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A computer vision approach for trajectory classification

Ioannis Kontopoulos[1,3], Antonios Makris[1], Dimitris Zissis[2,3], Konstantinos Tserpes[1]
[1] *Department of Informatics and Telematics, Harokopio University of Athens, Greece*
[2] *Department of Product and Systems Design Engineering, University of the Aegean, Syros, Greece*
[3] *MarineTraffic, Athens, Greece*

***Abstract*—Nowadays, the increasing number of moving objects tracking sensors, results in the continuous flow of high-frequency and high-volume data streams. This phenomenon can especially be observed in the maritime domain since most of the vessels worldwide are now transmitting their positions periodically. Therefore, there is a strong necessity to extract meaningful information and identify mobility patterns from such tracking data in an automated fashion, eliminating the need for experts' input. To this end, a novel approach is presented in this paper, which fuses the research fields of computer vision and trajectory classification, in order to deliver a high-precision classification of mobility patterns. The experimental results demonstrate that the classification performance of the proposed approach can reach an f1-score of over 95%.**

***Index Terms*—trajectory classification, computer vision, image classification, vessel monitoring, AIS**

I. Introduction

In recent years, the large volume of mobility data generated from thousands of tracking devices has attracted researchers' interest in data-driven, knowledge discovery techniques. Such techniques, that often include anomaly detection and trajectory classification, are able to detect patterns from the generated mobility data. Mobility data consist of trajectories of moving objects and can provide spatiotemporal characteristics that indicate anomalous or suspicious behavior. Today, although all larger vessels are obliged to carry an Automatic Identification System (AIS) transponder on board, smaller vessels have also adopted this technology. AIS is a vessel tracking protocol that allows vessels to broadcast information about their whereabouts and identity and to receive information by nearby vessels as well.

Characterizing parts of the trajectories can help the authorities in decision-making, thus improving the overall Maritime Situational Awareness (MSA). To promote the MSA, several supervised or unsupervised learning techniques were developed that take advantage of kinematic and spatiotemporal features of trajectories. In the literature, the field of trajectory classification has been extensively studied, but only in recent years the focus has shifted towards the maritime domain [1]–[7]. In all those studies, the context of the analysis is typically the physical world and the geography. Latitude and longitude are the basic features in a possibly multi-dimensional space (others can be the speed, direction, etc). However, experts rely heavily in the visualization of trajectories to manually identify parts of the trajectory that are of some importance. This provides an intuition to move the analysis in a different domain, leveraging computer vision techniques on classification. In computer vision, the most commonly used techniques include convolutional neural networks [8]–[10]. Before the widespread usage of neural networks, other techniques were also devised where researchers tried to extract features from an image or to predict textual information from pixels [11], [12]. One of the most common goals of computer vision and specifically image recognition is to classify a set of images to a predefined set of labels which are of interest.

Similarly, the main concept of our proposed methodology is to classify the mobility patterns of vessels to a set of predefined (possibly illegal) activities by visually representing them as images for the purposes of promoting the MSA at sea. The novelty of our approach lies in the usage of computer vision techniques for the classification of trajectories and the detection of activities in mobility data. The use of computer vision for the problem at hand and the main contributions that it offers are: a) The distinct visual difference most mobility patterns in the maritime domain have, allows for the increase in the classification performance of trajectories, b) The classification of trajectories even when the positional data are not given at fixed intervals (e.g. hourly) such as the AIS messages[1], a problem faced by time-series classification methodologies [7], c) A computer vision approach for trajectory classification skips entirely the pre-processing step regarding the understanding and analysis of data and feature extraction. The reason for this is that the same technique for classifying an image (e.g. Convolutional Neural Networks) can be applied for the classification of all of the mobility patterns since all mobility patterns are converted to images. Therefore, a computer vision approach for trajectory classification yields a promising universal approach for the classification of mobility patterns and d) Clustering constitutes often a preliminary step when dealing with trajectory classification techniques. Almost all of the well-known clustering algorithms require input parameters which are hard to determine [13]–[15]. As our method skips entirely this step, as stated above, we have eliminated the need of arbitrary user-defined parameters, making our approach scalable and robust.

