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Discovering Fishing Area from AIS Data

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***Abstract*—This paper presents a method to discover fishing areas from Automatic Identification System (AIS) data. AIS provides dynamic vessel movement information, originally for collision avoidance. This study analyzes vessel trajectories to detect fishing stops and applies density-based clustering (DBSCAN) to map fishing regions. Results show that the approach effectively identifies fishing activity zones, supporting fisheries management and combating illegal, unreported, and unregulated (IUU) fishing.**

***Index Terms*— AIS, DBSCAN, Fishing Area Mapping, Trajectory Analysis, Vessel Monitoring**

I. INTRODUCTION

The Automatic Identification System (AIS) is a self-reporting technology mandated on vessels to enhance collision avoidance and maritime safety. It continuously broadcasts dynamic information such as position (latitude, longitude), Speed Over Ground (SOG), Course Over Ground (COG), Rate of Turn (ROT), along with static and voyage-related details like MMSI number, vessel type, and destination. These high-frequency transmissions enable near real-time tracking of ships, supporting navigation, traffic management, and safety operations.

Beyond its original safety purpose, AIS data has become an invaluable resource for maritime domain awareness. Researchers and authorities use it for diverse applications including traffic flow analysis, port management, environmental monitoring, and, crucially, the identification of fishing activities. Monitoring fishing vessels is vital to ensure sustainable use of marine resources, manage fishing grounds effectively, and combat Illegal, Unreported, and Unregulated (IUU) fishing, which threatens fish stocks, marine habitats, and the livelihoods of coastal communities.

Historical AIS data contains rich trajectory information, offering insights into vessel movement patterns over time. By analyzing these trajectories, it is possible to infer behavioral signatures of fishing activity, such as frequent stops in certain regions, characteristic speed ranges, and directional changes associated with setting and hauling fishing gear. Advanced analytical methods, including clustering algorithms, can then be used to identify and delineate fishing grounds from large, noisy datasets.

This work aims to leverage historical AIS data to discover fishing areas through a structured methodology. The approach includes data preprocessing to clean and reduce the volume of AIS records, trajectory extraction to reconstruct vessel paths, identification of probable fishing stops using speed and direction thresholds, and clustering these stop points to reveal fishing areas. The resulting fishing activity maps can support fisheries management, policy-making, enforcement operations, and research on marine ecosystems, ultimately contributing to sustainable and responsible use of ocean resources.

II. LITERATURE SURVEY

Several studies have investigated clustering methods for analyzing vessel traffic and maritime activities using AIS data.

Zheng et al. introduced the K-means clustering algorithm to analyze traffic data in certain water routes. Their method aimed to organize data points into hierarchical clusters by maximizing intra-cluster similarity. However, the algorithm is sensitive to the initial randomly selected cluster centers, and determining the optimal number of clusters (k) is a challenging task with no general theoretical solution. To address these issues, they ran multiple experiments with varying k values and initial partitions to achieve consistent results [4].

Palma et al. proposed CB-SMoT, a clustering approach to discover interesting places within vessel trajectories by identifying stops and moves. Stops are semantically important trajectory segments where vessels remain stationary for a minimum time. CB-

SMoT detects low-velocity segments within trajectories as interesting places. Despite producing good results, the method struggles to discriminate fishing stops accurately, especially in cases of low-speed vessels near ports or when entering or leaving harbors [2]. To overcome limitations of speed-based clustering, Rocha et al. developed DB-SMoT, a Direction-Based Spatio-Temporal clustering method that uses variations in vessel course over ground (COG) as the main criterion to find clusters. However, DB-SMoT also faces difficulties distinguishing fishing stops since fishing vessels display significant COG variations when approaching or leaving ports, similar to other vessel maneuvers [3]. Mazzarella et al. proposed a hybrid method combining CB-SMoT and DB-SMoT to improve the mapping of fishing footprints and vessel activities at sea. This combined approach leverages the strengths of both algorithms for better identification of fishing behavior [1].Ester et al. introduced DBSCAN, a density-based clustering algorithm designed to discover clusters of arbitrary shapes in large spatial databases with noise. DBSCAN requires only a few input parameters and is effective at detecting clusters based on region density, making it highly suitable for spatial data analysis [5].

