software, a boat equipped with a Velodyne Lidar (360° laser scan) and a GPS can map its environment and generate both 2D and 3D occupancy grids. This software can be used on a USV for autonomous navigation, obstacle avoidance, or mobile object detection.

Karimanzira et al. [21] introduce an approach for constructing a generalized method to detect underwater objects in sonar images. The approach addresses various issues encountered during the object detection process, including automated annotation, the collection of extensive data sets, and optimization of hyperparameters. This method is particularly suitable for individuals without expertise in machine learning, as it leverages the principles of AutoML object detection within the realm of machine learning. By integrating transfer learning into an R-CNN model, a basic detector was trained and employed to gather and annotate a substantial data set, streamlining manual efforts. The efficacy of this approach was tested in a case study involving the identification of an underwater docking station. The detector demonstrated resilience across diverse sonar imaging systems and noisy images, indicating its potential as a capable underwater object detector in sonar images. Nonetheless, a drawback of the current method is its processing time, averaging 1.2 seconds per image. The forthcoming challenge lies in refining the algorithm to support real-time online processing. The outcomes of this research hold significant importance within the field of underwater detection, as the automation of data collection and policy-driven data augmentation are crucial prerequisites for efficient object detection in challenging environments where data acquisition is arduous and costly.

In this paper of Bhargave et al. [6], lies its intricate speed-controlling mechanism, which aims to intelligently regulate a vehicle's speed based on real-time data inputs and advanced control algorithms. This mechanism plays a pivotal role in achieving the system's overarching goals of enhancing road safety, optimizing fuel consumption, and ensuring compliance with speed limits.

Bhargave et al. [6] delve into the technical details of the speed-controlling mechanism, highlighting its integration with various sensors, control algorithms, and vehicle components. The mechanism operates in a closed-loop feedback system that continuously monitors the vehicle's environment, processes incoming data, and makes instantaneous adjustments to the speed.

One key aspect discussed in the paper is the utilization of sensors to gather crucial information from the vehicle's surroundings. These sensors include but are not limited to, cameras for road sign recognition, radar for distance measurement to the preceding vehicle, and GPS for obtaining accurate speed limits for different road segments. The authors emphasize that these sensors collectively form the sensory input for the control system.

The heart of the mechanism lies in the advanced control algorithms that interpret the data from these sensors. These algorithms analyze information such as road signs indicating speed limits, real-time traffic conditions, and the distance to the preceding vehicle. Based on this analysis, the control algorithms determine the appropriate speed for the vehicle at any given moment.

The authors elucidate how the control algorithms factor in various variables to make informed speed adjustments. For instance, if the system detects a lower speed limit through road signs or GPS data, it will command the vehicle to decelerate gradually. Similarly, if the distance to the preceding vehicle becomes too short, the control system may engage the braking mechanism to ensure a safe following distance.
A noteworthy feature of the mechanism is its ability to interface with the vehicle's throttle and braking systems. This interface allows the control system to exert direct control over the vehicle's acceleration and deceleration. The authors emphasize the importance of a seamless interaction between the control system and the vehicle's mechanical components to ensure smooth and precise speed adjustments.

Safety is a paramount concern, and the authors outline the incorporation of fail-safe mechanisms within the speed-controlling mechanism. These fail-safe mechanisms are designed to intervene in case of unexpected scenarios, ensuring that the vehicle's speed remains within safe limits even if the control system encounters difficulties.

2.2 Vessel Monitoring Systems

Deng et al. [11] designed a smart watercraft system to utilize an open platform for ship monitoring and dispatching. The main functions of the system include providing the exact location and other basic information of the ship, managing the ships coming into and out from the dock, communication platform through SMS, query function providing all information of a ship in sail, alarm system for fault detection in the ship, GPS anti-disassembly control system, playback option of monitoring information, and finally, manipulation of control charts, i.e. enlarging or zooming into particular places of electronic charts for detailed views. Database systems have also been implemented for the storage of information. Four kinds of databases have been used here which include ship management and video databases.

The system has been divided into multiple sub-parts consisting of different modules, each connected to the other for efficient usage during navigation. 'Ship-borne terminals and other user terminals' are the front face of the system providing the ship's status, and reports and receiving control commands from the dispatch center. 'Database subsystem' has all the staff and ship information stored, ready for retrieval according to user requirements. 'Map subsystem' as the name suggests, handles the maps used during navigation. The communication subsystem' handles the delivery of short emergency messages, information caching, etc. 'Mesh pipe system' stands for the network management system which makes real-time monitoring possible. 'Application subsystem' consists of multiple different modules working together for proper workflow. 'Monitoring Center Subsystem' allows users to access the dispatch status of their orders from the dock and place necessary queries for the dispatch center, improving the performance level of the overall system in the process. However, the system is too heavy keeping in mind the under-skilled ship authority that manages the ship. A more automated system is required for efficient usage of the already employed labor in the shipping industry.

Chang [9] discusses several technologies for ensuring maritime security and safety.

These technologies have been provided with a regulatory framework for all kinds of sea-going vessels which includes passengers, research, cargo, Rescue, and military ships. In this research, several well-qualified technical systems like Inmarsat C, AIS, DSC, and GSM are investigated while keeping in mind its coverage area, cost, reliability, etc. based on some sea trials and field analysis of its prototype subsystems. This paper also publishes the results of its testing of different technologies in the sea for ensuring maritime security. For conducting the study different subsystems like Ross DSC 500 Pro, Saab R3/R30, and Trimble Galaxy TNL 7001 were set for VHF, DHC, Inmarsat C, and AIS. SMS and GPS were set for measuring GSM data. Also, software was designed for receiving position reports and commands from monitoring centers. Sea trials were then performed under different weather conditions to check the results. Different kinds of technologies have different effects on their results. Inmarsat C's ALC can be remotely operated and can send its regular position reports at regular intervals and instantly when requested. It takes around 1 minute for the pooling command to reach the ALC, based on the timestamp. However, it can cause up to 5-10 minutes delay in delivering the reports, especially from the Land Earth station to the monitoring center via the Internet. AIS has a good report about broadcasting information. Dynamic positions such as GPS position, speed, and course are broadcast in 2-180 seconds. Details about voyage-related information are broadcast every 6 minutes. Every AIS message is tagged with MMSI which has made the system an ideal system. VHF DHC is very essential and much cheaper than AIS which can be used for ship monitoring and identification purposes. The tested VHF system can cover up to 40 nautical miles. It was observed that the position report sent by DHC with a resolution of 1/10000 minute was received and decoded by the base station in just 1 minute.

Ullah [37], focuses on four modules in their project- overweight detection, object detection around the watercraft, location detection, and lastly, weather forecasting, as the authors believe weather plays an important role in predicting launch accidents. The individual sensors for each detection purpose are connected to a microcontroller(Arduino) in the previous paper. For overweight detection, ultrasonic sensors were used to detect distance from the seabed when boarding passengers while stationary. If distance falls below a certain threshold, overloading is detected, and an SMS is sent for notification to the authority. In the case of object detection, IR transmitters and receivers are used for hindrance locating around the ship. The display shows whether the obstacle was located left, right, back, or front of the ship. However, there was a case where the detector failed to locate the object. For detecting the location of the watercraft, the NEO6 sensor is used to send location information via SMS. Finally, for forecasting the weather conditions, DHT 11 and BMP 280 sensors help to show the air pressure, humidity, and temperature at the time of boarding and throughout the journey. The display shows the information mentioned above. The limitations have not been mentioned in this paper and future work suggests making an application for customers ease of buying launch tickets, but nothing has been mentioned about upgrading the project.

In addition, it is crucial to monitor a ship's movement in its route and its surveillance system while they are in the sea. Antunes et al. [4] present a system for identifying grid-based ships which are deviating from usual travel routes, using unlabelled AIS data. This system follows an approach where it solves the problem with solubility and online learning of other grid-based systems by applying dynamic grid size which can be adjustable per ship's characteristics. For data and vessel grid search, a binary search tree is used. The results of this study are validated by the Portuguese Navy in Portuguese maritime trials. For calculating the deviation from the route based on AIS data, some systems are used to learn the patterns. Grid-based system: A neural network is used to construct a multidimensional Gaussian model of a vessel's behavior. Also, anomaly detection was tested which indicates the amount of ships visited in a particular location. Location with high scores is considered normal and location with low scores is considered abnormal. The vassal path was derived by using matrix calculation which considers ship trips, preferred routes, and other necessary scenarios. If the vessel's location does not match with the region where they are then the ship is flagged as suspicious. Vector-based system: The DP algorithm was used for detecting turning points. If a ship's position is far away from its start and end position then it considers the ship as threshold. The turning point that connects two straight lines, is simplified by the DP algorithm and then clustered by DBSCAN. Then the speed of the vessels, turning points, and traffic are analyzed and anomaly detection is performed. Density estimation and clustering system: Gaussian sum filtering model is an approach for tracking vessels at deep sea along with a 2-dimensional density estimator for calculating probability density from ship tracks. Also, another data model for vessel routes defines data classes for vessel objects, ports and offshore platforms, entry and exit points, vessel turning points, and sea lanes and routes. The vessel object stores different information such as MMSI, name, call sign, or size. The proposed algorithm detects the location from where the ship starts turning from its routes. In this way, this approach identifies the turning points and analyzes the data.

2.3 Location Based Models

Climate changes are happening so rapidly that it is difficult to keep track of immediate local weather conditions. With existing systems, only a few weather parameters are known, previous data cannot be stored, nor a fixed platform is available for proper browsing. Given the issues mentioned above, Ijraset [20] proposes a customized weather monitoring system that can provide real-time values on temperature, humidity, barometric pressure, air quality, light intensity, and rainfall in the environment. The proposed system uses sensors on the spot to get instant readings. The tools used are as follows: DHT11 sensor, MQ135 sensor, light intensity (BH1750) sensor, raindrop module sensor, BME280 sensor, and Arduino mega to measure the aforementioned parameters. The Arduino is connected to Raspberry Pi and the control code is written in the Arduino IDE in C++. External libraries like DHT11, light intensity, MQ135, and raindrop are included in the code. Node-RED is a graphical tool that can be utilized by non-programmers to interface hardware and software components together into one complete system. Influx Db is used as data storage for all the sensor readings collected. With front-end technologies HTML, CSS, JavaScript, Node.js, and React a user-friendly visual display can be created that can allow anyone to understand the output data without the acquisition of any prior skills or having to undergo any usage training. With the deployment of the sensors within the concerned environment, the reception of the most accurate information is possible. This paper claims that the suggested system is efficient, inexpensive, and can be easily implemented.

There have been many works in the field of modern technology to find the shortest possible routes for transport. Some of the technologies such as GPS technology, GPRS Technology, Google Earth, and Google Maps are among the technologies that have a significant impact on tracking and monitoring vehicles on the roads and maritime passages that have been discussed in the paper by Chadil et al. [8]. GPS is a network based on 24 satellites of the United States which mainly works based on radio signals in order to calculate the distance. GPS receiver receives the radio signal from more than three satellites for calculating two-dimensional position (latitude and longitude) and for computing three-dimensional position (latitude, longitude, and altitude) more than four satellites work at the same time. After finding the location, it can calculate both the average speed and the direction of the traveling ships. GPRS is an enhancement of the GSM network which mainly supports packet switch Data Services like email, web browsers, and short messages. GPRS operates based on GSM network infrastructure which utilizes available time slots during each time frame transmission. For that reason, traffic overloading can be avoided and can efficiently provide data services.

GPRS provides an end-to-end wireless architecture. Another very popular and free software that is used to check and display the locations of vehicles is widely known as Google Earth. Google Earth shows the Maps with the help of satellite images around the world. Google Map is a version of Google Earth that mainly displays the maps online using a web browser and a web server. It has its own programming language known as KML which is an extensible markup language that is written in order to describe how the objects are rendered. In this way, Google Earth detects the path of the vessels and tracks them by lifetime monitoring. Another most effective and commonly used image satellite system for ensuring maritime security and tracking water vessels is known as SAR, imaging system, and OSI system.

In the SAR imaging system, a radar continuously sends microwave pulses from a satellite or a spaceship. A large synthetic antenna aperture is created based on the distance between the ship and the satellite. The larger the aperture is, the higher the image resolution becomes. In this way, SAR creates high-resolution images with a comparatively small size of antennas. SAR has both its advantages and disadvantages. As the ships are made with metals, they reflect radar rays intensively which allows SAR to create bright dot images for each vessel. Also, it can provide reliable data in any weather conditions like rainy, sunny, or cloudy conditions. These are its main advantages. On the other hand, Its spatial resolution is limited and it can not detect images from objects having lengths more than 15 m. Also, satellite revisit to the target area is too long. Besides, human understanding of the images is so tough and it requires polari-metric techniques to color the images, which are the disadvantages of this technology. The OSI system's visible light spectrum is mainly used for imaging purposes. It has also some advantages and disadvantages like the SAR imaging system. OSI has a higher resolution which is why it can detect comparatively small ships. Moreover, human interpretation of the OSI images is easier than SAR images, so there is no need to use polarimetry. Besides, the taking of an optical satellite is simpler. What are the main advantages of this technology? The main disadvantage of the OSI satellite is, it heavily depends on weather conditions.

It can only operate in the daytime. Therefore, a combination of SAR and OSI technology can be very effective in tracking and monitoring the sea-going vessels.

2.4 Predictive, New Generation Networking Models and Protocols

Hosseini et al. [18] aim to quantify the resilience of an infrastructural system in waterway transportation due to the rise in accident cases in the US. The study focuses entirely on cargo vessels here as all accidents are linked to them and since the US economy is interdependent on them. Recently, Hosseini et al. [18] identified a flaw in their cargo system which is the inability to withstand certain weather conditions. Accurate measures are taken to deal with the issue however the engineers need a mechanism to predict and measure the strength of the new system and therefore to quantify it for better interpretations.

A Bayesian network model is proposed where it is singularly based on conditional probability, for all the aspects of this system to be judged accordingly. A tree structure is created where suppose, every intermediate or leaf node's probability of being functioning or not, is based on its parents' probability where Xi is a node and its probability is calculated as P(Xi) = P (Xi |Parents of (Xi)). The root node's probability is initially calculated and the rest are automatically figured in a forward propagation method. Every node here is a functioning unit of the system. This helps in visualizing an overall structure resembling a web where which factors determine the status of which unit, can be derived.

The junction tree algorithm is utilized here and since the tree may operate either way, a backward propagation analysis can be done as well. The metric used for calculating probability was changed according to different functioning units and Boolean, strings, and numbers were used. To check resiliency, the entire structure was divided into four groups where the initial stage is stability when there are no hindrances to the cargo vessels. Next is absorptive capacity where the system can absorb the damage and remain unaffected. Later comes, adaptive capacity where some changes are necessary to deal with the stimulus better. Last is restorative capacity where after a mishap has taken place, it is now the turn for the system to revert to its original state to a maximum extent. Hosseini et al. [18] conclude with the remarks that such a system has never been implemented before using conditional probability; however, this has enough scope to improve the assessment of waterway disasters by calculating the resiliency.