[1]https://help.marinetraffic.com/hc/en-us/articles/217631867-How-often-do-the-positions-of-the-vessels-get-updated-on-MarineTraffic-

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II. Related Work

With the adoption of the AIS from the International Maritime Organization (IMO) as a mandatory means of vessel monitoring, studies in the maritime domain focused on data collected from AIS receivers. Mazzarella et al. [3], analyzed the behavior of fishing vessels by detecting and clustering the stops and moves in their trajectory with the DBSCAN algorithm. As a result, each cluster indicated a dense area of fishing activity.

Souza et al. [5] presented three classification techniques with each technique aiming at the identification of a different fishing activity. The analysis is focused on three types of fishing vessels: i) trawlers, ii) longliners and iii) purse-seiners. Based on their trajectory behavior when engaged in fishing, authors determined that in each vessel type, a different classifier is suitable and therefore used three different classification models. Each classification model identifies parts in the trajectory that correspond to either fishing activity or not. The disadvantages of their proposed methodology are that each classifier performs a binary classification task and that the gear type is not always given by the AIS, making it harder to choose a proper classifier in a real-world application setting. Jiang et al. [16] presented classifiers which use neural networks and autoencoders achieving a high-accuracy classification performance. Their methodology is similar to that of [5], in the sense that they perform binary classification to detect when a specific type of fishing vessel is engaged in fishing activity.

Finally, a more recent study of Chen et al. [17] is similar to our own, in terms of converting AIS trajectories into a mobility-based trajectory structure (MB) that resembles a low-resolution image. The final result is a three-dimensional matrix, with the first two axes representing the spatial movement of the trajectory and the third axis representing its speed. The goal is to classify the transportation mode of vessel trips when travelling from an origin port to a destination port. A CNN is used for the classification of the matrices, resulting in a maximum f1-score of 84.7%. The main drawback of [17] is that it does not capture the behavior of the trajectory in its entirety, since the surveillance space is segmented into large cells, especially in cases where the vessels perform micro-movements that eventually form a different mobility pattern. The main difference of our approach and its novelty lies in the fact that high-resolution images can be generated by normalizing the space the vessel moves, capturing every aspect of the trajectory behavior during a mobility pattern, which can then be used by any image classifier.

III. Methodology

A. Maritime Patterns

In total, five different vessels' mobility patterns have been studied in our work:

Anchored: During this type of activity, vessels are anchored offshore in an anchorage area. When anchored, the vessel tends to move around the anchor and forms circular or semi-circular patterns (Figure 1a) due to the effects of the wind, the tide or sea currents.

Moored: During this type of activity, vessels are anchored inside a port. In general, mooring refers to lassoing, tethering or tying to any permanent structure. During this type of activity, the vessel is stopped and the vessel is constrained by the mooring buoys. Its motion is more limited compared to an anchored vessel (Figure 1b).

Underway: A vessel is considered underway when it is not aground, anchored or has not been made fast to a dock, the shore, or some other stationary object (Figure 1c).

Trawling: There are different kinds of fishing activities such as trawling and longlining. Trawling vessels typically keep their speed steady in order to stabilize the fishing net which is dragged by the boat. Moreover, trawling vessels do not travel at a straight line, but they tend to frequently change their course around the fishing area of interest (Figure 1d). The trawling activity can last from several hours to several days.

Longlining: Vessels engaged in longlining activity set fishing lines with baited hooks attached to them. While setting the lines the vessels travel at their steaming speed and they maintain a constant speed. When all lines are set, they are left in the water and the vessels drift slowly with them. Although the two fishing activities have some similarities such as frequent turns and similar speeds, their mobility pattern can differ visually (Figure 1e).

B. Image Representation

This section describes the approach that creates an image representation of the trajectories. To visualize and efficiently classify the movement patterns of the vessels, we need to capture two key features that characterize the trajectory patterns in the maritime domain: i) the shape of the trajectory and ii) the speed.

