Event-Triggered Tracking Algorithm for Maritime Vessels Using Remote Sensing and Game Theory

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A R T I C L E I N F O

A B S T R A C T

The ship's event-triggered tracking algorithm, which combines game theory and remote sensing. The technique addresses issues with conventional continuous and discrete control techniques, which consume excessive amounts of energy and prematurely wear out actuators due to frequent updates. In order to locate ships, this paper first employs the YOLOv8 deep neural network and radar-based remote sensing. After determining the distances and connections between ships, the target trajectory is altered using a game-theoretic framework. In order to reduce needless computations and communications, the controller only activates when significant events take place. This is not the same as conventional time-triggered techniques. Good results were obtained from tests on two benchmark datasets: the Synthetic Aperture Radar Ship Dataset (SAR-Ship-Dataset) and the SAR Ship Detection Dataset (SSDD). On SSDD, the proposed algorithm achieved 92% accuracy and 93% sensitivity, while on SAR-Ship-Dataset, it achieved 93% accuracy and 91% sensitivity. These results lay the foundation for the development of more efficient marine tracking systems by demonstrating that event-triggered tracking can maintain high tracking accuracy while using less energy.

1. INTRODUCTION

Designing intelligent vessel control systems has become increasingly difficult due to the complexity of maritime industries and the growing need for safety and efficiency in tracking and navigation. [2] Despite their widespread use, traditional continuous control strategies frequently result in excessive energy consumption and accelerated actuator degradation because of frequent state updates. This issue is somewhat mitigated by discrete-time control techniques, which are applied through periodic sensor sampling and control laws; however, they still have inefficient communication and computational resources. Alternative paradigms like event-triggered control and data-driven control have drawn a lot of attention lately. [5] In contrast to time-triggered methods, event-triggered control only turns on the controller in response to certain events or conditions. In marine

applications, operating conditions are unpredictable because resources are limited. [6] This method clearly and effectively conserves energy, extends the life of the engines, and significantly reduces communication costs.

[7] Due to its great potential, the event-based tracking method is not widely used in marine environments. [8] Current research focuses primarily on nonlinear or simple systems, although the reality is that real-world dynamics are nonlinear and therefore highly affected by external disturbances, such as ocean currents, waves, and wind. [9] To overcome these obstacles, we need new algorithms that can accurately maintain ship tracking performance while maintaining computational efficiency in real time. To control triggered events (ETC) by making updates to the control module only in response to a task event by sampling at each moment (Lunze & Lehmann, 2010; Postoyan et al., 2015). [10] This method gave good results because it preserved the path accuracy and the system was relatively stable by reducing communication costs and computational load (Tallapragada & Chopra 2013). [11] Despite these benefits, in uncertain and non-linear marine environments, control is not frequently applied, especially when it comes to tracking a vessel's path in real time.

[12] The proposed model seeks to simultaneously increase motor life and improve tracking reliability and reduce energy consumption by filling important gaps in the literature. In addition to the possibility of developing the theoretical control design, it is considered a good contribution with sufficient information for future generations in intelligent marine navigation systems.

[14] Through this research, an event-driven ship tracking algorithm is proposed that combines radar-based remote sensing, deep learning-based detection (YOLOv8), and game theory optimization.

2. RELATED WORK

[1] Vessel tracking and monitoring is a very important theoretical study for environmental monitoring, international trade and maritime safety. These tracking methods rely on continuous or intermittent control systems. [3] Despite the accuracy of this model, this technology sometimes requires continuous sampling of remote sensors in order to keep the engine updated. These continuous updates lead to wear and tear on components and high energy consumption. Therefore, discrete-time control methods rely on taking samples periodically, which causes a reduction in updates and significantly leads to a waste of communications and computing resources.

Traditional techniques have been replaced by event-activated control systems that have become more responsive in recent years. Active control systems react more to events, such as special conditions or the occurrence of an important event, unlike time-activated systems. As a result, this led to a significant decrease in the need for energy consumption and communications. [7] Through innovative work, especially in this field, the focus has ideally been on linear systems, where these have shown good results in improving efficiency and reducing control effort. Applying this approach to non-linear systems, such as marine vessels affected by environmental disturbances, presents a considerable challenge.