Currently, the network systems are being studied rigorously to develop better models which are more energy efficient. Noreen et al. [28] introduce LoRa, an LPWAN where it provides a highly energy-efficient data transfer over a wide area range network. Inherently it is a protocol and coincides with WSNs as both have similar requirements. The basic instruments needed to build this network are firstly a power source, heterogeneous sensor devices, memory, and an RF-based transceiver. The potential of this system is mentioned hierarchically with the top feature being the most beneficial one. Resistance to channel noise is emphasized more as this will be a life-saving feature during dangerous situation communications. There is long-term relative frequency and consequently Doppler effect and fading features.

Various FEC techniques are used during data transfer. The CR, which defines the amount of FEC, is high for LoRa. The bandwidth size of this network model is between 125kHz – 500kHz and the packet size may exceed up to 256 bytes. Another crucial feature is the spreading factor which primarily talks about how quickly data is transmitted. This aspect is linked with time on air for every data packet. Overall, the objective of this network is low-powered data transfer over a large geographical area. However, the major limitation of this model is the rate of data transfer. Due to consideration of the other factors, the amount of data that can be transferred per second is low and hence to receive clean data transmission over a wide area, data rate is sacrificed here. Prospects of LoRa are more intense inclusion of this network model and improving the data rate.

Global trade and the number of ships are increasing by the day. Therefore, the construction of waterway safety and maritime traffic management has become more important now than ever. Jing et al. [19] focus on the integration of 5G networks in the development of intelligent ship transportation systems. To ensure safety, wave height, wave approach, immersion level of the ship, current wind direction, the weight of the ship, and where the ship is headed; all this information needs to be generated so high-speed data transmission is necessary. This digital platform system allows ship and route identification and makes possible real-time monitoring of the 3D channels. With its advanced facilities such as multi-task frequency division technology and range loop broadcasting, the 5G network integration can be used for GPS positioning and routing technologies. Digital maps, video messages, and other services alike easily fill up the gap of communication between land and sea as well as among the ships in the sea providing higher precision, feasibility, and working of the system. Based on the vessel's course, location and other data the 5G ship traffic intelligent analysis and calculation platform will send a danger signal in real time if it detects any risk of collision. The calculation platform screens more than one vessel in the concerned sea area and estimates the extent to which damage can happen. At its resting state, the system exchanges information with the local control center and the nearby sea area over the 5G network. The AIS system computes the data and provides feedback automatically. The ship's trajectory is then easily and automatically figured out. Overall the system is divided into three main modules: the control module, the data transfer module, and the data collection module. The sub-parts consist of keyboard/LED modules as well as the AIS information sector, 5G technology module, signal collection, data processing, and display module. A virtual memory database is used along with other computing mechanisms to guarantee the right operation of VTS. Ocean target data processing is used to synchronize target data processing and the processed data is then related to other servers in the cluster so that in case of any failure the servers can be immediately automatically replaced. The main fields of its functions are in the areas of system applications, control and maintenance systems, and infrastructure with optimum services to ports and shipowners.

2.5 Holistic Approaches in Evaluating and Improving Waterway Systems

Lastly, Restrepo-Arias et al. [31] find out the main issues in inland waterway transport and what technology strategies are studied and used to solve these issues. The topics cover traffic monitoring, smart navigation, emission reduction, analytics with big data, and cyber security. River navigation is considered to have the least development in its advancement especially in developing countries due to factors such as insufficient infrastructure, lack of funds, poor regulations, and coordination among national institutions.

Traffic Management: In this section, proper vessel identification is one of the prime goals. Deep learning methods with networks are used to capture the identification numbers on each vessel. YoloV3 allows real-time detection in case. Water flow patterns are also another important factor the spans of vast currents play a significant role in regulating critical traffic areas. These measurements are done by capturing images and videos using various tools such as hyper-spectral cameras, photography and video cameras, satellite images, and the like. The data are primarily collected from the AIS system. Collision risk detection: To avoid ship collision the sizes of the ship are estimated using neural network technologies. Using the DarkNet53 network the body of the ship is collected in layers and multi-scale image pyramid features are used to have an approximation of the size. It is experimentally proven that ship detection with YoloV3-based technology has the highest accuracy in the face of adverse situations and different scenarios. AIS data cleaning: DBSCAN and real-time AIS are used to eliminate noise and make up for missing data for modeling ship routes and detecting trajectory errors.

For smart navigation, collision risks are used using data accumulated from the concerned vessel. River navigation management system uses the RIS to collect data. It has been found that there is a scarcity of river navigation charts which is an essential component for smart travel in the sea.

Emission reduction has also become a great issue in the sea. Heavy-duty diesel engines are used for large ships and gasoline engines are used for smaller ships with power ranging from 200-1000kW. In both cases, there are issues of significant greenhouse gas emissions and the release of other pollutants. To reduce these effects, more preferences are given to the use of other solutions such as LNG engines, hybrid propulsion systems, micro-turbines, etc. Huge volumes of a variety of data are collected from AIS, RADAR, LIDAR, VDES, etc. However, the necessary processing and data generation are not as robust as should be the case; Big Data analysis is becoming more prominent in these areas.

The field of cybersecurity in the maritime sector is still in its budding stages and the application of optical communication and quantum encryption is being progressed for advancement in this sector. Neural networks for sequential data LSTM, and GRU are applied to data accessed from AIS. For vessel detection Yolo, DarkNet, Auto-encoders, and SSD networks are mostly used. DBSCAN is an algorithm used for group data according to the various density points. IoT elements are used for data collection. Big data is managed using non-relational databases with frameworks such as HADOOP, SPARK, and MAP REDUCE algorithms. The main issues in dealing with big data so far are cleaning and noise elimination. According to this paper future works should include systems that are resilient to climate changes and are more sustainable. Constriction systems, storage ports, infrastructure, devices, and maintenance are also important areas for improvement.

2.6 Comparison Analysis Table for Existing Technologies

Study	Name	Inefficiency	Complexity	Accessible	Output	Cost
Abebe, A (2023) [1]	IR Vision	Extensive Hardware Required	Heavy Pre-Processing	**No**	Object Detection	40000 BDT
Ogunrinde (2023) [30]	Camera Radar	Extra Power Supply	Heavy Pre-Processing	**No**	Object Detection	311052 BDT
Bai. et. al (2022) [5]	LiDAR	False Detection of Dense Objects	Heavy Hardware	**No**	Object Detection	656809 BDT
Fuchs. et. al (2018) [17]	Forward Looking Sonar	Low Detection Range	Heavy Pre-Processing	**No**	Object Detection	112000 BDT
Nowosielski. et. al (2015) [29]	Night Vision	High False Positive Result	Heavy Pre-Processing	**No**	Object Detection	437325 BDT
Our System	Laser Model	Merged Lasers	Requires Image Processing	**Yes**	Distance, angle, speed & vessel type detection	54600 BDT

Table 2.1: Comparison Table of Different Available Technologies

There are currently, various types of models and sensors for object detection. In our paper, we are working with laser light and a camera to detect the ships and calculate the distance and speed. While IR vision cameras give 85.7% accuracy, however, due to the motion of cameras on boats, there is no guarantee for temporal consistency in detected frames. Moreover, using a Radar camera gives 84.9% accuracy, and using LiDAR for object detection provides 96.3% accuracy but both of them are less efficient. Working with a radar requires extra power consumption and LiDAR provides false detection when the number of vehicles is very dense, also LiDAR was giving frequently false detection of the roadside objects like trees. If we move on to the Ultrasonic Sonar system, it has a high accuracy but it has a very low detection range which makes it unfit for maritime ship use. On the other hand, forward-looking sonar has a large detection range but it can not perform its detection task while a large ship is in front of the sensor hiding a smaller ship behind the larger one. That sensor data only reveals the information of the big ship while having no clue about the smaller one. On the other hand, night vision cameras also give many false positive results. All of these modules and sensors are available in Bangladesh for use in water lands. However, there are technical complexities for all the sensors and modules. Using IR vision cameras, and Radar requires image preprocessing, and thousands of well-balanced image dataset is required for higher accuracy. There are hardware complexities in the case of LiDAR detection which requires a lot of hardware setup. For Sonar sensors, it's very difficult to manage datasets for ships for image preprocessing purposes. Lastly, using a night vision camera also needs image preprocessing and different types of necessary hardware.

From our approach, we have been able to derive the speed (relative and absolute), distance of the facer vessel from the host vessel, width, length, and the corresponding area of the facer vessel. The complexity of our system is low since each time interval will process the current incoming data and keep only a few parameters for speed calculation from the next incoming data and hence the data to compute with at a time is smaller in size than the other technologies. The light laser and camera used in our system are easily accessible to everyone and the cost is significantly low, compared to the rest as seen in Table 1 above. The respective costings are for one module in each paper above which means if more are needed, the cost will increase. The breakdown of our costing can be found from Table 2.1 and it is for the setup of one entire vessel and not just the laser model, unlike the other modules.

3 Methodology

In this pivotal chapter, we delve into the intricate methodology that forms the backbone of this paper, unraveling the systematic approach employed to address our research questions.

3.1 Work Plan

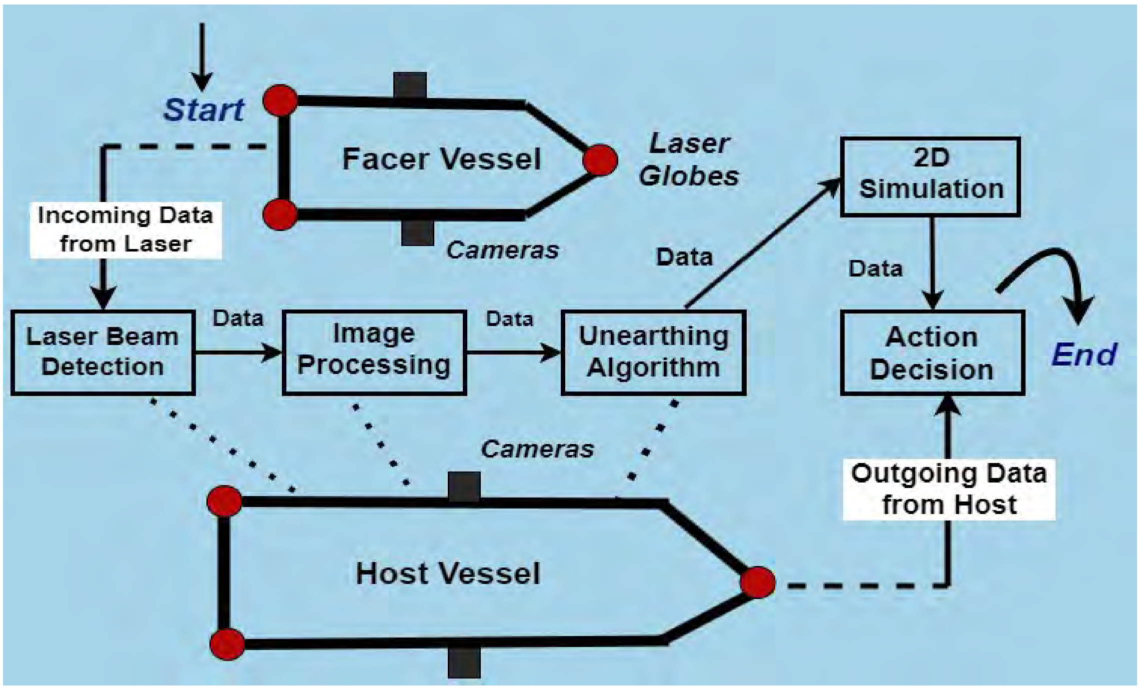


Figure 3.1: Work Plan Diagram

Lasers and cameras will be optimally placed on medium-large vessels at first. When two vessels will come close enough, to be detected by the cameras through the installed lenses, the images captured by the cameras will be processed through state-of-the-art algorithms such as YOLO models. The primary data for our system would be laser sphere diameters. This processed data will be instantaneously forwarded to our proposed algorithm called 'The Unearthing Algorithm', which will calculate the real-time distance between each laser beam and the host vessel and also the corresponding speed, width, and length of each vessel. Such information will allow us to find out the specific rectangular area of the facer vessels which will flesh out the identification of each facer vessel type as well. When the distances are calculated, this is done concerning the host ship and each host ship will have a safe radius around it, which cannot be penetrated by any vessel as whenever the facer vessel tries to cross that threshold, our system would immediately trigger an alarm for the facer vessel to understand that it is time to slow down and ultimately change direction. This safe distance will be calculated dynamically for each vessel type and the information required for this calculation can be taken from the ship speed documentation. As for the limitations of this model, since the proposed model is based on real-time marine vessels, we need this system to be implemented on real vessels, and a live simulation is required for an ethical verdict. Hence, our target is to provide a prototype model, which will be verified singularly module-wise.

3.2 System Architecture

Fundamentally, our proposed model focuses on vessel detection at nighttime. Hence, the usage of lasers will be fruitful in this work. The thick beam rays of the pre-calculatedly placed lasers on the facer vessel will give away its location into the darkness of the night. The system will initiate its operation when the cameras placed on the body of the host vessels, will detect the facer vessel using these lasers. The positioning of the lasers and the diameter of the captured beams would allow our model to calculate the apparent width, actual distance, width, and length. Using these variables, we will calculate the corresponding speed and area of the facer vessel.