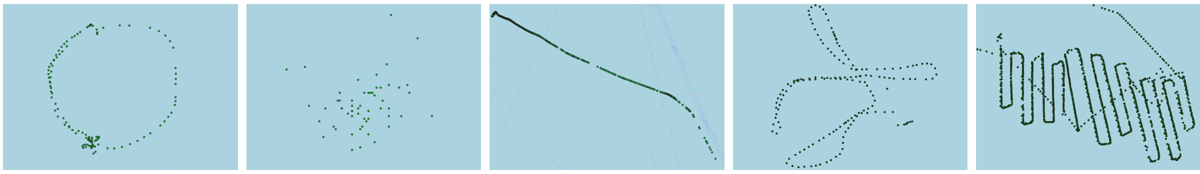
Shape of the trajectory. Although trajectories might form similar patterns, the distance each vessel travels through space is different. Therefore, the bounding box or the surveillance area in which the vessel moves needs to be normalized. To efficiently capture and place the shape of the trajectory inside a normalized bounding box we first need to define the total distance of both the x and the y axis in which the vessel moves. To do so, we measure the total horizontal distance (Eq. (1)) and the total vertical distance (Eq. (2)) the vessel travels based on the minimum and maximum longitudes and latitudes respectively. The total horizontal and vertical distance is defined as:

$$d_x = lon_{max} - lon_{min} \quad (1) \qquad d_y = lat_{max} - lat_{min} \quad (2)$$

Then, the distance each AIS position m has travelled from the minimum longitude and latitude can be calculated from the equations 3 and 4 respectively as follows:

$$d(m_x) = lon_m - lon_{min} \quad (3) \qquad d(m_y) = lat_m - lat_{min} \quad (4)$$

From equations 1,3 and 2,4, we can calculate the percentage of the total distance each AIS position m has travelled so far from the minimum coordinate in both x and y axes:



(a) Anchored vessel. (b) Moored vessel. (c) Vessel underway. (d) Vessel trawling. (e) Vessel longlining.

Fig. 1: The movement patterns of 5 distinct vessel activities during an 8 hour window.

$$norm(m_x) = d(m_x) \div d_x \quad (5) \qquad norm(m_y) = d(m_y) \div d_y \quad (6)$$

Given a predefined image size of $N \times N$, the exact position of m inside an image can be calculated as follows:

$$p_x = norm(m_x) \times N \quad (7) \qquad p_y = norm(m_y) \times N \quad (8)$$

Therefore, each AIS position is placed inside a normalized bounding box or a surveillance space of size $N \times N$ that is essentially an image representation. An example of the surveillance space normalization can be seen in Figure 2 where each green circle corresponds to an AIS position and $N = 10$. For each AIS position the corresponding longitude and latitude is denoted by the blue arrows.

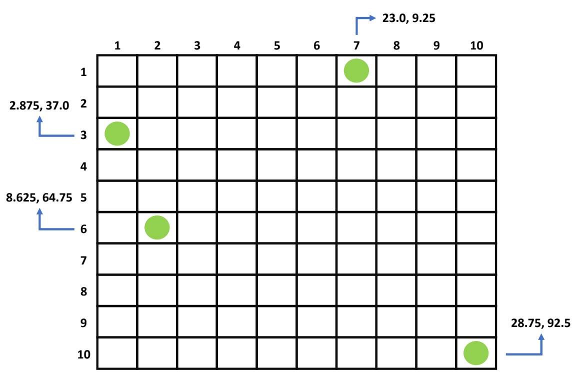


Fig. 2: Example of space normalization.

Finally, in order to make the pattern created by each trajectory more distinctive, a straight line between each temporally consecutive $pixel(pixel_x, pixel_y)$ or AIS position m is drawn using the Bresenham's line algorithm [18]. The Bresenham's line algorithm is a line-drawing algorithm that generates points that form a close approximation to a straight line between two points of an N-dimensional raster.