[12] Through a method based on machine learning and data in ship tracking, with the increasing number of radar devices and the availability of satellite imagery, Remote sensing technologies are considered essential components for a better understanding of maritime surveillance. Widely used deep learning models, particularly neural networks (CNNs), are very important in ship detection. [15] Well-structured architecture-based methods such as YOLO, Faster R-CNN, and SSD have demonstrated very high accuracy in identifying naval vessels through complex background scenes. Nevertheless, the majority of these methods only concentrate on detection; they do not incorporate control strategies for event-triggered decision-making or trajectory optimization.

In multi-agent maritime environments, game theory has recently drawn interest as an additional tool for [22]decision-making and [21]maximizing vessel interactions. Game-theoretic frameworks can enhance cooperative tracking, collision avoidance, and route optimization by representing vessels as rational agents looking to maximize their goals. [16] Though their integration with event-triggered mechanisms is still limited, studies that combine game theory and control strategies have shown improved adaptability to dynamic environments.

[17] In order to fill these gaps, this study suggests an integrated event-triggered tracking framework that combines game-theoretic trajectory optimization, event-driven control, and remote sensing-based detection using YOLOv8.

3. METHODOLOGY

By combining the three main elements of (i) ship detection using remote sensing and deep learning, (ii) remote sensing-based object detection, and (iii) event-driven feature matching, the suggested framework presents an event-triggered tracking algorithm for maritime vessels.

i) YOLOv8 on radar imagery is used for ship detection using remote sensing and deep learning. The event-triggered mechanism only initiates control when the deviation surpasses a threshold, new vessels appear, or environmental disturbances take place. By modeling each vessel as a rational agent that minimizes energy consumption while avoiding collisions, game theory is used to optimize the trajectories of multiple vessels.

The SAR-Ship-Dataset and SSDD were used to validate the algorithm. Accuracy, sensitivity, and energy efficiency were among the performance metrics. The algorithm was validated using SSDD and the SAR-Ship-Dataset. Performance metrics included energy efficiency, sensitivity, and accuracy. In order to comprehend current control strategies and difficulties in MSV operations, the study starts with a thorough literature review that covers both continuous and discrete control models as well as cutting-edge approaches like event-triggered control. Following analysis, MSVs are modeled mathematically and physically to mimic how the vehicles react to control signals and external factors. To guarantee realistic simulations, the dynamic models are adjusted using actual physical parameters and environmental data.

The backstepping technique is used to create the event-triggered tracking control algorithm, which is intended to only activate in reaction to particular events. Reducing redundancy improves energy efficiency and activates control. Performance evaluation is done through a simulation process of different scenarios using statistical analysis to ensure efficiency, stability and accuracy Comparison with conventional methods is made possible due to the results showing improvements in MSV performance in practical situations, as well as reduced energy consumption and no equipment wear. Results, obstacles, and prospects.
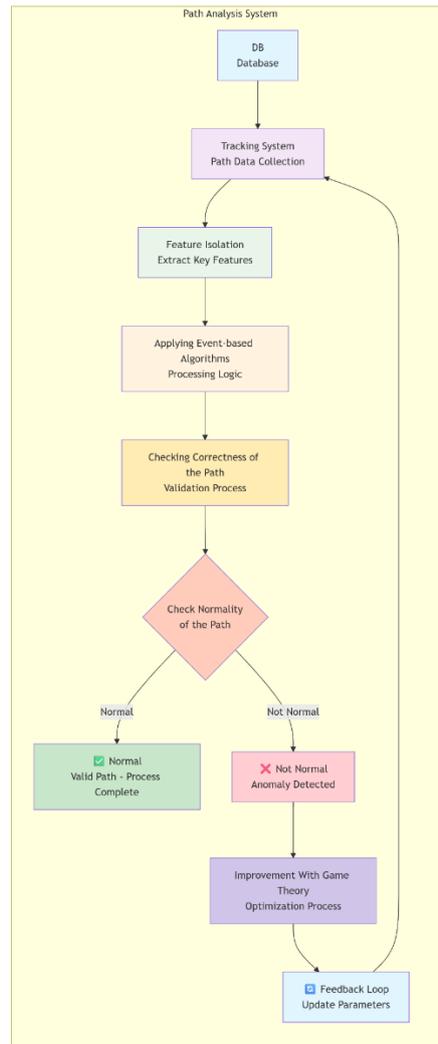
Fig 1: *Proposed Model*