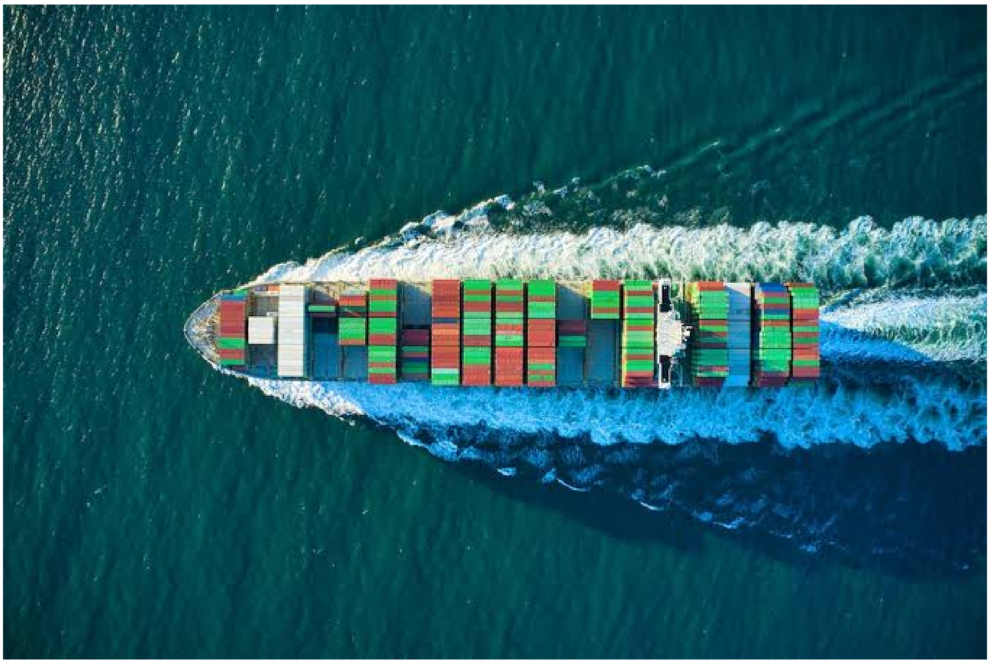


Figure 3.2: Aerial view of a cargo ship

Data regarding each vessel type, available on the water routes of Buriganga River to Barisal, will be already fed into the system to immediately, without any second of delay, identify the vessel type. Next in line, will be to map the safe distance, the distance required for this specific vessel type to come to a stationary position or decelerate enough to change its direction to avoid collision with the host vessel, for our system to track when that threshold was being breached and trigger the alarm instantly then. This calculation is crucial for our system as the efficacy of our system operation depends upon this functionality which is to signal the facer vessel to change direction of motion for collision avoidance.

The distance between each laser will be initially modeled and calculated for every vessel type, with considerations for the angles between every pair and the subsequent distances between lasers. Different weather conditions such as rain and fog, have also been considered to visualize the laser beam seen through the camera lens and unless it is not too thick, the rain or fog particles, the display of the laser beam will not be sufficiently distorted for the camera to capture and give an accurately processed data. Proper protection and insulation will be implemented in our system for the system to be protected from harm and for the passengers to be also protected from the lasers as any direct exposure to light lasers to the naked eye, will be detrimental.

Consequently, safety measures will be integrated cautiously into our system. Lasers will require electricity supply directly from the vessels and the cameras will support network protocols to be received from the station control room if necessary hence, our system will provide a holistic approach where detection is done by allowing sufficient time for reaction and action for the captains and the continuous assessment of the whole situation can observed locally and remotely as well.

3.3 Device Specifications

The following subsections contain detailed explanations of the requirements that were crucial in selecting the hardware components of our system.

3.3.1 Laser Light Designs & Requirements

The data from lasers are the grounding pillars of our system and hence we must pick an appropriate model for our light lasers that can be detected from afar and will help us to correctly calculate the variables. Another criterion that is imperative to fulfill, is that the power intensity of the laser does not exceed above the threshold of 100mW as this would start to ignite anything in its ray path as the heat energy produced is in great amount. Therefore, the beam diameter of the laser, the power intensity, and the presence of dust and air particles in the ray path are crucial to be chosen wisely here. The most basic laser available in shops is the 5mW (power intensity) light laser which has a range of less than 500m and the diameter of this ray is 1.2mm from a distance of 1m.

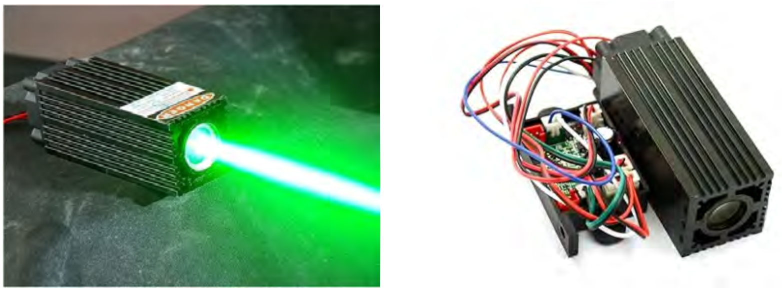
(a) No ray seen

(b) Vague ray seen from an angle

(c) Ray seen due to water particles

Figure 3.3: Different 5mW laser rays from a 20cm distance

Hence, such a minuscule diameter could never be captured on images and hence the laser we have chosen will have a beam diameter of around 50-60mm and this will be custom-made by changing the optical lenses inside the laser, according to our needs. The laser chosen for our system is the fat beam 50mW in Figure 3.4, a green-colored light laser that has a wavelength of 532nm. This laser is ideal for the work as its comparatively huge diameter will allow it to be captured from a long enough distance for the facer vessels to safely avert collisions. In addition, our modification will enhance its diameter to be larger which will only add ease to our computation.



(a) (b)

Figure 3.4: Laser Specifications

The specifications for this laser: as mentioned above, the power intensity for this model is 50mW which denotes that there will be no heating effect and hence no fire hazard related to lasers. The working voltage is 12V for DC however since it will not be possible to load and unload these lasers frequently for battery recharging, it is highly significant that the setup is done using an AC supply and hence this will require a voltage supply of 9-10V. Since there could be a shortage of power on the vessel, considering this scenario, the lasers will be equipped with capacitors to retain power for it, for absence of an electricity supply. The specific beam diameter for this model is 12-15mm however this will be customized to increase to 50-60mm. Additionally, this laser comes with a cooling fan to reduce any possible generated heat energy.

For customization of the laser beam diameter, methods such as collimating lens, beam expanders, etc. will work brilliantly to specifically increase the beam diameter by ensuring that the power intensity remains constant and there is no increased heat energy produced; the safety measures need to be taken up during this laser calibration. A collimating lens will decrease the rate of divergence of the beam and create more parallel rays to enhance the ray even more. This can be done by changing the focal length of the optical lens inside the laser. In this manner, the diameter can be controlled to satisfy our needs.

3.3.2 Improved Laser Model for Finer Detection

In addition, as one of the drawbacks of utilizing a bare laser is the uncontrolled dispersion of the light which will hinder the width measurement by the light splitting, and that collimating lens will only be reliable to a certain extent, we have introduced an encapsulation of the laser light to ensure an almost perfect resembling shape in the darkness of the night.
The preferable material for encapsulation is a transparent plastic sphere which will provide two benefits: The sturdiness and stability of using a plastic material will guarantee resilience at times of extreme weather which may lead to dis-balance of the vessel and distorting the alignment of the lasers on it. Secondly, the transparency will insinuate no useful light getting blocked by the thickness of the plastic material being used and these lead to an ideal choice inclination towards this plastic material. Polycarbonate is a type of plastic that has been found ideal to use in our scenario, which fulfills all necessary criteria of our case.

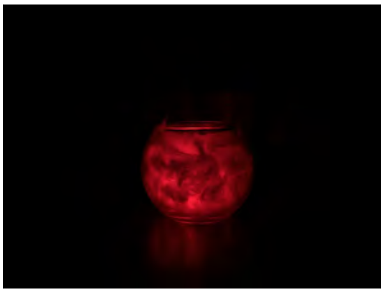
A spherical shape's diameter is needed only and the glowing sphere amidst the darkness will be more noticeable to the host vessel cameras. As for the trapping of the light inside the glowing sphere, the model itself needs to be lightweight as a heavy substance would be less stable and more prone to destruction by external factors around the vessel. The difficulty in balancing the lasers will hamper the whole architecture. Moreover, to prevent the laser light splitting, the light must disperse itself inside the sphere by the principle of reflection however, another soft and light material is required for this action which was chosen to be cotton in our design. This material is semi-permeable, allowing a sufficient amount of light to pass through, enough to be detected from outside.

(a) Prototype with Glass

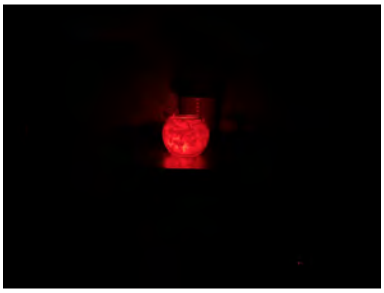
(b) Internal Blocking Material (Cotton)

Figure 3.5: Laser Model View

The prototype shown in above Figure 3.5 has been designed using a glass sphere due to an instant lack of available resources and consequently, no access to plastic circles however the main model will consist of a plastic sphere. This embryonic design is to establish the desired design of the proposed model for reference purposes only. In the figure presented below, this glass model is illuminated by the laser light and as it can be inferred from the images, the cotton inside the model meticulously encapsulates the light by allowing adequate light to pass through and elucidate the overall model structure for better capture by the camera. Meanwhile, it can be derived from the pictures that no light is being dispersed and in turn, there is no loss of light from the data.



(a) Up-close Shot of Model



(b) Model Shot from afar

Figure 3.6: Illuminated Sphere Model

3.3.3 Camera Model Imperatives

The second most important feature of our system is the camera quality. A standard camera will be able to detect thick lasers or spheres from afar however what we are targeting here is to be able to target the lasers from a very long range, instantaneously, so that more time is presented to the facer or host vessels to change direction for collision aversion. Hence, the specificity of the camera needs to be all of the following: the camera needs to be of high resolution as such high resolution will determine a greater number of pixels in each frame, and thus, a higher pixel count will ensure more accurate and precise calculation for our system.

Next, the camera needs to have a low horizontal field of view (FOV) specifically, as we need the camera to focus on a small number of areas so that the frames are not exhausted with too many details in them which would make it difficult to classify the lasers amongst everything else. Lastly, the camera should have a long-range view so that we have quicker detection, embedded in our system. These three combinations, provide the ideal camera for our work in developing this system. Existing security cameras are well-functioning in terms of short-range object detection. For better accuracy, therefore, a customized camera is recommended that is tailored to our needs for this system.

(a) (b) (c) (d)

Figure 3.7: Camera Inspection at Field Work

The camera images in Figure 3.7 represent a wide variety of devices ranging from smart-WiFi connecting ones to infrared and CCTV cameras which are suitable only to some degree as bullet cameras have a long-range distance to detect however resolution and FOV are not perfectly fit for our model. IR cameras are efficient however the colored output images will obstruct us from detecting the actual laser lights. Smart cameras have poor FOV so the accuracy of the calculations, cannot be relied upon. Hence, it is consequential to merge features of multiple camera models into one for the desired output.

3.3.4 Hardware Requirements for Architecture

Table 3.1 consists of the total cost of components required to implement our system onto a single vessel. All of these components will be fitted onto specific vessels such as cargo ships, steamers, ferries, trawlers, and bulkheads. Our main focus in this research was to decide on the laser and camera model. The microcontroller and HD display will be later used for system hardware when this system is embedded into an actual vessel. The installation cost of this system will vary from vessel to vessel and is unavailable to us at the moment. Hence, the table shows the total equipment cost for our work which stands at a maximum of 54600 BDT.

Hardware	**Specification**	**Quantity**	**Cost**
HD Display	10 inches	1	5000-7000 BDT
Camera	25.7 deg HFOV; 5MP	10	3000 x 10 = 30000 BDT
Raspberry Pi	at least 3B+	1	10000-15000 BDT
Laser Light	50mW	3	(500-700) x 3 = 1500-2100 BDT
Polycarbonate Sheet	For Spheres	3	250-500 BDT per meter squared

Table 3.1: Hardware Equipment & Costing

3.4 Image Processing for Vessel Classification & Detection

The spherical laser model has a diameter bigger than the beam width, thereby it aids in detection from a longer range. The significance of the spherical shape is that it prevents any distortion due to perspective vision resulting from the different heights of the cameras' positions and the objects detected since a sphere is symmetrical at every orientation. The cameras will capture images of the surroundings at a constant frame rate and the images will be converted into a binary format using the gray-scale filter. Given one frame at a time from each camera, the contours will be extracted to find the brightened spots. The radius of a contour will be multiplied by 2 to get the diameter, that is, the apparent width in pixels. The centroid of a contour will be used to find the angle of the beam concerning the ship's vertical line of axis following the conventions of bearing, starting from the north and progressing in a clockwise direction.

$$angle = \frac{(middle\, pixel\, number\, horizontally) * (FOV)}{Horizontal\, resolution\, of\, image} \quad (1)$$

The apparent width in pixels and the angle give information about the individual beams and are fed into the algorithm as inputs for further processing for every image captured.

3.5 Data Extraction & Evaluation

This subsection unveils the mathematical intricacies behind our work, showcasing the carefully crafted formulas that serve as the mathematical heartbeat of our analysis and algorithm.

3.5.1 Distance Measurement from Host Vessel

The apparent width in pixels is used to find an estimation of the distance of the host vessel from the detected beams. Depending on the camera specifications, there is always a constant value that maintains the inverse proportionality between the actual distance and the image width. This constant is denoted by k and is defined as:

$$k = \frac{(Horizontal\,resolution) * (Actual\,Beam\,width)}{2\tan(FOV/2)} \tag{2}$$

Multiplying this constant with the inverse of the apparent width gives us the distance.

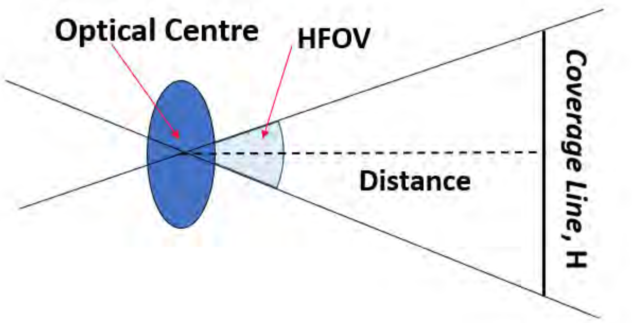


Figure 3.8: Optical Lens

$$Distance = \frac{H/2}{\tan(HFOV/2)} \tag{3}$$

$$H = \frac{(Horizontal\,resolution) * (Actual\,Beam\,width)}{image\,width\,in\,pixels} \tag{4}$$

$$Distance = k * \frac{1}{image\,width\,in\,pixels} \tag{5}$$

The distance and angle values can then be used to find the coordinates of the facer vessel beams to the host ship's central point.

3.5.2 Respective Beam Identification Based on Laser Light Data

The beams that belong to the same vessel move the same distance between two consecutive image frames. Since the precision of the calculation is very high, and the vessels have to maintain sufficient distance among themselves, considering the motion of the host vessel itself, any two facer vessels are never to have the exact apparent displacement at the same time. This allows for the classification of the detected beams into individual ships. At least two successive image frames are required for beam classification.

3.5.3 Ship Size Classification

The separated beams from the classification step are used to calculate the size of the individual ships. The difference between the angles of the beams and their distances gives us an estimation of the area of a given ship using the cosine rule.