Speed. Most common vessel types such as passenger, cargo or fishing vessels report a speed value between the range of 0 to 22 knots, $R = [0, 22]$. To represent the speed values of each AIS position m, the range R was segmented to 2-knot increments with each increment corresponding to a different RGB color value in the final image. Therefore, an AIS position with a speed value of $0 \leq s < 2$ has a different color value compared to an AIS position with a speed value of $2 \leq s < 4$. The 2-knot increment was chosen because we wanted a reasonable amount of color values (11 distinct color values against 22 color values with 1-knot increments) while maintaining a relatively high number of increments. Furthermore, fishing vessels typically report a speed between 2 to 4 knots while fishing [5], [6] which corresponds to a 2-knot increment. Since the speed can sometimes exceed 22 knots, speed values greater than 22 have the same color with the last increment ($20 \leq s < 22$). Moreover, pixels that do not contain an AIS position or a line drawn by the Bresenham's line algorithm are colored white and pixels that contain the lines between the AIS positions use the color of the first increment. Figure 3 illustrates a trawling trajectory that has been converted to a 224×224 image.

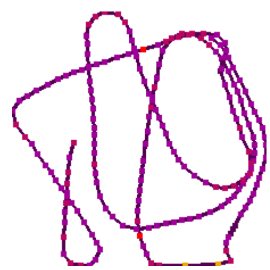


Fig. 3: Example of a trawling trajectory that has been transformed into an image.

C. Image Features

The next step of the approach is the selection of a proper methodology able to classify the trajectory pattern images. There are many methodologies in the literature that use Convolutional Neural Networks (CNNs) for the problem of image recognition that require a huge amount of data and a considerable amount of time for training. Therefore, to perform image classification, a methodology is required through which features can be extracted from the images that can then be fed to a common classifier such as Random Forests (RFs) [19]–[21]. For such a methodology, features that can capture the two key characteristics of a trajectory pattern – the shape and the speed – are required. To this end, we employed 2 types of features that are widely used in the literature, namely Hu invariant moments and Color histogram which describe the image in terms of shape and color respectively:

Hu invariant moments. They were first established by Ming-Kuei Hu and were used for visual pattern recognition

TABLE I: Image classification results.

Classifier	Temporal Window	Cross Validation			Hold-out		
	h	Precision	Recall	F1-score	Precision	Recall	F1-score
Random Forests	1	0.9843	0.9842	**0.9837**	0.9607	0.96	0.9601
	2	0.9483	0.9543	0.9494	0.9669	0.9666	0.9667
	4	0.9661	0.9674	0.9649	0.9743	0.9766	**0.9767**
	8	0.9755	0.9705	0.9723	0.9735	0.9733	0.9731
Classifier	**Temporal Window**	**Cross Validation**			**Hold-out**		
	h	**Precision**	**Recall**	**F1-score**	**Precision**	**Recall**	**F1-score**
Support Vector Machines	1	0.9344	0.9396	**0.9311**	0.9487	0.9466	**0.9468**
	2	0.9063	0.9012	0.8988	0.9171	0.9133	0.9109
	4	0.8651	0.8567	0.8528	0.9366	0.9333	0.9337
	8	0.8341	0.8088	0.8015	0.8623	0.86	0.8583
Classifier	**Temporal Window**	**Cross Validation**			**Hold-out**		
	h	**Precision**	**Recall**	**F1-score**	**Precision**	**Recall**	**F1-score**
Logistic Regression	1	0.9504	0.9487	**0.9486**	0.9601	0.96	0.9599
	2	0.9306	0.9336	0.9296	0.9343	0.9333	0.9325
	4	0.9118	0.9176	0.9109	0.9665	0.9666	**0.9665**
	8	0.8942	0.8984	0.8927	0.8533	0.8533	0.8533

[22]. The main idea behind these features is that any geometrical pattern or shape can be represented by a density distribution function with respect to a pair of axes fixed in the visual field [22]. Therefore, the Hu invariant moments are seven features suitable for identifying shapes such as trajectory patterns or handwritings and letters. The Hu invariant moments have been successfully used since then for tasks such as plant classification [23], biometrics-based identification [24] and object recognition [25].

