On Background Subtraction for Target Tracking in Complex Multi-Radar Marine Data Set

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***Abstract*—Maritime surveillance and traffic control heavily rely on Automatic Identification System (AIS), which can be easily manipulated and is dependent on GNSS, therefore they are susceptible to jamming and spoofing, especially in areas of high economical and geopolitical interest, e.g. the Baltic Sea. The development of frameworks to augment the traffic assessment, such as automated Multiple Target Tracking (MTT) algorithms on maritime radar, is currently dependent on synthetic data where common scenarios present in real-world data are not properly emulated. This work presents a collection of data sets from X-band radar ground station, and their respective AIS data, installed in a busy port region with several challenging scenarios for data processing and target tracking providing real-world cases for MTT development and evaluation. The present data set is heavily contaminated by static structures with no relevance for surveillance and traffic assessment, which can be considered as a background layer. Thus, two methods are presented and evaluated to filter the radar pixels related to background structures in order to improve MTT algorithms.**

***Index Terms*—X-band radar, radar data set, multiple object tracking, background subtraction.**

I. Introduction

Marine radars are extensively utilized for maritime surveillance to detect and track targets within a designated region of interest (ROI). The data acquired from these radars can either undergo pre-processing for manual inspection or be directly fed into advanced multiple target tracking (MTT) algorithms. These algorithms are responsible for the recursive estimation of both the number of targets (e.g., vessels) and their kinematic properties. Additionally, many MTT approaches, such as Extended Object Trackers (EOTs), include the estimation of target extensions [1], [2], [3].

The research and development of these algorithms in the academic community, however, suffers from the lack of publicly available data sets for development and evaluation and rely mostly on simulated data. The work [4] describes a data set of a dynamic X-band radar sensor installed in a moving vessel, along with respective AIS information as reference (ground-truth) for three scenarios recorded in the Baltic Sea. The sensor used has relatively low resolution, the scenarios have few targets with short tracks and the observed noise is mostly dominated by sea clutter. More recently, a review article [5] analyzed more than 30 published perception datasets, where only five of them contain marine radar data, e.g. Jang et al. [6] released data sets from different sensors including X-band and W-band radars, LiDAR, RTK-GNSS and stereo camera. Despite the diversity of sensors and scenarios on data sets listed in [5], they all tailor autonomous navigation applications and are not suitable for surveillance or maritime traffic assessment, specially due to the use of short-range sensors and their installation in a moving vessel.

In order to promote the advances in MTT development and research for maritime surveillance and traffic control, this paper presents HAXR, a comprehensive open access data set of multiple static radar stations in a complex port-operation scenario. Along the radar data, correspondingly cleaned up AIS data is provided, which can be used, at some extent, as reference to benchmark the performance of tracking algorithms.

Due to the high resolution of the sensors and heterogeneous environment, the data is heavily polluted by persistent detections of objects irrelevant in MTT context, e.g. the shore lines, and the port infrastructure and therefore are treated as background. For this reason it is also evaluated two unsupervised adaptive background subtraction algorithms to remove the undesired artifacts.

The present paper three-fold, therefore, contributes in the following three areas:

- First to our knowledge, publicly accessible open access X-band radar data set from multiple stations in a complex port-operation area with several important and challenging scenarios for MTT algorithms;
- AIS information over the covered area, which can be used as (a limited) ground-truth reference;
- An adaptive and unsupervised background subtraction tool for pre-processing the raw data, removing the non-moving structures, sensitive to environment changes such as tide variation and static-to-moving vessels.

The above-mentioned data is publicly available in [7] with additional meta information and technical details of data formats, as well as utility scripts for data loading.

II. Data Set

The data set is a collection of X-band radar data recorded by 13 ground marine radar stations with different ranges in a busy port region with partially overlapping areas. For each station it is provided three non-consecutive hours of data in a standardized format and same time coverage. Additionally, it is also provided the corresponding AIS data collected in the entire region for the same period.

Each station is equipped with 21 feet high gain antennas and a beamwidth less than 0.36°, ranges varying between 1.8 and 6 km and rotation periods from 2.3 to 3.3 seconds. The values of coverage range and the rotation speed for each station can be easily retrieved from the data.