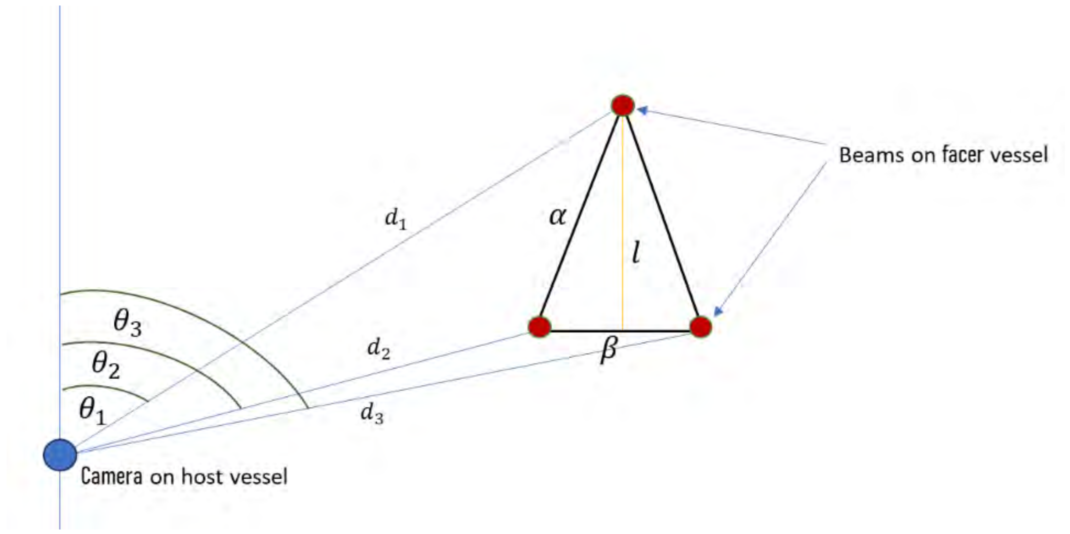


Figure 3.9: Size Estimation

Using Cosine rule,

$$\alpha = \sqrt{d_1^2 + d_2^2 - (2.d_1.d_2.\cos(\theta_2 - \theta_1))} \tag{6}$$

$$\beta = \sqrt{d_2^2 + d_3^2 - (2.d_2.d_3.\cos(\theta_3 - \theta_2))} \tag{7}$$

Using Pythagoras Theorem,

$$l = \sqrt{a^2 - (\frac{\beta}{2})^2} \tag{8}$$

The size in turn can be used to determine the type of the vessel; other information can also be derived based on the documentation of the vessel type.

3.5.4 Ship Velocity Measurement & Detection

Two types of speeds can be calculated. The apparent speed is the speed concerning the perspective of the host vessel. The absolute speed is the actual speed with which a given facer vessel is moving. The different beams from two successive images are classified first and their differences are used to find the distance moved. The distance is then multiplied by the frame rate to find out the speed.

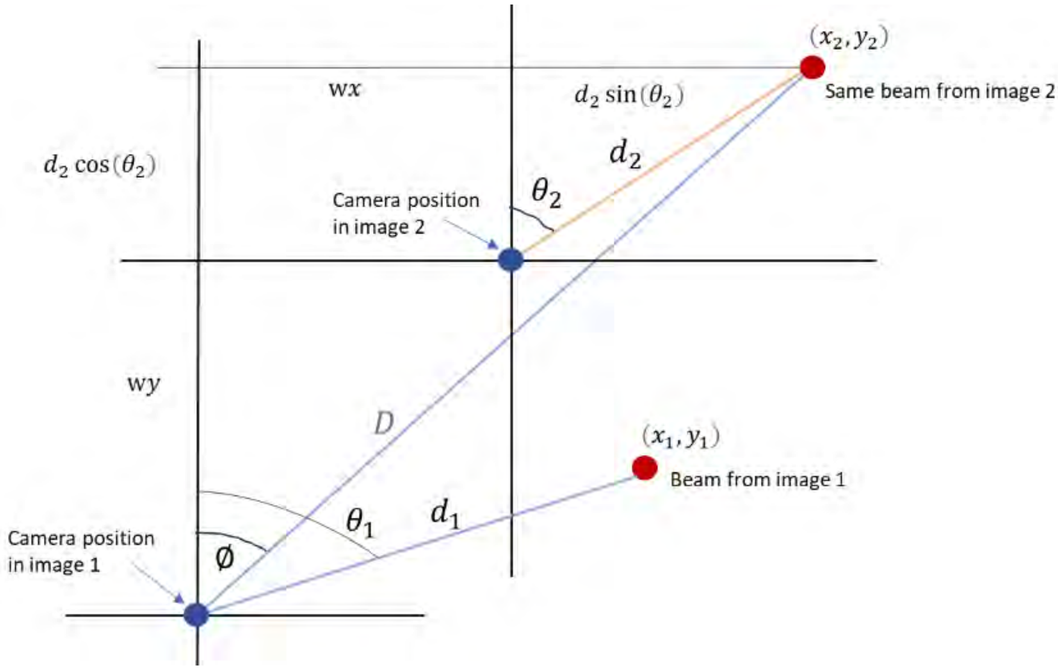


Figure 3.10: Velocity Calculation

$$wx = horizontal\, speed\, of\, host\, vessel$$

$$wy = vertical\, speed\, of\, host\, vessel$$

$$Absolute\, speed\, of\, facer\, vessel = (\sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}) * (frame\, rate) \quad (9)$$

$$Apparent\, speed\, of\, facer\, vessel = (\sqrt{(d_2 \sin\theta_2 - x_1)^2 + (d_2 \cos\theta_2 - y_1)^2}) * (frame\, rate) \quad (10)$$

The direction of motion can also be determined using the arc-tan of the coordinates of the beams. To normalize these values concerning the host ship's vertical line of axis, they are shifted by certain angles according to the quadrants they are in.

3.6 Unearthing Algorithm (Design)

Figure 3.11 represents the overall working architecture of our produced algorithm. The numbers are the step-by-step functions of our algorithm where each functionality is based on the result of the previous module. Our algorithm will activate once the images from image processing, have been polished and the laser sphere diameters have been properly annotated. Once the algorithm processing completes, based on the calculations, an alarm may be triggered by the algorithm later to signal the incoming facer vessel to change its direction.

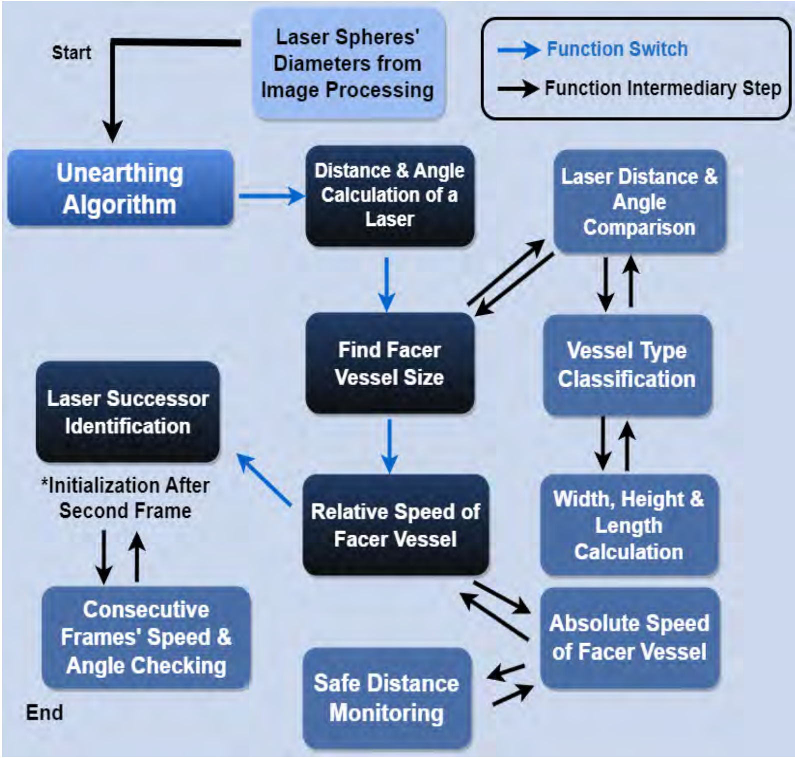


Figure 3.11: Algorithm Workflow

The algorithm of our proposed system requires two sole classes to be made at first where the first is called the Ship class.

```
Class Ship:
    Method Initialize(beam):
        area → 0
        lasers → beam
        type → None
        abs_speed → None
        app_speed → None
        Call findFacerVesselSize with lasers
    Method findFacerVesselSize(lasers):
        width → 0
        length → 0
        height → 0

        For each laser in lasers:
            For other_laser in lasers:
                If laser ≠ other_laser:
                    temp_angle → Absolute angle difference between laser and other_laser
                    l1_distance → Distance from laser
                    l2_distance → Distance from other_laser

                    temp → Calculate distance between laser and other_laser using trigonometry

                    If width is 0:
                        width → temp
                    Else:
                        If temp > width:
                            length → temp
                        Else:
                            length → width
                            width → temp

        Calculate height using geometric relationships
        area → Compute the rounded product of height and width

        For each key in shipDictionary:
            If shipDictionary[key] is equal to area:
                type → key
                Break
        Return rounded area
```

Figure 3.12: Ship class

Each vessel is considered a ship in our code and we know, that each ship will be placed with 3 lasers hence 3 individual beams would be considered one entire ship the corresponding data, when received, will be turned into an object of this Ship class. The attributes used, are necessary for further calculation where there is absolute speed, which is the actual real-time speed of this facer vessel; apparent speed which is the relative speed of the facer vessel for the host vessel; area and type which will determine what exactly is this ship. The class method, 'findFacerVesselSize', uses the law of cosine trigonometry rule to determine the actual width and length of the facer vessel by calculating the angle of each pair combination and the respective distance between each laser. A triangle is created, which is used to determine values of the width and length of the vessel. A global dictionary exists in the code, which maps the dimensions of a vessel to every type out there and this is used to derive the vessel category.

```
Class LaserBeam:
    Method Initialize(angle, apparent_width):
        Set self.angle ⟶ angle
        Set self.distance ⟶ apparent_width
        Compute and set self.point based on spatial relationships
```

Figure 3.13: Laser class

Each laser data will be converted into an object of the laser class where each object will only have its apparent width, angle, and coordinate from the host vessel's center.

```
Function distance(point1, point2):
  Return a measure of spatial separation between point1 and point2

Function distance_single_point(point1, point2):
  Return a measure of spatial separation between point1 and point2

Function classify_beams(b1, b2):
  Identify spatial relationships between beams in b1 and b2
  Initialize an empty list boats to store identified relationships

  For each pair of beams (b1[i], b2[l]) and (b1[j], b2[m]) and (b1[k], b2[n]):
    If these pairs exhibit consistent spatial characteristics:
      Add information about the relationship to boats

  For each remaining beam i in b2:
    If i has not been associated with any relationship:
      Add information about its isolated presence to boats

  Return boats
```

Figure 3.14: Miscellaneous Methods

Next in Figure 3.14, we see two functions that utilize the proportionality constant, k to derive the actual distance of each laser from the camera, based on its apparent width and the other function derives the same distance from the coordinates. The 'classify_beam' function is crucial to the code as this function determines how many facer vessels are currently being captured by the camera. Since the ratio among the lasers' distance would be the same for each facer vessel, this piece of information is utilized to find out how many vessels are there because at a given time, tens of laser beam data will arrive to the model and then we need to perform ship classification here.

```
Function findVelocityOfFacerVessel(beam, v):
  Determine differences in horizontal and vertical components:
    horizontal_difference ⟶ v[0] - host_h_speed
    vertical_difference ⟶ v[1] - host_v_speed

  Calculate velocity magnitude, considering frame rate:
    magnitude ⟶ calculateMagnitude(horizontal_difference, vertical_difference)
    scaled_velocity ⟶ round(magnitude, 2)

  Return scaled velocity:
    Return scaled_velocity
```

Figure 3.15: Velocity Calculation

In Figure 3.15, the 'findVelocityOfFacerVessel' function simply calculates the absolute velocity of the facer vessel by using the relative horizontal and vertical velocities concerning the host vessel.

```
Function laserSuccessorChecker(givenLasers, predecessorLasers):
  # Iterate through each laser in the givenLasers
  For each beam in givenLasers:
    # Initialize an empty list to store differences between beam angles and predecessorLasers angles
    beamDifferenceWithAll ⟶ []

    # Iterate through each laser in the predecessorLasers
    For i ⟶ 0 to len(predecessorLasers) - 1:
      # Calculate the absolute difference between the angles
      difference ⟶ abs(beam.angle - predecessorLasers[i].angle)

      # Append the difference to the list
      beamDifferenceWithAll.append(difference)

    # Find the minimum difference and its index
    minDifference ⟶ Minimum value in beamDifferenceWithAll
    minDifferenceIndex ⟶ Index of minDifference in beamDifferenceWithAll

    # Assign the predecessor and ship attributes to the current beam
    beam.predecessor ⟶ predecessorLasers[minDifferenceIndex]
    beam.ship ⟶ predecessorLasers[minDifferenceIndex].ship

    # Append the current beam to the lasers list of the predecessor ship
    predecessorLasers[minDifferenceIndex].ship.lasers.append(beam)
```

Figure 3.16: Successor Method

Another crucial feature that needed to be included in the code, is to be able to identify from consecutive frames, which lasers belonged to which incoming successive lasers, as in which laser data is the updated data of which past laser data as this is required to calculate the distance covered and the respective velocity. The time interval between each frame is close to 0s and hence on average, the angle change of a laser will be very close to zero. Therefore, the incoming data with which the previous data will have the least difference in angle will be its successor. This is how the laser data are mapped with each other. This is shown in Figure 3.16.

Altogether, the entire code will be working on top of a while loop where the condition of this while loop is that none of the facer vessels has penetrated the safe distance boundary. There will be continuous data, incoming from image processing to our code model; every laser data will be converted into an object then this list of objects will be passed through the 'classify_beam' function to be sorted out into groups where now, these groups will be converted into an object of Ship class. When the second set of data arrives, the above-mentioned process will be performed however, the additional step is to find the successor of the previous laser data and now their corresponding velocities to be calculated. These velocities will allow our system to make decisions from now onwards to decide when to trigger the alarm or just observe the facer vessel's journey around us. The safe distance for every category of ship with varying speeds will be fed into our system during the installation period.

4 Vessel Model Visualisation

In this dedicated section, we illuminate the virtual realm where our research takes shape, delving into the construction of a modeling framework and a sophisticated simulator.