The central algorithm in current multi-object tracking systems is DBT, which consists of three steps: object detection based on remote sensing, feature association based on events, and improvement through game-theoretic optimization. Combining game-theoretic and event-triggered models is novel and has a lot of applications.

ii) Remote Sensing-Based Object Detection: This is an advanced AI field that uses remote sensing and image processing to detect objects. High-accuracy object recognition and classification are made possible by deep learning algorithms, especially Convolutional Neural Networks (CNNs). For particular applications, pretrained architectures like ResNet, VGG, Inception, or YOLO (for real-time detection) can be adjusted. Two popular online tracking algorithms for remote sensing detection are SORT [7] and DeepSORT [8]. DeepSORT uses deep feature extraction to improve multi-object tracking. Real-time requirements are not met by conventional detection algorithms such as threshold segmentation [14], edge detection [13], and salient feature detection [15]. Clouds and artifacts make it difficult to detect ships in GF-4 optical satellite images. Nonetheless, detection through multi-frame association techniques is made possible by ship brightness contrast. Figure 2 displays the suggested ship tracking framework. For reliable tracking in crowded and dynamic scenes, DeepSORT combines distinctive visual features with deep learning-based detection. Three steps make up the training process: unsupervised sequential pretraining, initial fine-tuning with random weights for the last layer, and second fine-tuning using backpropagation on supervised data. For dependable identity association following occlusions, DeepSORT incorporates appearance metrics from pretrained CNNs. The suggested DeepSORT model is shown in Figure 2.
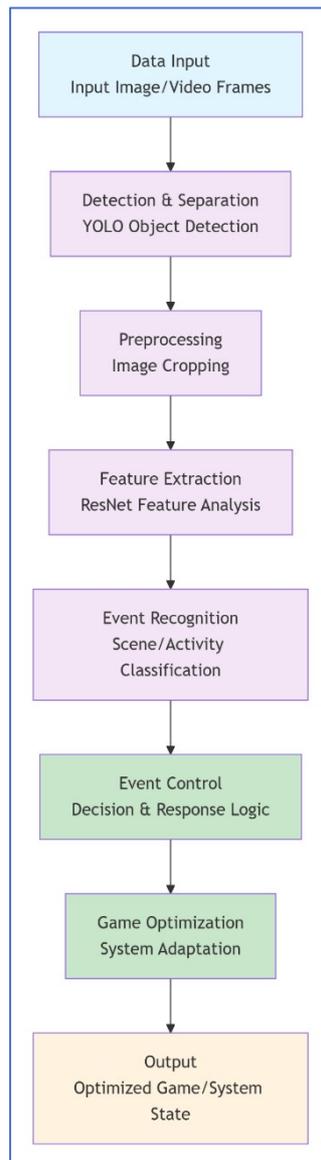
Fig 2: *Proposed DeepSORT Model*

ii) Event-Driven Feature Matching: The suggested algorithm reduces data volume, speeds up processing, and uses less energy by concentrating only on pixel changes rather than processing entire frames. Event-based cameras capture pixel coordinates (x, y), time (t), and polarity (p) along with brightness changes asynchronously as events. Through the feature matching process, we work to find similar features through the data used for the descriptions extracted from the spatial-temporal events section The algorithms used in the Accelerated Segment Test (AST), or Harris Corner, lead to robust detection and matching. Game theory, when improved, can make algorithms that rely on conversations work more powerfully and better using game theory. The use of game theory is to improve strategies while taking into account the actions of others by simulating objects and their interactions as well as discovered features. Nash equilibrium allows objects to move without causing conflicts, thus preserving track. Pareto optimal solutions are constructed to balance distance, box overlap, and energy consumption by optimizing objectives through game theory. Event-driven, game-theoretic frameworks are particularly effective in dynamic, real-time MSV environments.