The position coordinates of every station are anonymized with the same reference point. Fig. 1 shows the relative positions of each station as well as their respective covered range and the overlapping areas. Fig. 2 presents a snapshot of one station demonstrating the complexity of the environment often not easily achievable with simple simulated data, e.g. multi-path echoes, water trails and tide variation on static structures. The collected data were originally recorded in the

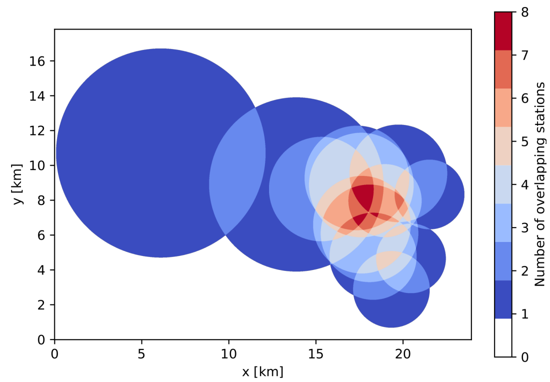

Fig. 1: Spacial distribution of radar stations coverage. The color scheme shows the areas with overlapping coverage and the respective number of stations.

Fig. 2: Snapshot of one radar data station projected to latitude and longitude coordinates. Colored pixels are radar points encoded by their intensities (amplitudes). Blue triangles are AIS information.

ASTERIX Category 240, defined by Eurocontrol [8], where each radar point is represented by a grid cell in polar domain and contains six values: the starting and ending values in range (distance to the sensor origin), the starting and ending values in azimuth, the radar intensity and its timestamp.

The data is pre-processed and converted to Hierarchical Data Format, version 5 (HDF5), which has open libraries in the most popular programming languages (e.g. Python, C++ and Matlab), is fast and efficient for reading and writing operations and optionally applies compression for reduced storage volume. In order to keep the data as close as possible to its raw representation, the same structure is used as in the ASTERIX protocol, i.e. radar points represented by grid cells in polar domain each one parameterized by the six values above-mentioned.

In addition to the radar data, anonymized AIS messages from the same covered area are provided. The available data are the messages timestamp, the 2D positions in polar coordinates w.r.t. the sensor origin, and a fictitious identification number, unique for the same vessel, so that tracking/identification across different radars is possible.

The HAXR data set provides a number of challenging scenarios. Those include object occlusion, merging objects, multi-path reflections, distance-dependent sensor resolution, non-convex target shapes, heavy background structures and noise generated by targets (e.g. water trails), to name a few. Some of these scenarios are shown in Fig. 3.

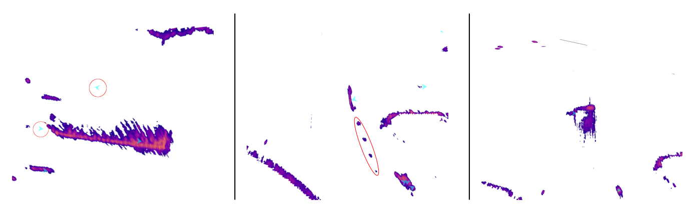

Fig. 3: Radar points (color-encoded intensities) and AIS data (blue triangles) of different scenarios. (left) Two occluded objects in the same line of sight of a larger object w.r.t. the sensor. (center) Radar signals reverberating in the object, resulting in an echo pattern. (right) Due to the high resolution of the sensors and the proximity of the station, targets can show non-convex shapes with high granularity.

Additionally, marine radar reflections in port regions and in-land waterway scenarios are heavily contaminated by persistent static infrastructure, such as shore lines, moored vessels and aid to navigation devices (e.g. maritime buoys), as shown in Fig. 2, and usually not seen in simulated data.

III. Background Subtraction

As shown in the previous section, background points from static structures poses a relevant challenge on MTT algorithms, and due to its persistence in time it cannot be removed by classical clutter removals and noise suppression tools. Thus, for such data set it is mandatory the use of a background subtraction tool for suppressing points of no relevance on target tracking.

In this paper we propose two unsupervised adaptive filtering approaches: a moving window histogram and a weak multinomial distribution estimator. Neither of the methods rely on manually labeled data and can adjust the filter mask in regions where the static features change through time, e.g. moored vessels that start to move or infrastructure that appear/disappear with changes in tides. Extending the work of [9], which restricted evaluation of the estimator to simulated data and did not provide a baseline comparison, we conduct experiments on a real-world data set and benchmark the weak estimator against a moving window histogram.