4.1 Modelling of Host Vessel with Equipment Placement

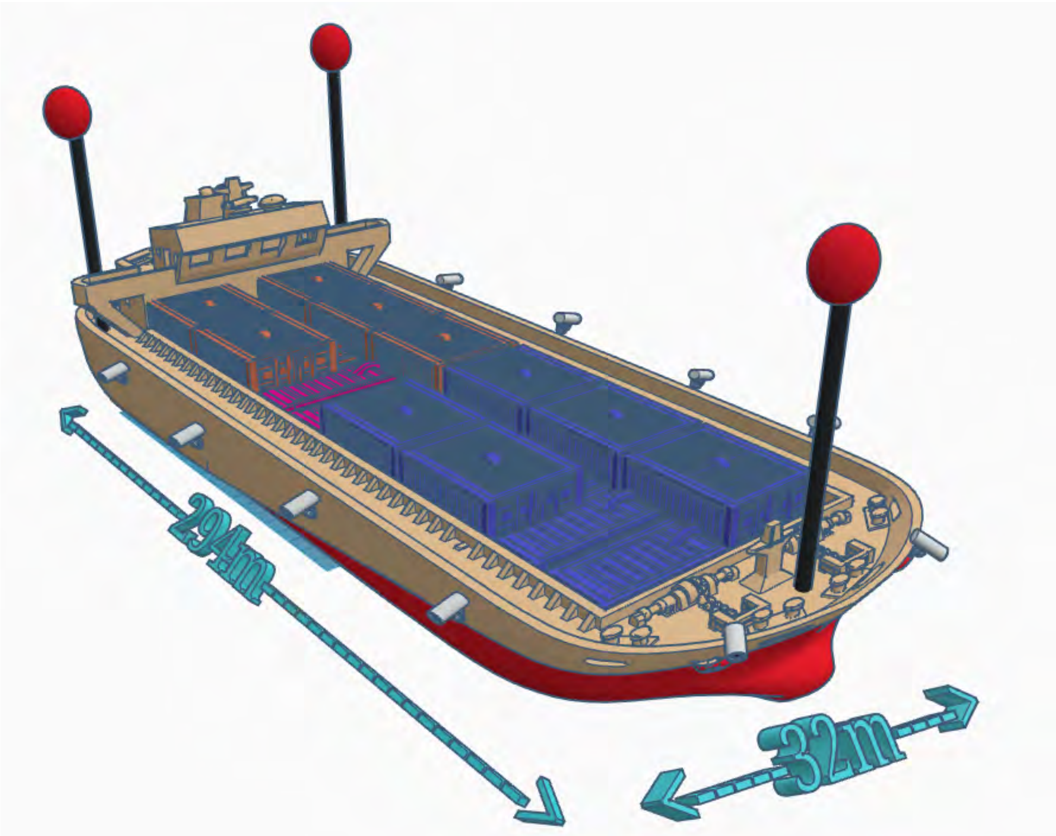


Figure 4.1: Cargo Vessel

The models depicted in Figure 4.1 and Figure 4.2, are of a cargo vessel and a speed boat. For now, we are considering the cargo vessel to be 294 meters in length and 32 meters in width. And, the speed boat is to be 80 metres in length and 15 metres in width. We are considering maritime vehicles such as passenger launches, steamers, etc. to be the size of a speed boat. However, the cargo vessel is as it is. The placement of the laser lights is done in a way so that our algorithm can calculate the maritime vehicle's length and width and detect the type of vessel it is, as mentioned previously. In the models, we have placed two lasers at the two corners of the vessel's back and one laser at the front tip. Also, the cameras used, have a low FOV of 25.7 degrees. We have placed ten cameras on three sides of the vessel to cover any blind spots left to cover. The cameras are placed on the sides of the vessel around more than halfway of the length and at the front, exactly at the tip. During the calculations, we have assumed that the lasers are exactly at the three edges of the maritime vehicle.

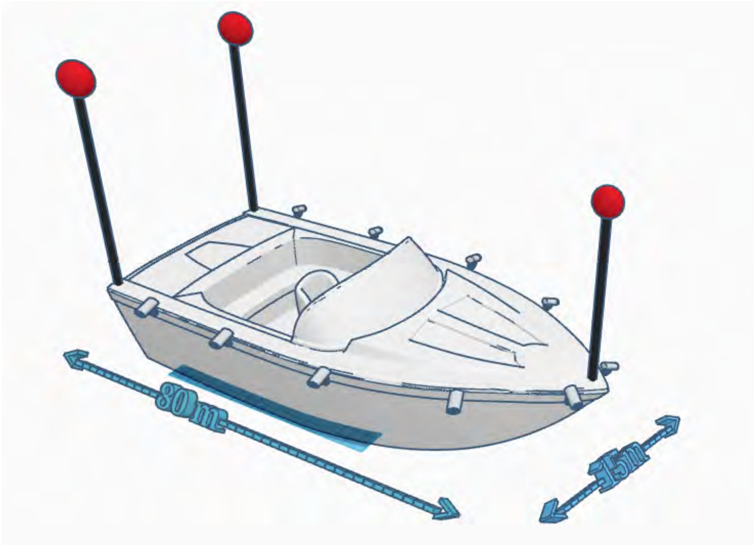
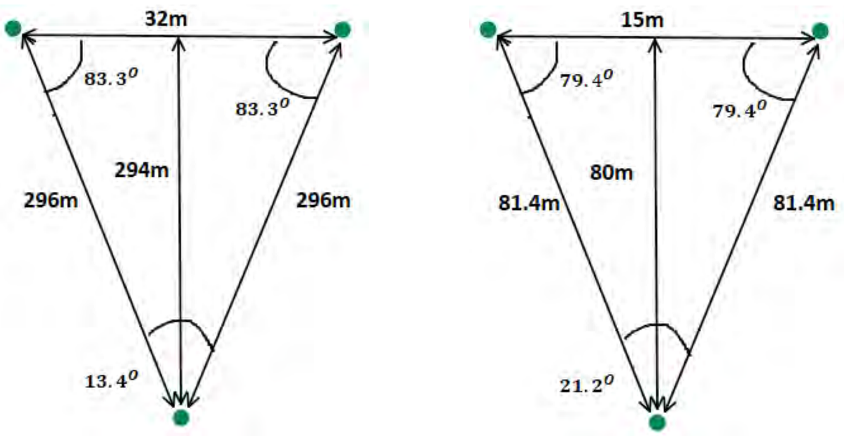


Figure 4.2: Medium-Small sized vessel representation



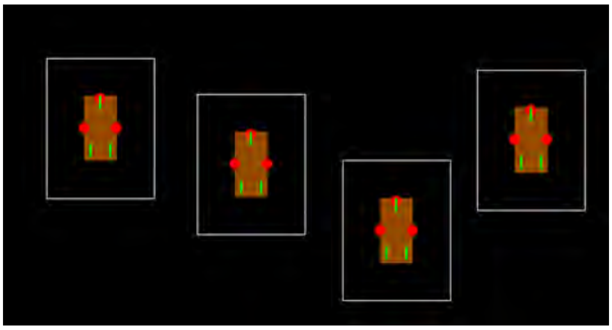
(a) Cargo Vessel (b) Passenger Vessel

Figure 4.3: Annotations from aerial view

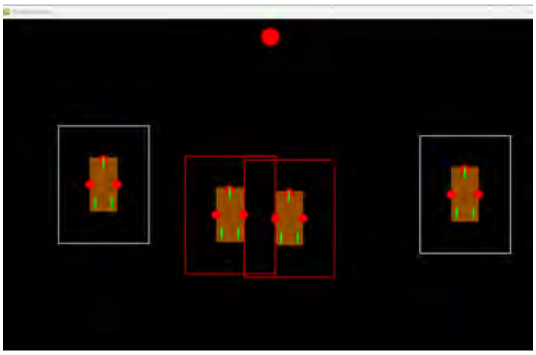
4.2 Simulation of Host & Facer Vessels

4.2.1 Initial Phase of Simulation

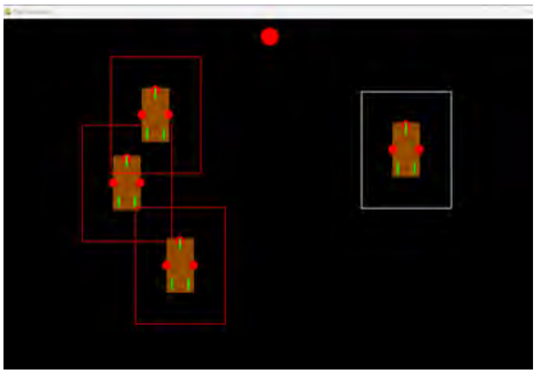
A simulation was created using PyGame, with Python version 3.11 implemented in PyCharm, to visualize our proposed laser-based system. The simulation shows how multiple ships, in this case, 4 ships, interact when any one ship touches or enters the boundary of a safe distance around the ships. The boundary indicates the minimum distance surrounding the ships and should be maintained while sailing to avoid collisions. The simulation shows an ideal case where the ships are shown to be of the same size with identical speed and safety boundaries for simplicity. The red dots represent the cameras and the green dots symbolize the lasers on every vessel. These values can be changed if needed to fit ships of different specifications. The code utilizes the ship's position, speed, dimensions, boundary distance, etc. to decide whether a boundary has been breached. The red circle on top of the screen indicates an alarm in a ship in a real-life scenario. A red circle indicates that at least 2 ships are prone to collision with each other, creating awareness for the ship sailors to change the course of sail or alter their travel speed well ahead of time to avoid collision.



(a) Initial position of multiple ships with no collision



(b) When 2 ships intersect each others' safety boundary



(c) Safety boundary intersection among 3 ships

Figure 4.4: Different Scenarios in Simulator

4.2.2 Enhanced Simulator

The simulator was developed further to replicate a real-life scenario as closely as how ships travel in the river bodies of Bangladesh. The simulator was automated to show multiple ships sailing on a single screen where if a ship enters the safety boundary of another ship, the ships deviate their path by changing their angle by a mere 5 degrees. Collision probability is rechecked and the angle deviation of the ships continues as long as both ships are out of each other's safety boundary. In reality, the direction control of a ship stays manual, in the hands of the ship operators since issues such as infrastructure limitation and lack of skill of workers persist. The simulator acts as a top view of a real-life scenario at a busy riverway. However, the simulator does not cover automatic original direction retrieval after collision avoidance, since our research work does not focus on automation. The figure below shows a snapshot of the automated ship simulator at a random instance.

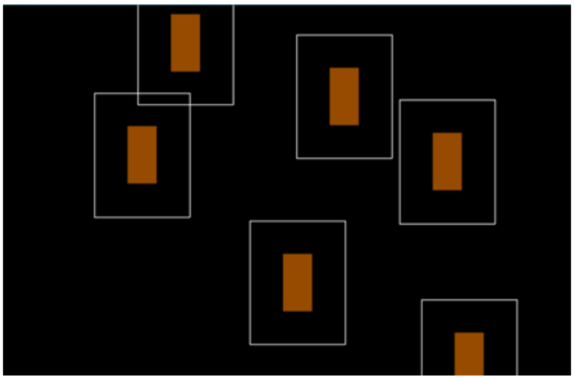


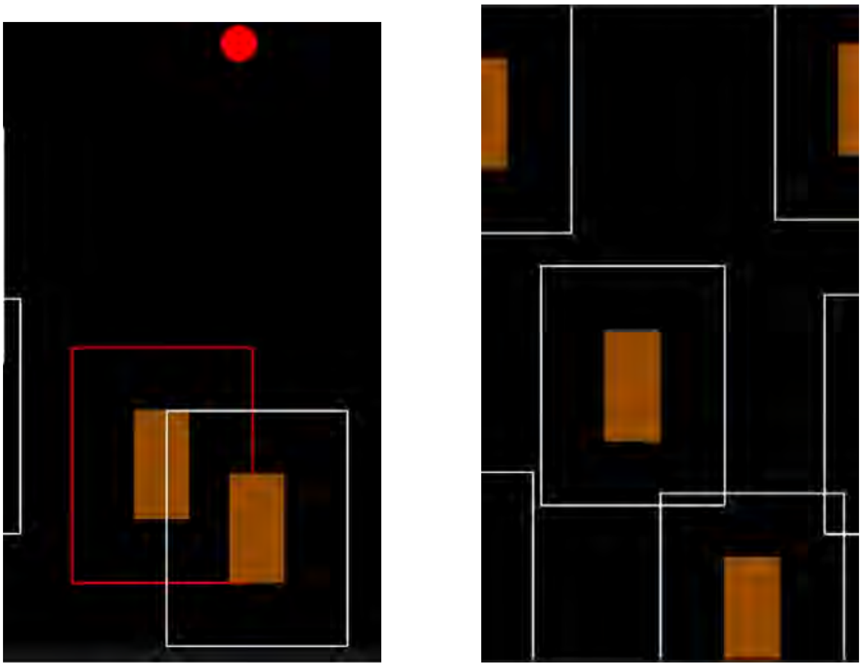
Figure 4.5: Automated Simulator instance

One specific scenario in the simulator is visible below. The two ships zoomed upon can be seen traveling very close to one another, but since the safety boundary is not crossed by either of them, the ships can safely cross one another in a diagonal direction, which is the original direction in this case. The scenario is broken down into three consecutive instances from left to right reading order.

(a) 1 (b) 2 (c) 3

Figure 4.6: Scenario 1

Below is another scenario where a collision possibility was detected and the boundary shows red. The left image in Figure 4.7a shows the collision detection. The right image shows that the ships will be deviating from their paths after collision detection. By the time the deviation takes place, similar to a real-life scenario, more ships can come closer which will then be dealt with again independently.