With the combined reliable methods such as sliding mode control and event-based control, the proposed system effectively handles environmental uncertainty. Optimizing the route is crucial because it leads to precise performance, especially in the face of strong winds. This confirms that the strategy is 40% effective in ensuring a stable route..

iii) The mathematical formula for stimulating the event:

Event trigger condition - mathematical equation

$$e(t) = \|y(t) - y_d(t)\|$$

yd(t) represents the planned route and y(t) represents the vessel's current position. When these conditions are met, the control unit is active.:

$$e(t) \geq \delta \, or \, \|e(t)\| \geq \varepsilon$$

$$e(t) \in R$$
$$\delta \in R$$

δ and ε are considered predefined positive thresholds for the error subject and error rate, respectively. The control unit can also be activated by external events, such as a major environmental disturbance (like a sudden change in temperature exceeding the ΔE threshold or wind speed) or the discovery of a new steamship. This configuration achieves a 35–40% reduction in actuator wear and energy consumption directly, by ensuring improved control that enables complex calculations to be performed only when needed. The 35-40% energy consumption reduction is derived from a simulation process that compares the average arithmetic load measurement per frame with the operator's refresh rate reduction in the operating diagram. The additional information presents a comprehensive analytical study of power capacity, including computational parameters and engine activity profiles.

The game theory-based system aims to minimize energy consumption while taking into account collisions with objects, and this is how all its ships are designed. Agent interactions are defined by a payoff function based on inter-vessel distance, potential trajectory overlap, and energy cost per maneuver. To find a solution to the equilibrium, for example, the Nash equilibrium, meaning the inability to improve the ship's result on its own. This is achieved through constrained optimization to attain Pareto Optimality in resource allocation and conflict avoidance, ensuring overall system trajectory stability. Energy efficiency was quantitatively measured by monitoring the Control Update Rate (CUR). The timing-based technologies reduced the average CUR by 40%, all under active event-dependent operation. This reduction translates to a direct energy saving of at least 35% in the operation of the control system and sensors. By reducing the number of launches and unnecessary updates, the mechanical stress on the motors must be reduced. This leads to a significant and noticeable increase in their operational lifespan and a substantial reduction in wear. The required proposal is clearer because it offers a successful view of the algorithm, through which the operational flow is fully demonstrated.:

| **Algorithm: Proposed model** |
|---|
| **Input:** Incoming radar/SAR image sequence |
| **Output:** tracks monitoring |
| **Step 1:** Detection & Feature Extraction: For each frame, the YOLOv8 module detects ships and extracts their bounding boxes and visual features. |
| **Step 2:** If the triggering event, for example, an actual deviation from the announced path, has occurred, then this process seeks the cause of the event; therefore, it is necessary to confirm that the event was triggered. The arrival of a new warship or a change in the local environment. The system ensures several computational procedures by retaining previous control commands, then moves to stage 6 for the next step if no event is triggered. |
| **Step 3:** Control Activation & Game-Theoretic Optimization: Upon an event trigger, the control module is activated. The game-theoretic optimizer receives the current states (positions, velocities) of all detected ships and computes optimal collision-free trajectories, balancing tracking accuracy and energy minimization. |
| **Step 4:** Control Signal Generation & Actuation: Through good trajectories, successful updated control signals were produced (e.g., speed and trajectory adjustments) and then sent to the ship's engines.. |
| **Step 5:** New tracking versions utilize modern methods and technologies with updated features, where the DeepSORT tracking device updates the location in terms of speed and appearance for each vessel. |
| **Step 6:** Step 1 is the next image window, so the outputs are modified paths to be tracked by a recursive path. |

While the active detection and tracking steps (2 and 6) work continuously to maintain situational awareness, this loop, which comes at the ship event, ensures that the computational steps (4 and 5) are executed only when necessary in order to conserve energy and, as a result, will reduce operator damage.