Color histogram. The color histogram is a representation of the distribution of colors in an image. Specifically, the histogram represents the number of pixels that have a specific color out of a predefined list of colors. The list or the range of the colors is given by the number of bins that is used for the histogram. In our case, the number of the bins is equal to the number of the color values as described in Section III-B. Color histograms are a common practice and have been used for content-based image retrieval [26], [27] and vehicle color recognition [28].

IV. Experimental Evaluation

A. Dataset Description

The first dataset used contains AIS messages collected from a Terrestrial AIS receiver (T-AIS) that covers the Saronic Gulf (Greece) and contains high quality AIS information without gaps of information. The AIS messages used for our ground truth dataset contain activities that have been extracted from vessels engaged in the following activities: underway, anchored and moored – hereafter **patterns A**. The vessels have been monitored for almost one and a half month period starting at February 18^{th}, 2020 and ending at March 31^{th}, 2020. The dataset provides information for 1229 unique vessels and contains $11,769,237$ AIS records in total. A small sample of the dataset can be found here [29].

The second dataset that was used was provided by MarineTraffic[2] and contains AIS messages from January 1^{st}, 2018 to February 28^{th}, 2018 in the seas of Northern Europe. The AIS messages used for our ground truth dataset contain the following activities: trawling, longlining, moored and underway – hereafter **patterns B**. The total number of AIS messages of this dataset sums up to $61,050$.

In order to provide good-quality representations of vessel activities to the classifiers, 200 representative images from each class from both datasets were selected. The resolution of the images in both datasets is set to 224×224. This resolution is also used by CNNs trained with the ImageNet[3] dataset and allows for a straightforward comparison between our methodology and CNNs in the future.

B. Experimental Results

To evaluate the image features, we selected three well-known classifiers, namely Random Forests (RFs), Support Vector Machines (SVMs) and Logistic Regression (LR). For each classifier we performed a 10-fold cross validation on the first dataset (**patterns A**), keeping at each fold 90% of the data for training and 10% of the data for validation and reported the macro-average results. Furthermore, at the end of each cross validation, we selected the model with the best classification performance out of the 10 generated models (one for each fold), and we tested it against previously unseen data of vessel activities. We repeated each experiment four times for four different temporal segments or windows of the trajectories: $h = 1, 2, 4, 8$, where h is the number of hours. Specifically, the trajectories of each vessel activity were segmented into equally-sized temporal-window trajectories of length h. Table I presents the results of the 10-fold cross validation for each experiment and the classification performance achieved in previously unseen data (Hold-out).

It can be observed from the results that all of the classifiers achieve a f1-score of over 90% most of the times with the Random Forests yielding the best classification performance on the unseen data for each temporal window with a maximum

[2]https://www.marinetraffic.com

[3]http://www.image-net.org/

f1-score of 97.67%. The rest of the classifiers do not fall further behind, with the SVMs achieving a maximum f1-score of 94.68% and the LR achieving a maximum f1-score of 96.65%. Finally, on the one hand, we can observe that the Random Forests classifier yields a rather ascending f1-score with respect to the ascending temporal window h. This can be explained by the fact that the mobility patterns of the vessels require some time to form [6]. On the other hand, we can also observe that the rest of the classifiers do not follow the same "ascending f1-score pattern", but they tend to fluctuate and be more unstable. Our results fully agree with other studies of image classification in the literature [19]–[21] which consider Random Forests to be the most suitable classifier for the task.