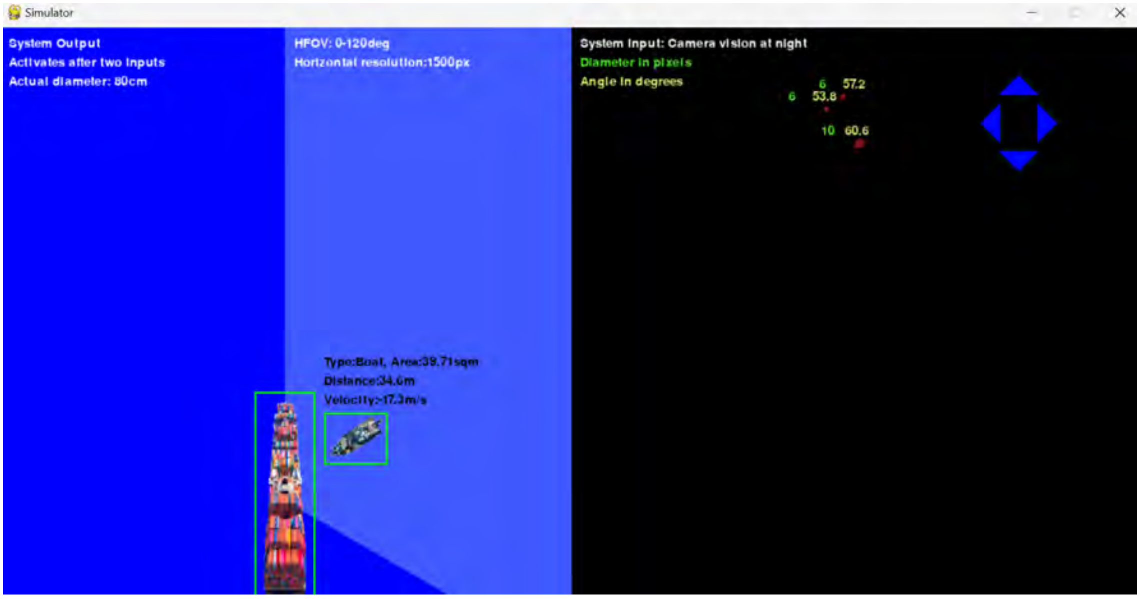
(a) Collision probability detected

(b) Deviation after collision probability detection

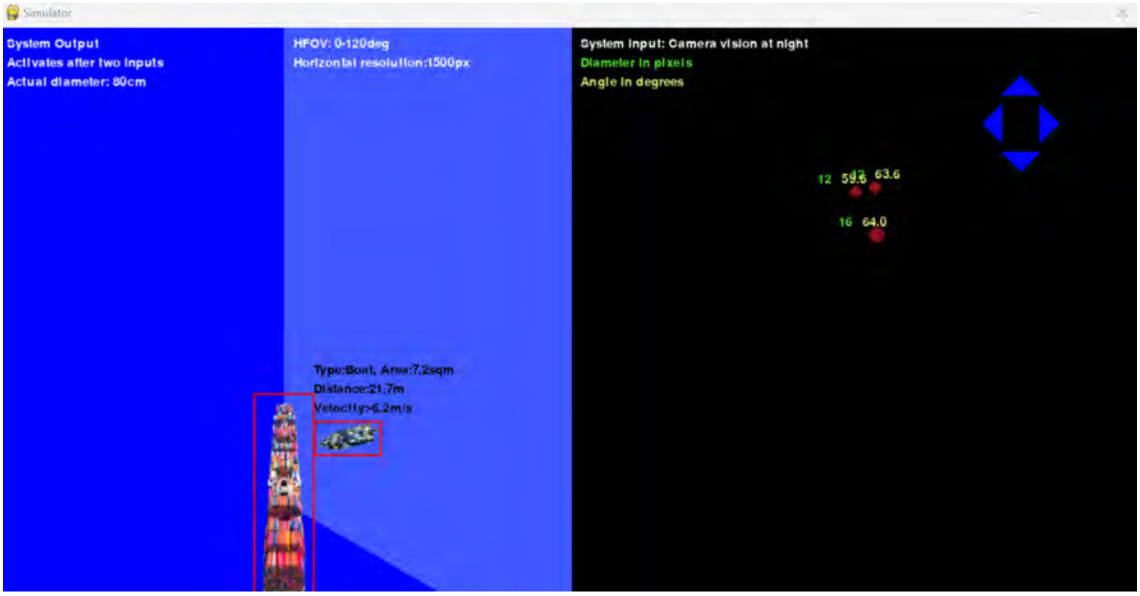
Figure 4.7: Scenario 2

4.2.3 Modified Simulator

The simulator was further redesigned with a new interface and integrated with the Unearthing algorithm to depict our proposed architecture. In this modified simulator, the new interface contains a host vessel(cargo vessel) and a facer vessel(fishing boat) along with its calculated values like area, distance, and velocity. Also, there's a controller to move the facer vessel and the background of the vessels has been given blue to represent a river. The values along the facer vessel are being calculated using the unearthing algorithm, from the host vessel's cameras. Moreover, the simulator includes captured laser beams' diameter in pixels and angle in degrees, which are calculated after image processing. The safe boundary line exists as implemented before. The figure below shows the modified simulator interface for the same scenario as in Figure 4.7.



(a) No collision probability detected



(b) Collision probability detected

Figure 4.8: Modified simulator scenario

5 Evaluation of Metrics

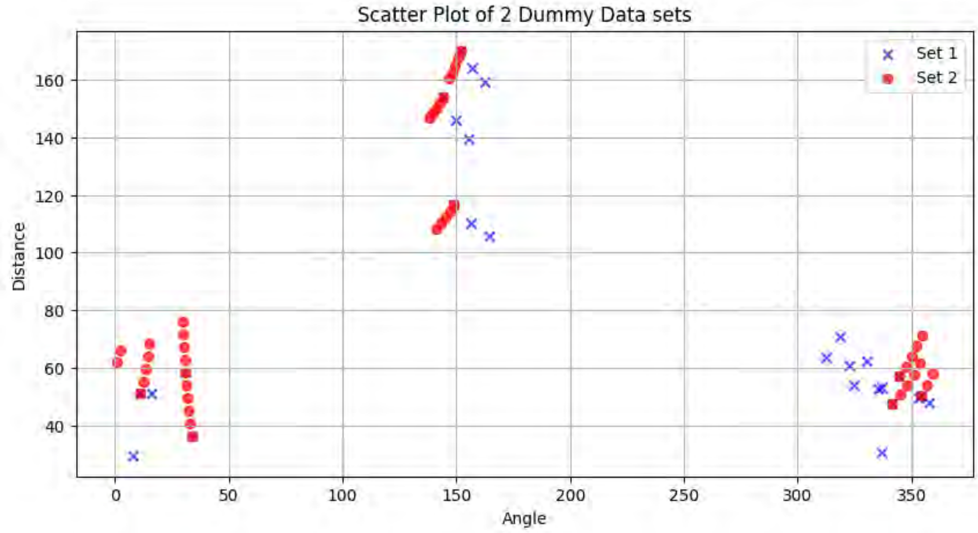
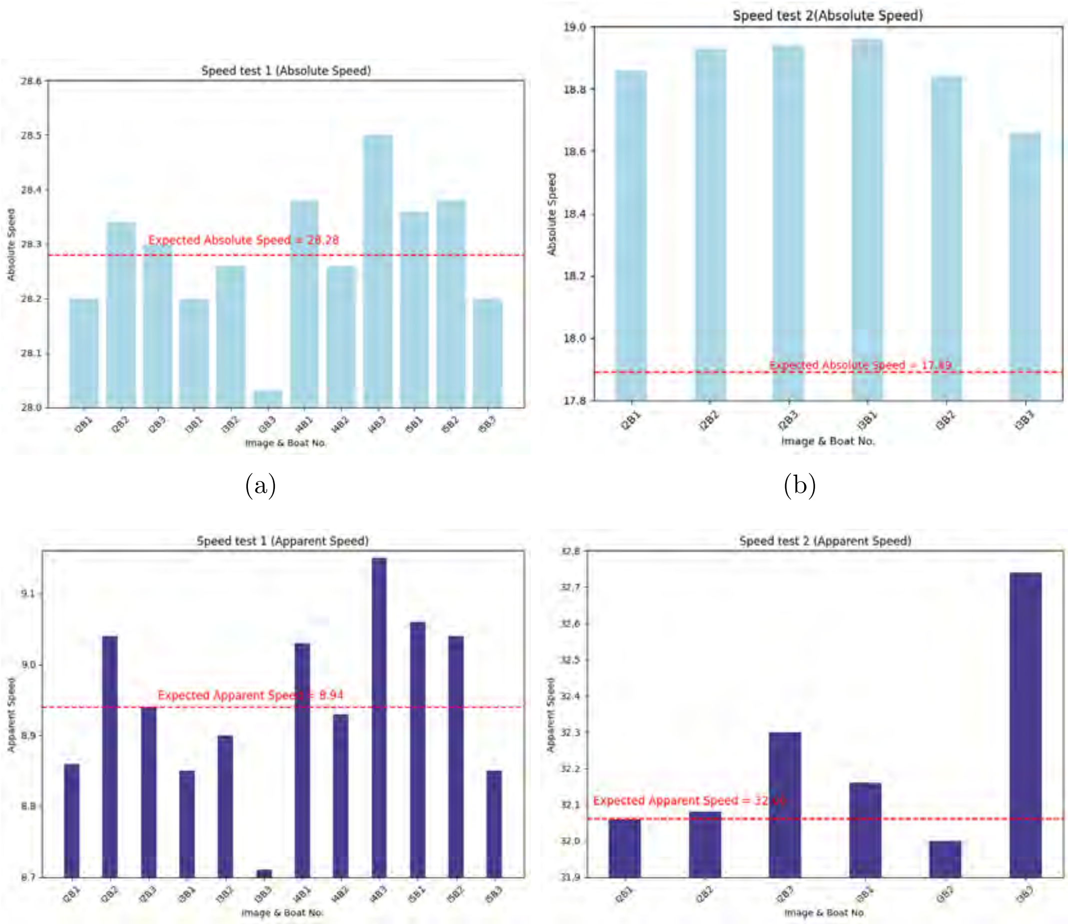


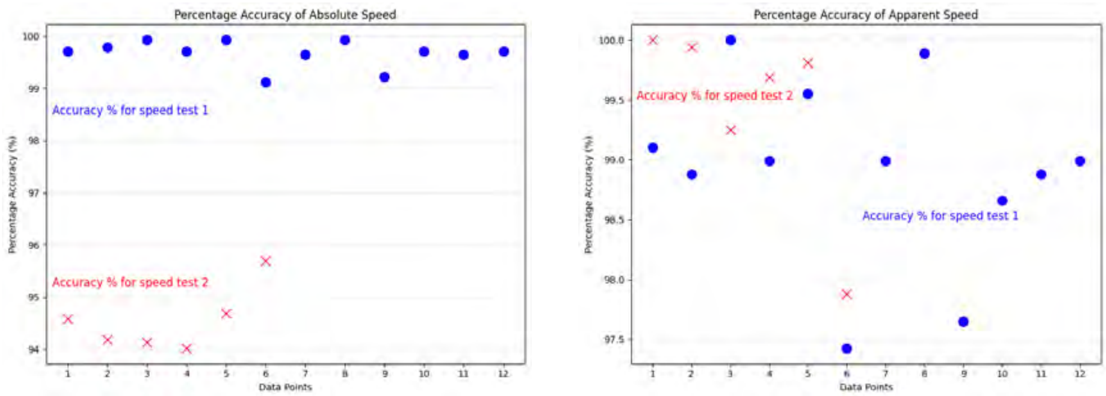
Figure 5.1: Dummy Data Scatter Plot



(a) (b)

(c) (d)

Figure 5.2: Speed Test for Absolute & Apparent Speeds



(a) (b)

Figure 5.3: Accuracy Percentage of Speed Tests

In Figure 5.1, two dummy data sets were introduced which are shown as a cross and dot in a scattered plot. In the plot, each circle or cross represents a laser beam placed on the vessel. Set 1 is represented by crosses and set 2 is represented by dots. There are various clusters depicted in the graph at various angles and distances to represent the real-life scenario of ships in Bangladesh's local waterways. For instance, the dots near (0,62), show that one of the laser beams got covered by another, and due to this only two dots are shown at this coordinate. Also, the crosses near (330, 65), clearly show three lasers depicting a ship to be present at that precise location. In such a manner, the plot is trying to give a vivid picture of ships in the river representing them as clustered dots and crosses.

In Figures 5.2(a) and 5.1(b), set 1 and set 2 were used to plot a bar chart of the absolute speed of the ships against their image and boat number. For set 1, it is clearly visible that in 5.2(a) the maximum number of the boats' absolute speeds are near to the expected absolute speed which is 28.28 km/h. On the other hand, for set 2, the speeds are much higher than the expected speed which is 17.89 km/h.

In Figure 5.2(c), data from set 1 is plotted to make a clear picture of the apparent speed between the ships, and then a similar is done from set 2 also in Figure 5.2(d). So, as it is shown the expected apparent speed from set 1 is 8.94 km/h, and most of the apparent speeds of the boats are closer to it. Also, the apparent speeds from set 2 have a similar pattern to set 1, that is they are closer to the expected apparent speed which is equal to 32.06 km/h.

Data points from Figure 5.2 have been used to provide percentage accuracy between the two-speed test sets. As shown in Figure 5.3(a), the percentage accuracy of absolute speed for set 1 shows a pattern at around 99-100 percent. And, for set 2 it shows data points to be in the range of 94-96 percent. However, in Figure 5.3(b), there is no pattern found in set 1 for percentage accuracy of apparent speed. So, it is showing a pattern only for set 2 around 99-100 percent.

6 Experiment Analysis & Findings

This chapter talks about the real-time experiment description and the accuracy of the findings from the output results.

6.1 Experimental Setup

This portion of the chapter highlights the necessary experimental setup of the demonstration and the required equipment.

6.1.1 Layout of the surrounding

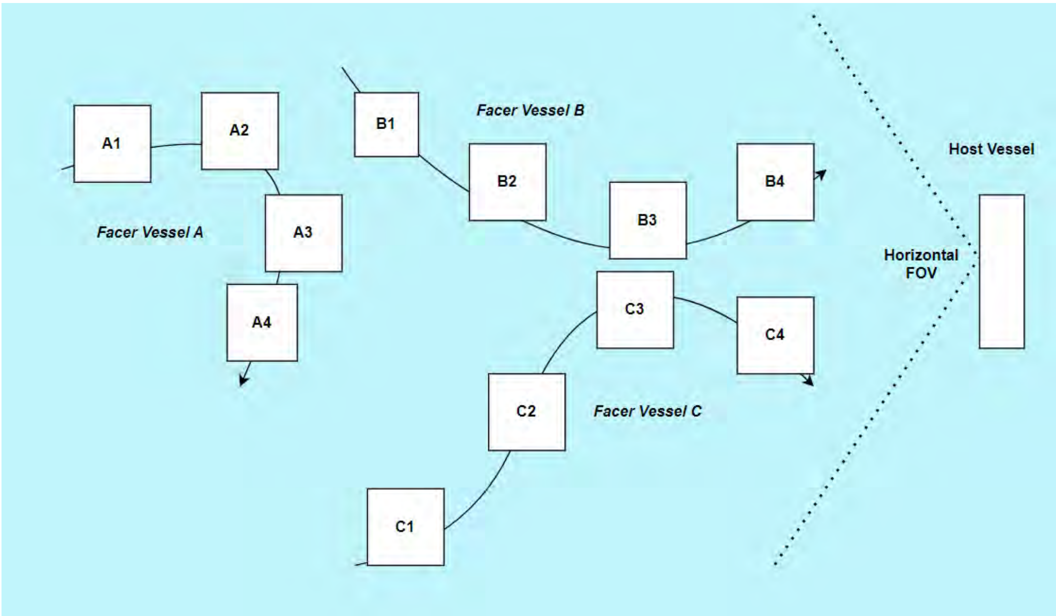


Figure 6.1: Demonstration Arrangement

For experiment setup, due to the inaccessibility to experiment with maritime locations, the following experiment has been conducted on a rooftop location for ease. However, the necessary conditions required for fruitful and unbiased work where accurate data can be collected have been ensured for accurate data collection.