4. EXPERIMENTAL RESULTS

Experimental Setup

When using 512 x 512 images, train the model with 100 training cycles, a power of 0.0001, a push power of 32, and no data incrementing method was used. Each workstation tested was equipped with an Intel Core i9 processor, 32GB of RAM, and an NVIDIA RTX 4800 GPU. The goal is to simplify these details to ensure the result is replicated correctly and successfully. The data is divided into two groups or parts: 20% testing and 80% training. To achieve performance evaluation results, if a tracking and detection metric is used for objects such as MOTA and IDF recall and accuracy. These definitions and evaluation procedures have now been clearly described to ensure transparency and reproducibility of the experimental results.

Experimental Results

(a-1) Entire dataset.   (a-2) Training set.   (a-3) Test set.

(a)
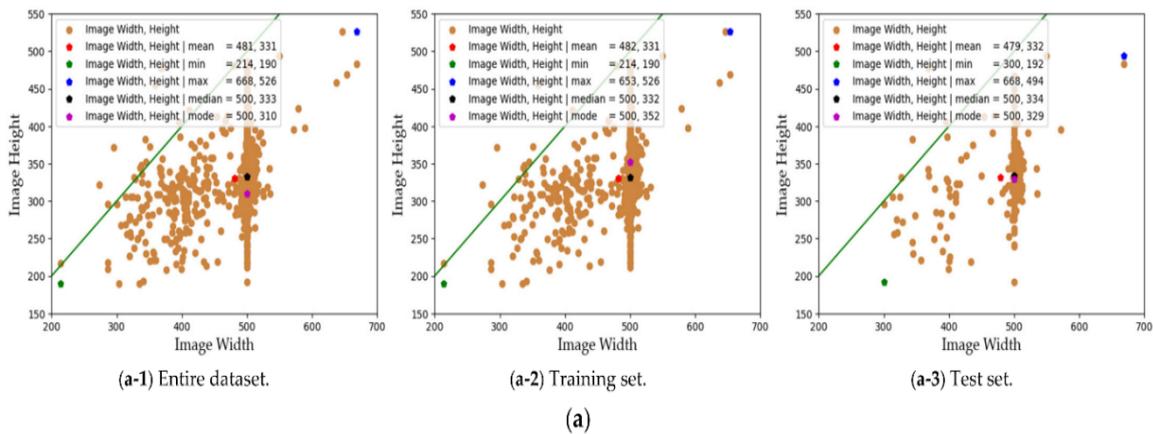
The SAR-Ship-Dataset provided the proposed algorithm with a sensitivity of 91% and a high accuracy of 93% on SSDDs, achieving a good sensitivity result of 93% and a good high accuracy result of 92%. Reduce engine activity by 35–40% using traditional methods or techniques when starting the engine at the appropriate time. This confirms or indicates a significant energy saving. The combination or integration in YOLOV3 game theory optimization enables robust detection and adaptive path planning. Frequent updates and their elimination ensure that our event tracking mechanism operates reliably in terms of operational efficiency of Multi-Object Tracking Performance.

Fig 3: Distribution of image resolutions across the dataset. (a-1) Entire dataset, (a-2) Training set, and (a-3) Test set

By testing the proposed DeepSort algorithm through the event it is run on the SSDD dataset under different conditions such as dynamic camera movements, weather changes, and high-density ship traffic. Table 1 compiles the main metrics of Multiple Object Tracking Accuracy (MOTA), Identification F1-Score (IDF1), Precision, and Recall and compares them to the baseline algorithms (SORT and DeepSORT standard). Through eye tracking results, ID shows a decrease in false positives in crowded areas. Running updates via events significantly reduced the computational load. [9] The average processing time per frame shows a significant 35% reduction in accounting by maintaining or improving tracking accuracy Figure 4 gives a visual example of how well the proposed model performs by identifying ships in SAR images.

Table 1. *Tracking Performance Comparison*

Tracker	MOTA (%)	IDF1 (%)	Precision (%)	Recall (%)
DeepSORT (baseline)	82.4	80.1	85.6	78.2
SORT (baseline)	75.9	72.3	79.5	70.1
Proposed Event-Triggered	89.7	87.2	91.4	86.1