A. Moving-Window Histogram

Let the data set be defined as

$$\mathcal{D} = \{\mathbf{z}_i\}_{i=1}^{N}, \quad \mathbf{z}_i = (x_i, y_i) \in \mathbb{R}^2. \tag{1}$$

The ROI domain can be partitioned into R bins along the x-axis and S bins along the y-axis with edges $x_0 < x_1 < \cdots < x_R$ and $y_0 < y_1 < \cdots < y_S$ respectively. Each rectangular bin is then defined as

$$B_{r,s} = [x_r, x_{r+1}) \times [y_s, y_{s+1}), \tag{2}$$

for $r = 0, \ldots, R-1$ and $s = 0, \ldots, S-1$. A two-dimensional histogram is then represented by the matrix $\mathbf{H} \in \mathbb{N}^{R\times S}$, whose entries are

$$H_{r,s} = \sum_{i=1}^{N} \mathbf{1}_{B_{r,s}}(x_i, y_i), \tag{3}$$

where $\mathbf{1}_{B_{r,s}}(\cdot)$ denotes the indicator function defined as

$$\mathbf{1}_{B_{r,s}}(x, y) = \begin{cases} 1, & (x, y) \in B_{r,s}, \\ 0, & \text{otherwise.} \end{cases} \tag{4}$$

For each time step j, a histogram H_j is created and a set of w consecutive histograms are accumulated

$$\mathbf{H}^k = \sum_{j=k-w}^{k} \mathbf{H}_j. \tag{5}$$

For grid cells where the static background is present, the number of pixel occurrences are expected to be high, while cells with temporary occurrences from moving vessels will show low values. Therefore, applying a threshold t on the maximum number of pixels allowed in each cell defines the mask $\mathbf{M}$, for instance $\mathbf{M}_{r,s}$ is considered a background cell if $H_{r,s} > t$ and a foreground otherwise.

B. Weak Multinomial Distribution Estimator

Assuming the same ROI partitioning as in (3), additionally defining a maximum number of possible occurrences $\nu \in \mathbb{N}^+$ of radar pixel in each grid cell, the possible values in $0 < H_{r,s} \leqslant \nu$ are mutually exclusive and can be modeled as a multinomial distribution governed by $P = [p_1, p_2, ..., p_\nu]^T$, with $p_i = P(H_{r,s} = i)$ and $\sum_{i=1}^{\nu} p_i = 1$. The intention is to estimate all p_i for $i = 1, ..., \nu$. An memory-efficient and fast-adaptive approach for this estimation is using the stochastic learning-based weak estimator [10]. Here the exercise is to iteratively estimate $\Psi(k) = [\psi_1(k), ..., \psi_\nu(k)]^T$ of P, where $\psi_i(k)$ is the estimate of p_i at time k. Then, the value of $\psi_i(k)$ is updated as

$$\psi_i(k+1) = \begin{cases} \psi_i + (1-\lambda)\sum_{j\neq i}\psi_j, & H_{r,s} = i, \\ \lambda\psi_i, & \text{otherwise.} \end{cases} \tag{6}$$

where $0 < \lambda < 1$ is a user-defined *learning rate*. High learning rate leads to fast convergence and higher estimation variance, while lower values have the opposite effect [10]. Equation (6) can be re-written as

$$\psi_i(k+1) = \begin{cases} \lambda\psi_i + (1-\lambda), & H_{r,s} = i, \\ \lambda\psi_i, & \text{otherwise.} \end{cases} \tag{7}$$

This estimation is then used to define the adaptive mask replacing the number of pixels $H_{r,s}$ by the highest probability value in $\Psi_{r,s}(k)$. Since the mask is estimated in each data frame, only one-frame histogram is needed, resulting in reduced memory requirements for implementation. This method had shown promising results [9] and therefore was evaluated in this complex data set.

IV. Results

In order to evaluate the proposed background subtraction algorithms, one station of the data set was manually labeled, annotating pixels that belong to targets of interest, while the non-annotated pixels are considered as background. Both algorithms were tested with radar points in polar and Cartesian domain, where the latter was obtained from simple trigonometric conversion.

Two metrics have higher priority, the number of background points that are not removed (false positive), which shows the inability of the algorithm on filtering undesired points, and the number of true target points that are removed (false negative), possibly distorting the state estimation of the targets. Therefore, the precision and recall metrics, respectively, were evaluated, where higher values of precision implies more efficiency in filtering background points while higher recall show that few actual target points were wrongly removed. As the main goal is to achieve the highest possible values of both metrics simultaneously, they can be combined in the F1-score [11], commonly used in classification evaluation.