As seen in Figure 6.1, the diagram represents the skeleton of the experiment body. Three water vessels have been mimicked to help us collect the readings. The vessels marked in the diagram, A, B & C, are the corresponding labels of the vessels. To mold these vessels, painting canvases were used with different sizes (to insinuate different sizes of vessels such as cargo vessels and steamers). The arrowheads in the diagram point towards the direction of motion of the vessels and it can be inferred that none collide with each other, as of now. The starting positions are letters with 1 at suffixes and the ending positions are the ones with 4. The host vessel will maintain constant monitoring and the camera has been set at the center of the host vessel for this experiment. The horizontal or landscape orientation of the camera was used to model the horizontal FOV of the camera of the host vessel.

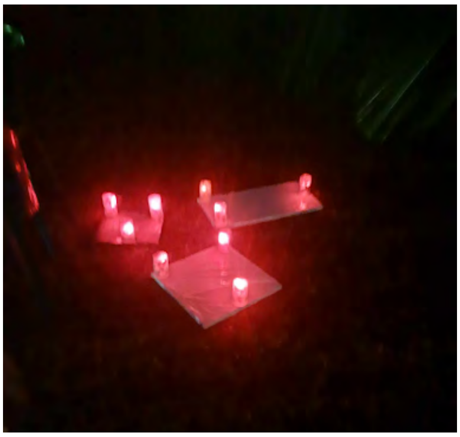
6.1.2 Laser Placements

The original model for lasers required to be made of plastic for the aforementioned benefits however due to the unavailability of spherical designs in the marketplace, cylindrical-plastic containers were applied to the experiment however, the encapsulation technique, overlooks the long shape of the container and hampers nothing in the experiment by not presenting any false positive results.
As shown in the modeling section, the laser light containers were similarly placed on the water canvases where two lasers were placed at the two edges of the rear of the canvases and one laser at the front but on the middle point, resembling an isosceles triangle for proper ship type classification later.

(a) Laser model for experiment

(b) Illuminated Version of Laser

(c) Orientation from a Distance



(d) Real-Time Setup of Three Vessels

Figure 6.2: Experiment Equipments

The illuminated laser light in Figure 6.2b was placed upside down on the water canvases and in total, 9 laser lights can be derived from the images captured from the experiment. The lightweight of these models mitigated the movement of the canvases throughout the experiment even more.

6.1.3 Data Collection Procedure

Initially, we randomly placed one or two ships (water canvases) in front of the camera at the start of the experiment at the designated marked places shown in the diagram. We have drawn the entire skeleton onto the ground to properly experiment. From then onwards, continuous images were captured as the direction and distance of the respective three vessels changed. The vessels were moved in the direction shown in the figure. The type of images captured from the experimental environment is shown in Figure 6.3.

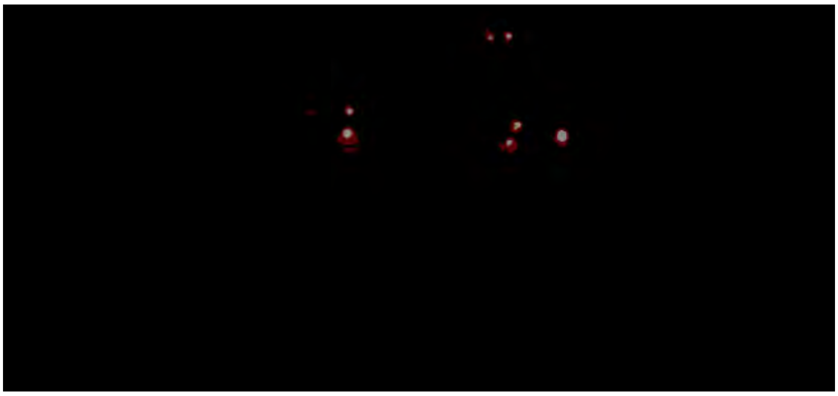


Figure 6.3: Captured Image Enhanced

To calculate the individual distance of laser light from the host vessels, we have utilized measuring software to measure the distance between the center of the laser container to the center of the host vessel's camera. The following images showcase the procedure of measuring the distance using the app.

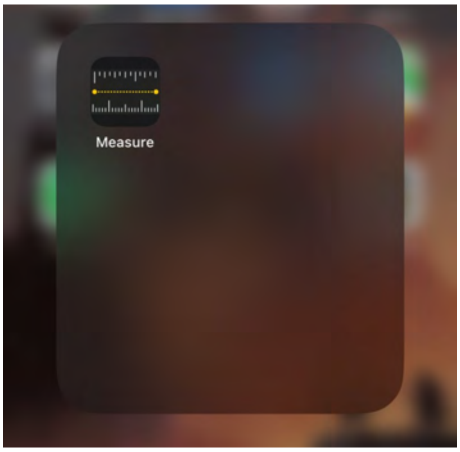
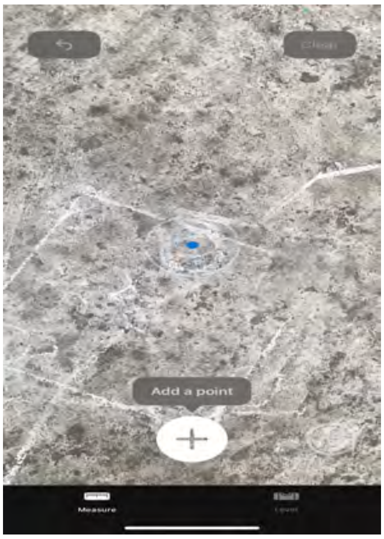


Figure 6.4: Utility App for Distance Measurement

As shown in Figure 6.5, the app mitigated the distance calculation part by accurately pinpointing the centers of the facer vessels and the host. Using the app, the distance can be dragged towards the center and hence whichever manner or orientation the ship was in, the distance could be calculated. If the phone moved or heaved uncontrollably, it can be taken back to where it was before and the distance itself would change accordingly, again to the previously calculated correct distance and hence these minor issues were tackled easily.



(a) Laser Center Blue Dot

(b) Center of Host Vessel Camera

(c) Dragging the distance from laser to host

(d) Actual Distance between one laser & host

Figure 6.5: Camera Inspection at Field Work

Next for angle calculation, we have primarily used threads to accurately measure the angle between the center of laser light and the camera center. We have considered the extreme right side of the host vessel to be at 0 degrees and therefore considered the inner scale of a protractor to measure the angle. Figures 6.6 show that procedure. The orange line is the thread, being used to measure the angles.

(a) Angle Measurement from Host Vessel Center

(b) Angle Measurement Continuation

Figure 6.6: Threading Procedure

In addition, the thread pieces used to measure the angle were cautiously cut at the endpoints and the actual length of the entire thread was measured using a measuring tape to crosscheck with the calculated distance from the app used earlier. We segmented each laser light's thread separately, as shown in Figure 6.7 next, and discovered close accuracy with both measurements.

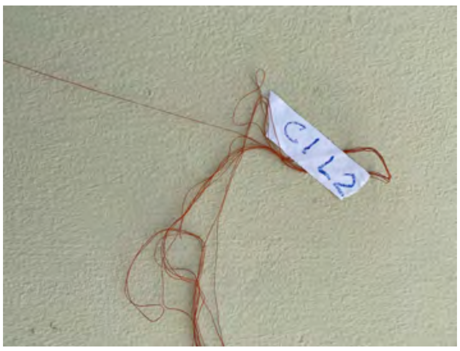


Figure 6.7: Comparison Thread of Vessel C's 2nd laser

This sums up the entire procedure for the data collection of the experiment which will be next used for comparison with the output data from the Unearthing Algorithm. This will be sufficient to check the actual accuracy of the algorithm in real-time scenarios.

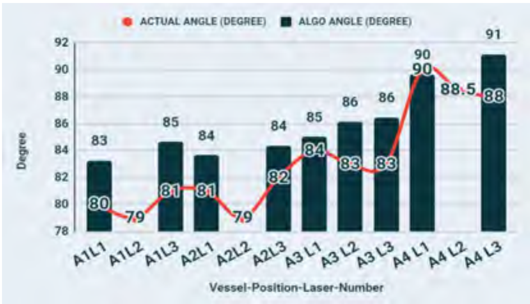
Table 6.1 next, presents the total collected data from the experiment. The data from the Unearthing Algorithm output will be used to compare with these data to calculate the error percentage.

Facer Vessel Corresponding Measurements from Host Vessel		
Vessel Position Laser Number	Angle (Degree)	Actual Distance (m)
A1L1	80	8.62
A1L2	79	8.89
A1L3	81	8.70
A2L1	81	8.08
A2L2	79	8.29
A2L3	82	8.71
A3L1	84	7.33
A3L2	83	7.62
A3L3	83	8.16
A4L1	90	7.41
A4L2	88.5	7.16
A4L3	88	7.51
B1L1	68	5.92
B1L2	69	6.32
B1L3	74	6.01
B2L1	73	4.77
B2L2	70	5.11
B2L3	72	5.26
B3L1	79	4.33
B3L2	74	4.43
B3L3	79	4.29
B4L1	79	3.46
B4L2	76	3.77
B4L3	83	3.73
C1L1	107	6.12
C1L2	115	6.41
C1L3	114	6.14
C2L1	98	5.46
C2L2	97	6.20
C2L3	99	5.88
C3L1	91	4.53
C3L2	89	4.88
C3L3	91	4.92
C4L1	96	3.26
C4L2	88	3.65
C4L3	96	4.06

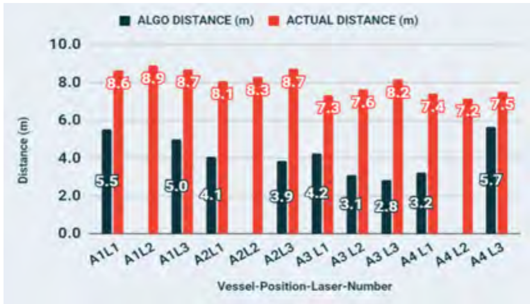
Table 6.1: Experiment Data Collection

6.2 Unearthing Algorithm Output & Findings

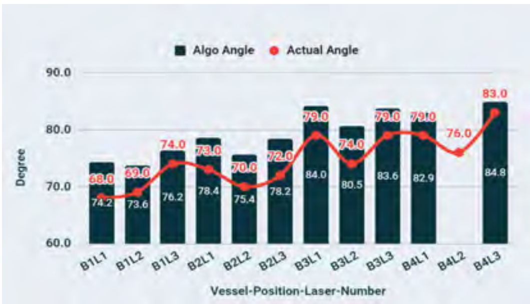
Table 6.1's data has been collected after running the experiment and next, through image processing, the captured images are used to distinguish the collective lasers of one vessel. Next, this new layer of data was fed into our algorithm to calculate the angle and distance again to check accuracy. The images below, showcase the 'Unearthed' angle and distance of various images of the experiment.



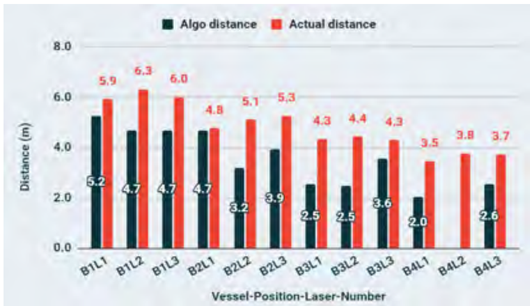
(a) Vessel A's Lasers' Angles at 4 Positions



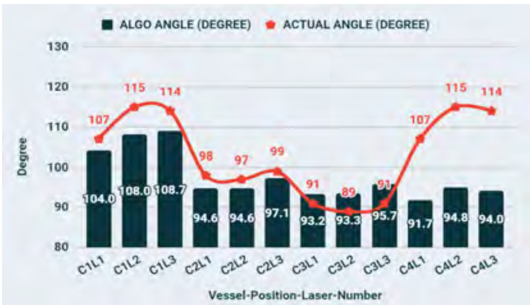
(b) Vessel A's Lasers' Distances at 4 Positions



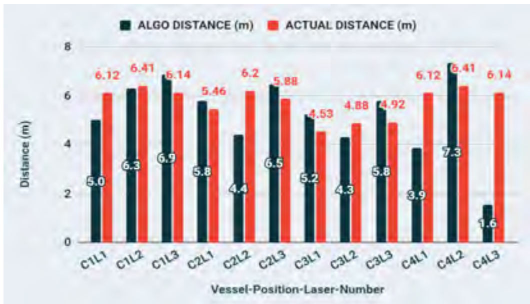
(c) Vessel B's Lasers' Angles at 4 Positions



(d) Vessel B's Lasers' Distances at 4 Positions



(e) Vessel C's Lasers' Angles at 4 Positions



(f) Vessel C's Lasers' Distances at 4 Positions

Figure 6.8: Data Comparison Visuals

From the above graphs, it can be derived that there are dissimilarities between the measured and algorithmically calculated data. The data points in the images, which have the missing blue bar, are an indication that image processing was not able to detect some of the laser diameters. However, other than this discrepancy, the near, equivalent heights of the bars in the angle and distance graphs show, accuracy in calculating the correct distance and angles of the vessels as anticipated. Mainly, the differences were present in Vessel A's data which was the furthest from the host vessel. As for Vessel B & C, the differences are minimal.

6.2.1 Classification Test Analysis

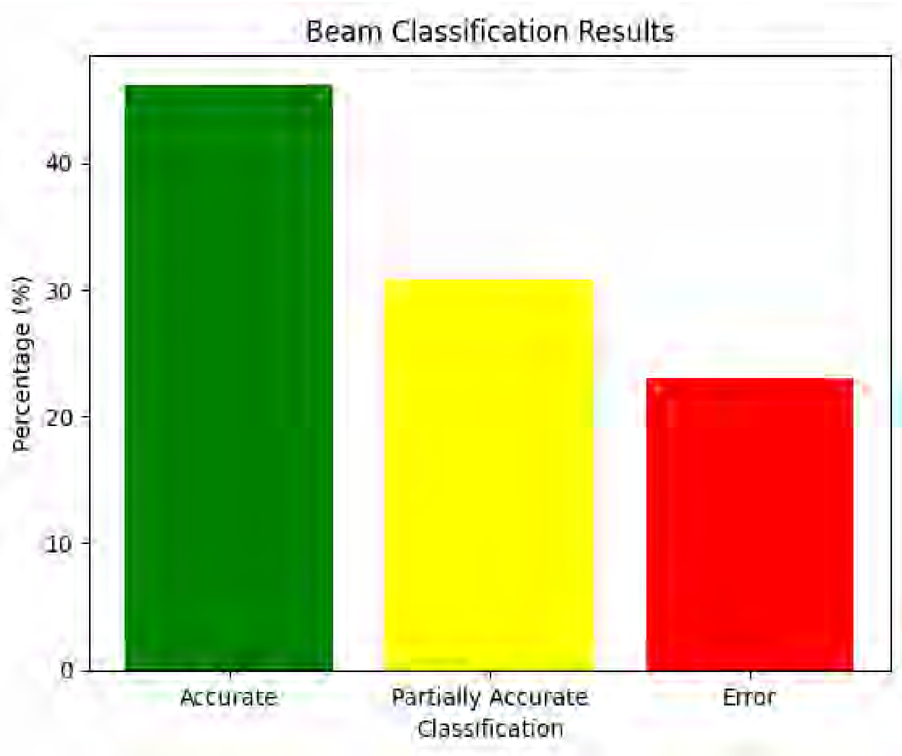


Figure 6.9: Classification Types

The graph in Figure 6.9 represents the accuracy of beam classification from the practical experiment done by capturing real-time images. As for the misclassification and to reduce the errors, constraining the differences in angle and distances will reduce errors but is dependent on proper distance calculation. Hence, with more accurate equipment to measure, these errors can be reduced by a larger amount.