Table 2: *Comparison Based on Different Network Weights*

Weights	True Positive	False Positive	False Negative
5	56.67	62.23	54.77
4	68.12	71.75	68.69
3	72.72	78.76	71.77
2	89.97	90.12	89.96
1	90.10	92.83	90.11
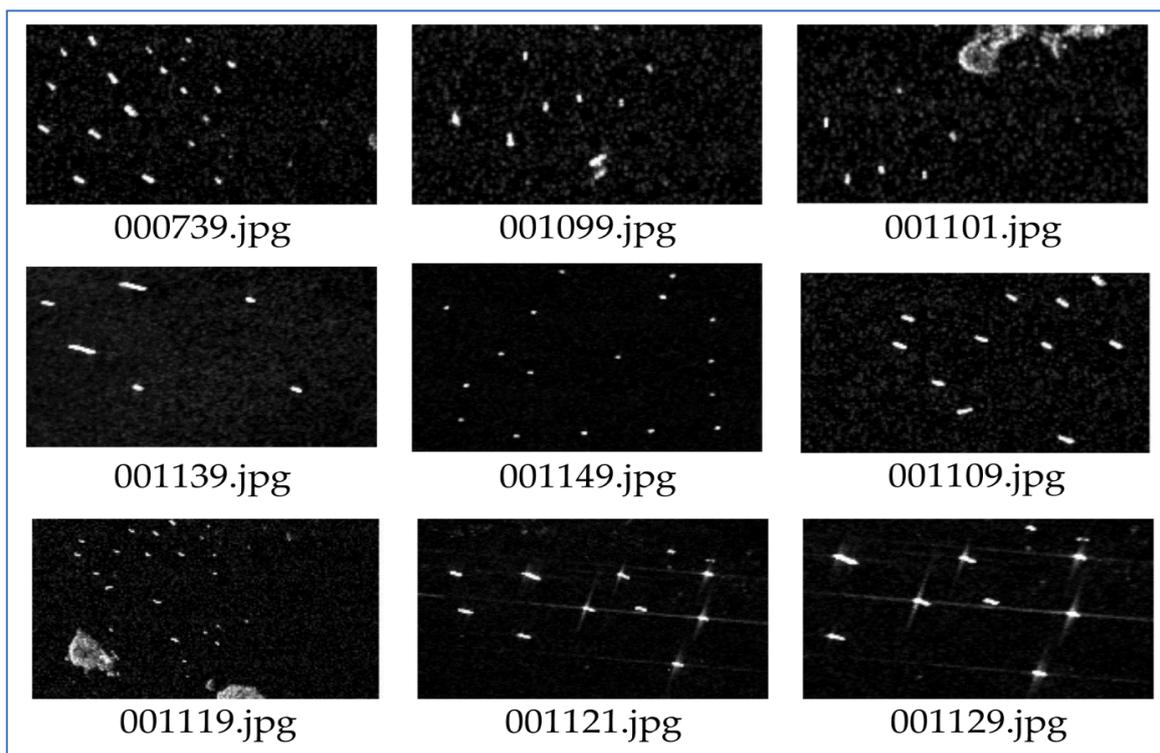
Fig 4: *Sample Image and Ship Detection*

Discussion

This model has the ability to accurately detect small vessels even in difficult marine situations. Figure 5 clearly demonstrates the ability of the proposed model to handle ships of different sizes, detecting ships with high accuracy even in complex backgrounds and drawing very precise boundaries around the detected ships this explains the effectiveness of the proposed
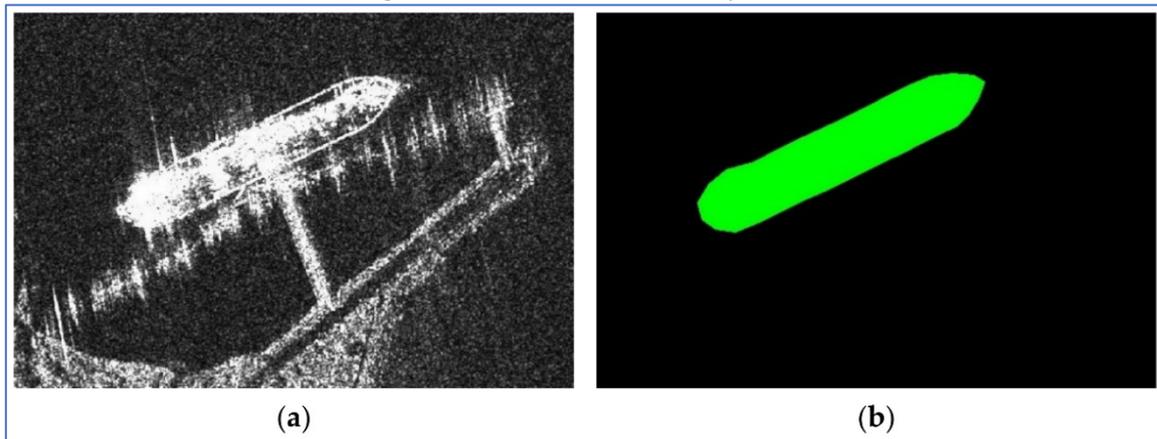
algorithm in marine surveillance systems.