Furthermore, we compared our results with other methodologies for trajectory classification that are illustrated in this recent survey of Wang et al. [30]. State-of-the-art methodologies for trajectory classification include the use of well-known classifiers such as RFs on features extracted from the data points of the trajectories. To this end, we extracted three features from the trajectories during each type of activity (Anchored, Moored and Underway): the average speed of the vessel, standard deviation of its speed and the haversine distance between the first and the last vessel position. These features were selected because they demonstrate distinct differences between these specific activities. A moored vessel typically has a zero speed while an anchored vessel moves with slightly greater speeds on average due to the effects of the wind. A vessel underway has typically much higher speeds and the distance between the first and the last position is greater compared to the distance of anchored or moored vessels. These features were then fed to two classifiers, Random Forests and Support Vector Machines. The methodologies used in the comparison are shown below:

- M1: the proposed methodology of this paper (image classification with Random Forests).
- M2: the Random Forests classifier with the features extracted from the AIS messages of the trajectories.
- M3: the Support Vector Machines classifier with the features extracted from the AIS messages of the trajectories.

After the feature extraction, we performed 10-fold cross validation for each methodology similarly to the previous experiment. The temporal length (h) of the trajectories used in this comparison is equal to 8 hours. Table II illustrates the cross-validation macro average results of the comparison between the different approaches. Results show that our proposed methodology (M1) surpasses the other methodologies (M2,M3) in terms of classification performance. M1 achieved a f1-score of 97.23% and (M2,M3) achieved a f1-score of (96.18%, 91.1%) respectively.

To further evaluate our methodology on vessel activities of utmost importance to the maritime authorities, we performed 10-fold cross validation on the second dataset (**patterns B**) that contains fishing vessels engaged in trawling, longlining, moored or underway. A fishing vessel is typically moored at a port, then travels towards a fishing area and is finally engaged in the fishing activity. After the fishing ends, the vessel travels back to the port and moors. Similarly to the first set of experiments, at each fold 90% of the data is kept for training and the rest 10% of the data is kept for validation. Finally, the best model is used to test the classifier against unseen data. For this experiment, only the Random Forest classifier was used since the previous set of experiments demonstrated that it has the best classification performance. Furthermore, we only used the temporal window of 8 hours due to the fact that fishing activities can last from several hours to several days [6]. The results of this experiment are shown in Table III that demonstrates a high classification performance.

Finally, we compared the image classification methodology to the approach proposed in [6] for the fishing vessels (M4) where they use a set of features suitable for the fishing activities. Moreover, we also used the methodology of the previous experiment (M2) which uses features that are suitable for patterns A. Similarly to the previous set of experiments, we performed 10-fold cross-validation for each classifier in trajectories of 8-hour length. The macro average results are reported in Table IV. The results again validate that the proposed approach (M1) is more accurate than the set of features selected specifically for the classification of fishing activities (M4). Furthermore, results demonstrate that the methodology M2 does not perform well (f1-score of 76.2%). This is explained by the fact that the features used for patterns A are not able to discriminate between patterns B. On the other hand, the proposed methodology (M1) is able to perform well in both sets of patterns due to the fact that the patterns have distinct visual differences, thus eliminating the need for different feature selection for different mobility patterns.

TABLE II: Comparison of methodologies on patterns A.

Methodology	**Cross Validation**		
	Precision	**Recall**	**F1-score**
M1	0.9755	0.9705	0.9723
M2	0.966	0.9603	0.9618
M3	0.924	0.9138	0.911

TABLE III: Image classification results for fishing vessels.

Experiment	**Precision**	**Recall**	**F1-score**
Cross Validation	0.9686	0.9652	0.9653
Hold-out	0.9887	0.9885	0.9885

TABLE IV: Comparison of methodologies on patterns B.

Methodology	**Cross Validation**		
	Precision	**Recall**	**F1-score**
M1	0.9686	0.9652	0.9653
M2	0.7523	0.772	0.762
M4	0.8455	0.8436	0.8446

V. Conclusion and Future Work

In this work we presented a novel approach for trajectory classification which employs a computer vision technique. The aim of our approach is to provide a high-precision classification of different vessel mobility patterns and to create a universal approach for the classification of vessel activities. The classification performance of the proposed methodology was evaluated on two real-world datasets and demonstrated an f1-score of over 95%.

As a future work, we aim at developing an online system which will be able to create images from AIS messages and classify them in real-time. Finally, it is within our future plans to evaluate the classification performance of CNNs that use transfer learning.

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