These metrics were evaluated in one hour of continuous data. Fig. 4 shows the F1-score per frame for both algorithms applied in polar and Cartesian domains. The results show that the multinomial algorithm have more consistence performance, due to its fast convergence on estimating the occurrence probabilities [10], therefore allowing the use of more fine-grained grids, while the sliding-window histogram requires coarser grids and long-period windows in order to properly differentiate the static structures from dynamic objects, thus its precision, and consequently its F1-score, are highly affected.

The overall inferior results of the multinomial algorithm in Cartesian domain can be explained by the distance-dependent sensor resolution and the conversion of radar point coordinates. Higher distances w.r.t. the sensor show less points for the same area, which would require a non-uniform grid or variable probability thresholds. These effects are less prominent in the histogram approach due to bigger cells and the long period windows, turning the algorithm less sensitive to the pixel occurrences thresholds.

Fig. 5 shows a snapshot of one time frame with the raw data, the points manually labeled (ground-truth), and the output of the tuned background subtraction algorithm, where it is possible to see that most of static points were removed while the target measurements are still present.

V. Conclusion

HAXR presents a collection of X-band marine radar data set along with AIS data containing several complex environments

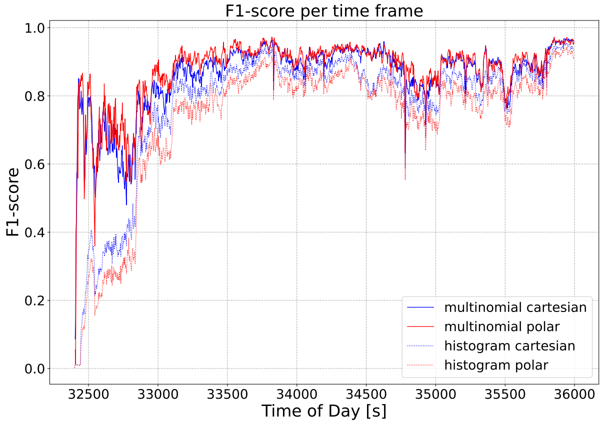

Fig. 4: F1-score per time frame for the sliding-window histogram (dotted lines) and multinomial distribution (solid lines) applied in Cartesian (blue) and polar (red) domains.

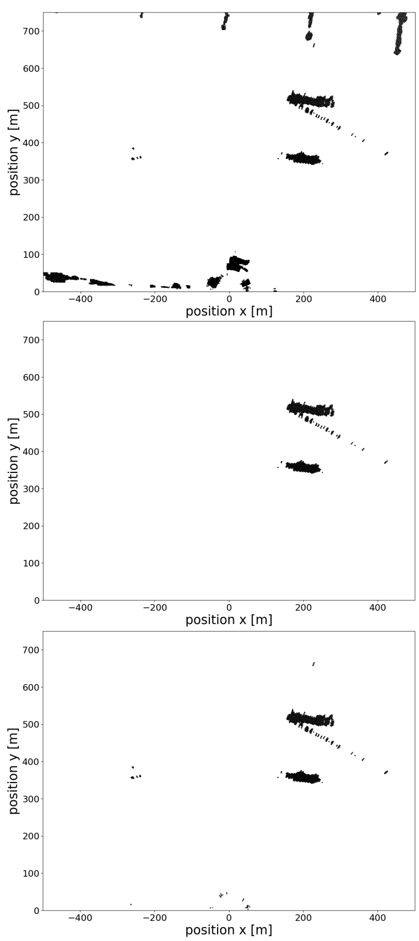

Fig. 5: One time frame snapshot. Raw radar points (top), labeled targets (center) and the estimated foreground (bottom).

and challenging scenarios for MTT algorithms. This data set provides a unique source for algorithm development and evaluation for safety and security applications on maritime surveillance and traffic control, often not available for research purposes.

The availability of AIS data, reporting vessels position and pseudo-ID can be used, with some restrictions, as reference for algorithm performance evaluation as well as labels for supervised and semi-supervised learning algorithms such as deep learning.

Two unsupervised and adaptive background subtraction algorithms are proposed for filtering radar points associated with static structures, which are irrelevant to target tracking. The results demonstrate that the multinomial approach effectively reduce the number of points unrelated to moving targets, making them suitable for pre-processing in MTT algorithms.

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