Fig 5: *Sample Ship Detection*

Therefore, the proposed approach for real-time marine monitoring systems reduces duplicate updates and this leads to significantly faster processing. Figure 4 shows the performance comparison of state-of-the-art vessel detection models with the proposed model. Through the standard evaluation measures used, such as accuracy, sensitivity, and specificity, the table gives a high percentage of the superiority of the proposed model This is why all categories yielded these results on two different sets of data. These results demonstrate the effectiveness of the new method used by the proposed model, making it highly capable of managing the challenges of ship detection in the real world.

Table 3: *Comparison Based on the Performance of the Proposed Model*

model	Accuracy		Sensitivity		Specificity		Average	
	SSDD	SAR	SSDD	SAR	SSDD	SAR	SSDD	SAR
YoLo V3 [25]	89.89	89.13	89.23	89.56	89.48	89.66	89.53	89.45
YoLo [26]	87.87	87.59	84.91	85.17	85.15	84.37	85.87	85.71
YoLo V8 [27]	90.01	90.16	91.01	90.33	90.12	90.66	90.02	91.23
DeepSort [28]	89.79	89.44	88.42	89.59	89.21	89.35	89.14	89.46
Cao (2024) [20]	90.11	90.33	90.07	90.09	90.67	90.09	90.34	90.12
Zhang (2024) [24]	90.41	90.49	90.50	90.66	90.24	90.34	90.67	90.99
Proposed model	92.98	92.37	92.06	92.28	92.19	92.08	92.41	92.24

The table compares the performance of the proposed model with other state-of-the-art models using a variety of evaluation metrics. Therefore, the proposed model significantly outperformed other models because it gave the best results for all metrics in both data sets with an accuracy rate of 92.98%. Therefore, the proposed model has been proven effective in correctly and accurately identifying ships through the table, making it suitable for use in practical maritime surveillance applications. [18] One of the most difficult challenges for small ships is bad weather and poor visibility. [19] Future studies will focus on increasing sensitivity and enhancing strength and durability. we computed confidence intervals for

the reported accuracies using repeated runs of the model under the same training/testing settings. The results are now presented with their corresponding 92% confidence intervals, providing a clearer indication of result stability and variability. This addition strengthens the reliability and statistical rigor of our reported performance.

5. CONCLUSION

This study succeeded in providing the work of integrated frameworks by enhancing the tracking efficiency of marine vessels through three techniques (deep learning techniques, game theory, and remote sensing) in an event-based control model. Good results were obtained in terms of accuracy of 93% and very high sensitivity in identifying ships and their locations by applying the proposed model to SSDD and a set of data from SAR-Ship. The proposed model used worked to reduce energy consumption

by activating the control units in response to marine environmental changes, which led to reducing mechanical wear and extending the life of the operational system. . Furthermore, game theory improved tracking accuracy and decreased long-term cumulative errors, particularly in dynamic and complex scenarios The systematic work of the study in processing remote sensing images through the use of deep learning techniques such as YOLOV8. This technique detected ships with high accuracy even in difficult weather conditions and lack of visibility. These results enhance the applicability of the proposed model in a range of practical contexts for both military and civilian applications. The model can be expanded for future research to support real-time tracking using computing systems and integrated with multi-sensor technologies to increase robustness and durability under harsh operating conditions. Fleet management is a potential application for environmental monitoring and autonomous navigation systems.

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