III. METHODOLOGY

This study proposes a methodology to discover fishing areas from historical AIS data, as illustrated in Fig 1.The dataset consists of nearly 1TB of AIS records.The raw data is stored in CSV format and loaded into a PostgreSQL database using Python scripts for efficient querying and processing. The AIS dataset contains numerous features, but for this study, only the following fields are considered: Timestamp, MMSI (Maritime Mobile Service Identity), Latitude, Longitude, Speed Over Ground (SOG), Course Over Ground (COG), and Rate of Turn (ROT). Latitude and longitude data points are used to plot ship positions accurately.

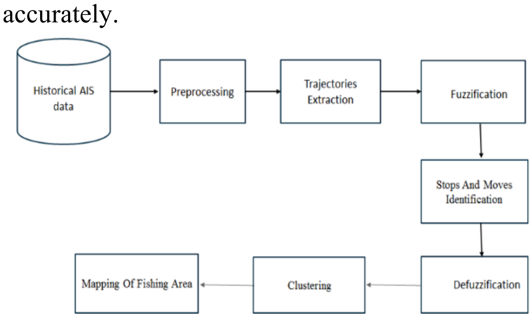

Fig 1: Design Methodology

A.Data Preprocessing and Trajectory Extraction

The first step involves preprocessing the historical AIS data to reduce redundancy and noise. Points located within a 1-kilometer radius are grouped together, and the centroid of each group is computed to represent the cluster. Points far from the centroid within the same group are discarded to minimize data volume while preserving spatial accuracy.Next, the data is segmented by MMSI, so that all points corresponding to a single vessel form a distinct group. These points are then used to extract vessel trajectories, which can be visualized in Google Earth Pro to verify spatial patterns and movement behavior.

B.Identification of Stops and Moves

The trajectory is partitioned into smaller segments known as stops and moves. Stops represent atomic points where the vessel is stationary or moving slowly, which are critical for identifying points of interest such as fishing activities. Moves represent the spatial segments between stops.Two methods are used to identify stops:

- CB-SMoT (Clustering Based on Speed and Mobility Thresholds): This method detects stops based on speed variations, particularly focusing on trajectory segments where the speed is between 3 and 5 knots, indicating potential fishing activity.
- DB-SMoT (Direction-Based Spatio-Temporal Clustering): This method incorporates the direction of the vessel's movement, identifying stops where significant changes in course over ground occur.

The final set of stop points is derived by combining results from both CB-SMoT and DB-SMoT methods to improve accuracy in detecting fishing stops.

C.Clustering and Mapping of Fishing Areas

The identified stop points are aggregated using a clustering algorithm to locate probable fishing areas and evaluate their spatial extent. This clustering helps to group closely located fishing stops, providing a map that highlights key fishing zones.

IV. IMPLEMENTATION

This section describes the implementation steps involved in plotting ship coordinates, extracting their trajectories, identifying fishing stop points, and finally delineating the fishing areas.

A.Plotting the Location of Ships

To visualize the locations of ships, we used the Google Earth Pro application. The historical AIS data stored in a PostgreSQL database was first queried to extract relevant fields such as timestamp, latitude, longitude, MMSI number, Speed Over Ground (SOG), and Course Over Ground (COG).

The extracted data was converted into KML (Keyhole Markup Language) files using the Python library *simplekml*. KML is a standard format for displaying geospatial data in applications like Google Earth. Each coordinate pair was added as a newpoint in the KML file, with a circular icon to represent ship locations. Ship details (timestamp, MMSI, SOG, COG) were embedded in the point descriptions.

B.Trajectory Extraction

For trajectory extraction, the AIS data was again queried from the PostgreSQL database and loaded into a list in Python. Preprocessing involved grouping nearby points (within a 1 km radius). For each such group, the centroid was calculated, and only the point closest to the centroid was retained to reduce noise and redundancy.Next, the data was grouped by MMSI number so that all points belonging to the same vessel were collected together, forming individual ship tracks. These filtered and grouped points were then written into KML files and visualized in Google Earth Pro, showing the trajectories of individual vessels.Fig.2 below shows Trajectory of ship with MMSI number 25719700.

Fig 2 : Trajectory of ship with MMSI number 257197000

C.Fishing Stop Points

To identify fishing stop and move points, we followed a preprocessing pipeline similar to trajectory extraction. AIS data was queried, loaded into a list, and grouped into clusters with a 1 km radius threshold. Each cluster's centroid was calculated, retaining only the point nearest to the centroid.Points were then grouped by MMSI number to obtain the vessel tracks. For each track, potential stop (fishing) events were identified by applying behavioral criteria:

- Speed Over Ground (SOG) between 3 knots and 5 knots.
- Change in direction (turning angle) between 90° and 150°.