6.2.2 Image Processing for Experiment

For extracting the diameter and centroids of the beam models, OpenCV has been used. The image is first converted to a gray scale format using a binary threshold which varies with the intensity of the light and can heavily affect the region of contour captured. Next, the contours are detected using cv2.findContours, and their centroids are calculated. By approximation of a polygon around the contours, the bounding circles are found and the centers and diameters are estimated. The angle is then calculated by multiplying the x-coordinate of the centroids with the horizontal FOV and dividing by the horizontal resolution of the camera.

7 Future Research

The image processing of our work needs to be further improved to better detect laser beams in river bodies as the ideal scenario is, for the cameras to be able to detect smaller radii of laser lights from afar and distinguish the lasers perfectly. Moreover, there will be various types of vessels outside Bangladesh that will not have known dimensions as they differ in length, height, and width. So, more research is required to implement our work not only in the inland waterways but in a broader perspective so that other countries can use it too. Also, autonomous ship detection needs to be researched as done in a simulator.

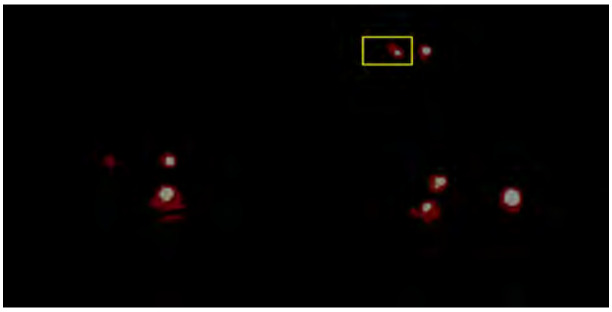
Furthermore, camera specification needs to be upgraded in a budget-friendly manner as at the moment, the camera specifications are gravitating towards expensive models and hence for developing countries to adopt this architecture, a cheaper model needs to be built. It is required, to improve the detection of laser beams and to withstand the heavy weather conditions in the waterways as well. Lastly, further research can be conducted on how the current laser model can be enhanced even more for the lasers to be detected from a much larger distance as this would allow any incoming vessel towards the host, more time to steer away.

8 Conclusion

8.1 Research Work Limitations

While images were captured, some of the laser beams overlapped from the camera's field of view. Consequently, after image processing, it was not able to differentiate how many vessels were at that precise location. The infused laser lights merged into one according to the software. As a result, it provided inaccurate data as a larger laser light gestures the vessel, it belongs to, to be much closer to the host which may lead to false alarms in a real-time scenario. This would cause inconvenience for the passengers of both vessels. This stands to be a major drawback and causes unnecessary havoc around.

(a) Scenario 1



(b) Scenario 2

(c) Scenario 3

Figure 8.1: Merged Laser Lights

Another limitation of our work is, as there is no direct electricity supply to the lasers, they are dependent on their batteries and at times may also be dependent on AC supply from the vessels themselves. As a matter of concern, spare or backup batteries need to be carried in the vessel to be safe or capacitors should be embedded into the laser model circuitry for backup when there may be power outrage in the vessels as without electricity, this architecture will collapse momentarily.

In drawing things to a close, if the laser beams are at a greater distance from the host vessel i.e. more than 400m, then it would be difficult to perform image processing for that particular vessel as the laser models would be minuscule to detect.

8.2 Ending Remarks

In a nutshell, our goal is to modify the laser and camera modules to enhance the performance of our system and guarantee a longer range to detect facer vessels which is undoubtedly, also reliable to be a deciding factor in maritime travelling. Currently, our range is a few hundred metres however we are aiming to prolong it to over a thousand metres. The existing works on waterway transportation are abundant and accessible as many sensor-based and new networking protocols are being used to make the system more efficient. Using these technologies, there have been visible improvements in the vessels. Nevertheless, the accident rate in Bangladesh has increased over the past years and hence, we are introducing a more affordable system that will convince the private company owners of water vessels to implement our system into theirs for safer maritime travel. Therefore, the goal of our paper is broader as it may help out other third-world countries with a similar structural problem and slightly culture-specific as well since the ambiance of waterway transportation is very different and informal than first-world countries; we have to take up individual affordable technical modules as shown in our system and later, combine them into a new infrastructure to make maritime traveling safer in inland waterway transportation of Bangladesh.

Bibliography

[1] Abebe, A. (2023). *Self-Supervised Learning for Robust Maritime IR/Vision Feature Extraction*. PhD thesis, Wien.

[2] Ahmed, M. S. and Juel, M. T. I. (2020). Iot based smart watercraft system. In *2020 IEEE Region 10 Symposium (TENSYMP)*, pages 1249–1252. IEEE.

[3] Amabdiyil, S., Thomas, D., and Pillai, V. M. (2016). Marine vessel detection comparing gprs and satellite images for security applications. In *2016 International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET)*, pages 1082–1086. IEEE.

[4] Antunes, N., Ferreira, J. C., Pereira, J., and Rosa, J. (2022). Grid-based vessel deviation from route identification with unsupervised learning. *Applied Sciences*, 12(21):11112.

[5] Bai, Z., Bi, D., Wu, J., Wang, M., Zheng, Q., and Chen, L. (2022). Intelligent driving vehicle object detection based on improved avod algorithm for the fusion of lidar and visual information. 11:272.

[6] Bhargave, S. S., Jadhav, M. V., and Patil, A. S. (2018). Automatic vehicle speed control system. *International Journal of Innovative Science and Research Technology*, 3(1).

[7] Bondi, E., Seidenari, L., Bagdanov, A. D., and Del Bimbo, A. (2014). Real-time people counting from depth imagery of crowded environments. In *2014 11th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS)*, pages 337–342. IEEE.

[8] Chadil, N., Russameesawang, A., and Keeratiwintakorn, P. (2008). Real-time tracking management system using gps, gprs and google earth. In *2008 5th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology*, volume 1, pages 393–396. IEEE.

[9] Chang, S.-J. (2003). Vessel identification and monitoring systems for maritime security. In *IEEE 37th Annual 2003 International Carnahan Conference onSecurity Technology, 2003. Proceedings.*, pages 66–70. IEEE.

[10] Chen, Y., Yang, T., Zhang, X., Meng, G., Xiao, X., and Sun, J. (2019). Detnas: Backbone search for object detection. *Advances in Neural Information Processing Systems*, 32.

[11] Deng, H., Wang, R., Miao, K., Zhao, Y., Sun, J., and Du, J. (2018). Design and implementation of ship gps monitoring and dispatching system for intelligent transportation system. In *Proceedings of the International Conference on Information Technology and Electrical Engineering 2018*, pages 1–5.

[12] Detsis, E., Brodsky, Y., Knudtson, P., Cuba, M., Fuqua, H., and Szalai, B. (2012). Project catch: A space based solution to combat illegal, unreported and unregulated fishing: Part i: Vessel monitoring system. *Acta Astronautica*, 80:114–123.

[13] Dobbins, J. P. and Langsdon, L. C. (2013). Use of data from automatic identification systems to generate inland waterway trip information. *Transportation research record*, 2330(1):73–79.

[14] Dzaferagic, M., Marchetti, N., and Macaluso, I. (2021). Fault detection and classification in industrial iot in case of missing sensor data. *IEEE Internet of Things Journal*, 9(11):8892–8900.

[15] EFFECTOR, E. (2020). Project-"an end to end interoperability framework for maritime situational awareness at strategic and tactical operations". *Grant agreement ID*, 883374:2020–2022.

[16] Fang, J., Sun, Y., Peng, K., Zhang, Q., Li, Y., Liu, W., and Wang, X. (2020). Fast neural network adaptation via parameter remapping and architecture search. *arXiv preprint arXiv:2001.02525*.

[17] Fuchs, L. R., Gällström, A., and Folkesson, J. (2018). Object recognition in forward looking sonar images using transfer learning. In *2018 IEEE/OES Autonomous Underwater Vehicle Workshop (AUV)*, pages 1–6. IEEE.

[18] Hosseini, S. and Barker, K. (2016). Modeling infrastructure resilience using bayesian networks: A case study of inland waterway ports. *Computers & Industrial Engineering*, 93:252–266.

[19] Jing, M. and Zheng, W. (2020). Research and application of real-time ship traffic intelligent analysis and calculation platform under 5g background. In *IOP Conference Series: Earth and Environmental Science*, volume 446, page 052093. IOP Publishing.

[20] Joseph, F. J. (2019). Iot based weather monitoring system for effective analytics. *International Journal of Engineering and Advanced Technology*, 8(4):311–315.

[21] Karimanzira, D., Renkewitz, H., Shea, D., and Albiez, J. (2020). Object detection in sonar images. *Electronics*, 9(7):1180.

[22] Konvention, S. (2010). International convention for the safety of life at sea.

[23] Lee, S., Park, B., and Kim, A. (2018). Deep learning from shallow dives: Sonar image generation and training for underwater object detection. *arXiv preprint arXiv:1810.07990*.

[24] Manik, J. A. (2022). 27 killed as cargo ship collides with ferry in bangladesh. The New York Times.

[25] Mia, M., Islam, M. S., Islam, M. A., Islam, M., and Uddin, M. (2021a). Brief analysis of inland waterway accidents in bangladesh: Causes and solutions. In *12th International Conference on Marine Technology (MARTEC 2020) At: Faculty of Engineering–Pattimura University, Ambon, Indonesia*.

[26] Mia, M. J., Uddin, M. I., Awal, Z. I., and Abdullah, A. (2021b). An era of inland water transport accidents and casualties: The case of a low-income country. *Journal of International Maritime Safety, Environmental Affairs, and Shipping*, 5(2):32–39.

[27] Nguyen, D., Vadaine, R., Hajduch, G., Garello, R., and Fablet, R. (2021). Geotracknet—a maritime anomaly detector using probabilistic neural network representation of ais tracks and a contrario detection. *IEEE Transactions on Intelligent Transportation Systems*, 23(6):5655–5667.

[28] Noreen, U., Bounceur, A., and Clavier, L. (2017). A study of lora low power and wide area network technology. In *2017 International Conference on Advanced Technologies for Signal and Image Processing (ATSIP)*, pages 1–6. IEEE.

[29] Nowosielski, A., Małecki, K., Forczmański, P., Smoliński, A., and Krzywicki, K. (2020). Embedded night-vision system for pedestrian detection. *IEEE Sensors Journal*, 20(16):9293–9304.

[30] Ogunrinde, I. O. (2023). Multi-sensor fusion for object detection and tracking under foggy weather conditions.

[31] Restrepo-Arias, J. F., Branch-Bedoya, J. W., Zapata-Cortes, J. A., Paipa-Sanabria, E. G., and Garnica-López, M. A. (2022). Industry 4.0 technologies applied to inland waterway transport: Systematic literature review. *Sensors*, 22(10):3708.

[32] Rong, H., Teixeira, A., and Soares, C. G. (2020). Data mining approach to shipping route characterization and anomaly detection based on ais data. *Ocean Engineering*, 198:106936.

[33] Ruma Paul, Michael Perry, H. S. (2021). Bangladesh launch fire kills 38 people. REUTERS.

[34] Saravanan, K., Aswini, S., Kumar, R., and Son, L. H. (2019). How to prevent maritime border collision for fisheries?-a design of real-time automatic identification system. *Earth Science Informatics*, 12:241–252.

[35] Shamrat, F. J. M., Tasnim, Z., Nobel, N. I., and Ahmed, M. R. (2019). An automated embedded detection and alarm system for preventing accidents of passengers vessel due to overweight. In *Proceedings of the 4th International Conference on Big Data and Internet of Things*, pages 1–5.

[36] Uddin, M. I. and Awal, Z. I. (2020). Systems-theoretic approach to safety of inland passenger ship operation in bangladesh. *Safety science*, 126:104629.

[37] Ullah, A., Mimu, S. R., Biswas, A., Rasel, M. G., and Mozib, M. (2019). Smart iot based launch activities monitoring system for reducing the accident occurs on the river. *Journal of Sensor Research andTechnologies*, 1(3).

[38] Xiao, F., Ligteringen, H., Van Gulijk, C., and Ale, B. (2013). Nautical traffic simulation with multi-agent system for safety. In *16th International IEEE Conference on Intelligent Transportation Systems (ITSC 2013)*, pages 1245–1252. IEEE.

[39] Xie, H., Wang, D., Gan, S., Li, Z., and Liang, S. (2022). Intelligent vessel scheduling system for the controlled inland waterway based cps. In *2022 IEEE 25th International Conference on Intelligent Transportation Systems (ITSC)*, pages 85–90. IEEE.

[40] Yasir, S. (2021). At least 32 dead as boat capsizes in bangladesh. The New York Times.

[41] Zhang, M., Zhang, D., Fu, S., Kujala, P., and Hirdaris, S. (2022a). A predictive analytics method for maritime traffic flow complexity estimation in inland waterways. *Reliability Engineering & System Safety*, 220:108317.

[42] Zhang, X., Yan, M., Zhu, D., and Guan, Y. (2022b). Marine ship detection and classification based on yolov5 model. In *Journal of Physics: Conference Series*, volume 2181, page 012025. IOP Publishing.

[43] Zhao, L. and Shi, G. (2019). Maritime anomaly detection using density-based clustering and recurrent neural network. *The Journal of Navigation*, 72(4):894–916.

[44] Zissis, D., Chatzikokolakis, K., Spiliopoulos, G., and Vodas, M. (2020). A distributed spatial method for modeling maritime routes. *IEEE Access*, 8:47556–47568.

[45] Zoph, B., Cubuk, E. D., Ghiasi, G., Lin, T.-Y., Shlens, J., and Le, Q. V. (2020). Learning data augmentation strategies for object detection. In *Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part XXVII 16*, pages 566–583. Springer.

[46] Zunair, H., Hasan, W. U., Zaman, K. T., Haque, M. I., and Aoyon, S. S. (2018). Design and implementation of an iot based monitoring system for inland vessels using multiple sensors network. In *2018 2nd International Conference on Smart Sensors and Application (ICSSA)*, pages 38–43. IEEE.