Points satisfying both the SOG and angle conditions were classified as stop points (probable fishing locations), while all others were marked as move points. Both stop and move points were saved in KML format and visualized in Google Earth Pro. Fig.3 displays the identified stop and move points in ship trajectories.

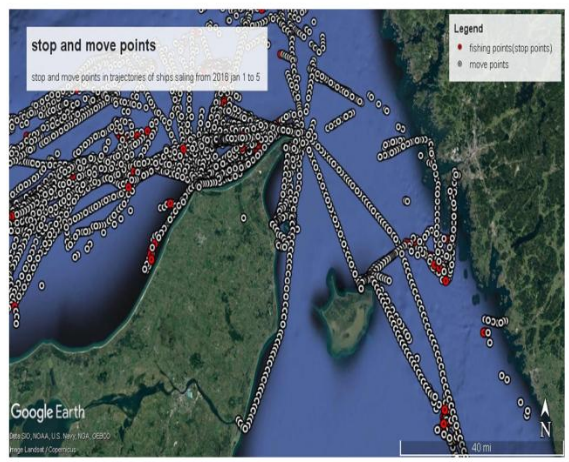

Fig 3: stop and move points in trajectories of ship saling.

D.Fishing Area

Finally, to delineate fishing areas, only the **stop points** identified in the previous step were selected and clustered using the **DBSCAN** (Density-Based Spatial Clustering of Applications with Noise) algorithm. DBSCAN group nearby dense points together while marking sparse regions as noise.The resulting clusters represent probable fishing areas based on ship stopping behavior. The clusters and their constituent points were visualized on Google Earth Pro. Fig.4 shows the fishing areas.

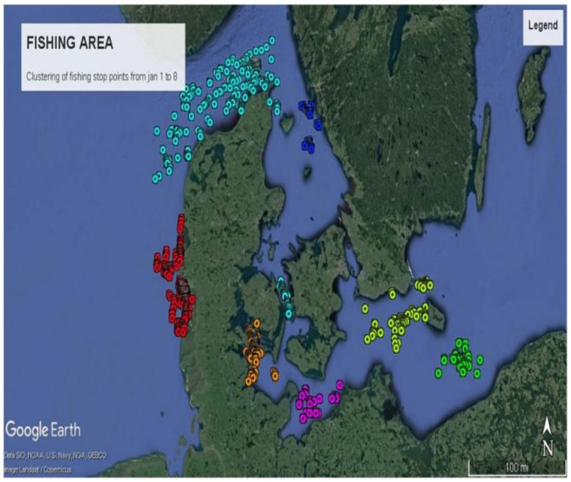

Fig .4 : Fishing area

V. CONCLUSION

This paper presents a systematic approach for discovering fishing areas from Automatic Identification System (AIS) data through trajectory analysis and density-based clustering. By preprocessing raw AIS data, extracting vessel trajectories, detecting probable fishing stop points using speed and direction criteria, and applying DBSCAN clustering, this method effectively identifies regions of concentrated fishing activity.

The results demonstrate that this approach can produce clear, interpretable maps of fishing areas, supporting fisheries management, monitoring, and policy development. Such maps are valuable tools for authorities tasked with regulating fishing effort, preserving marine habitats, and combating Illegal, Unreported, and Unregulated (IUU) fishing. This contributes to sustainable fisheries management and the long-term health of marine ecosystems.

Moreover, the methodology highlights the potential of combining traditional geospatial analysis with data mining techniques to extract meaningful insights from large, complex datasets. The use of open-source tools and accessible platforms like Google Earth Pro also demonstrates a practical, cost-effective workflow suitable for a wide range of agencies and researchers.

Future work will focus on refining stop detection thresholds for different fishing methods, improving clustering accuracy by incorporating environmental and operational variables, and integrating additional data sources such as Vessel Monitoring System (VMS) records or satellite imagery. There is also scope to develop automated systems for real-time monitoring of fishing activity and detection of suspected IUU operations in unrestricted or protected zones. By advancing such methods, this research aims to contribute to improved governance of marine resources and more sustainable use of the oceans.

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