Semi-supervised trajectory classification using Convolutional Auto-encoders

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ABSTRACT

Massive volumes of high-frequency and high-volume data are constantly being generated by the vast amount of available tracking sensors of moving objects. This phenomenon can be strongly observed in the maritime domain since most of the vessels transmit their location periodically. Automated methodologies able to extract meaningful information from vessel data is of utmost importance since it can reveal abnormal or illegal vessel activities in due time. Supervised deep learning approaches such as convolutional neural networks (CNNs) require a large-scale annotated image dataset. Thus, semi- and unsupervised feature learning algorithms which learn image features from unlabelled data are able to mitigate this problem. To this end, in this work we propose a semi-supervised convolutional autoencoder (CAE) model for trajectory classification which is able to provide high-precision classification of mobility patterns. Experimental results demonstrated that the vessel activity classification performance can reach an F1-score of over 94%.

CCS CONCEPTS

• **Computing methodologies → Machine learning**; **Unsupervised learning**; **Neural networks**; • **Information systems**;

KEYWORDS

neural networks, auto-encoders, semi-supervised learning, trajectory classification, AIS

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1 INTRODUCTION

Maritime surveillance is a key factor for passengers, vessels and cargo safety. As a result, the Regulation 19 of the International Convention for the Safety of Life at Sea (SOLAS-V[1]) came into force at July 2002, that obliges large cargo vessels to fit and use Automatic Identification System (AIS) for reporting their position, speed and heading, for serving surveillance purposes. This regulation resulted in an abundance of data that completely changed the maritime surveillance landscape. Since then, smaller vessels started using AIS transponders, such as yachts or fishing boats ([23]), that transmit their position and route to nearby vessels in order to avoid collisions. Furthermore, data regarding the vessel's origin and destination, its type, size and draught are also periodically transmitted by AIS equipped vessels, thus providing a rich data set for further analysis.

Consequently, the respective maritime authorities can exploit such data for vessel tracking and analysis of their behavior for the detection of possible abnormalities or illegal activities, which may happen due to an engine failure, an accident in the sea, or on purpose. Another example is that specific fishing activities (e.g., trawling) and fishing gear are strongly linked to the indigenous fauna, thus a mechanism that identifies such operations is of utmost importance both for the maritime authorities and the movement of specific sea animals. Building on the ideas of previous works in the field of anomalous vessel behaviour detection and trajectory classification [15–17, 35], this work focuses on a semi-supervised methodology for the extraction of maritime traffic patterns, which can be the basis for detecting such behaviours. Specifically, this work builds upon [15, 16] where vessel trajectories are transformed into image vectors and are then classified using either Convolutional Neural Networks (CNNs) or Random Forests after image features have been extracted. The main difference of this work is that Convolutional Auto-encoders (CAE) are exploited for the

[1]http://solasv.mcga.gov.uk/regulations/regulation19.htm

classification of vessel trajectories. Although classic auto-encoders (AE) are often limited to learning low-level structures of an image such as lines and edges, convolutional auto-encoders can cope with multidimensional images. The main advantage of CAEs over traditional supervised CNNs is their ability to achieve high classification performance in many applications [10]. Therefore, it is worth evaluation in this application scenario.

The rest of this paper is structured as follows. Section 2 describes the state-of-the-art in unsupervised learning and semi-supervised trajectory classification. Next, Section 3 presents the methodology of the current research work including the transformation of trajectories to images and the Convolutional Auto-encoders model. Finally, Section 4 presents the experimental evaluation of the proposed methodology and Section 5 concludes the merits of this work.

2 RELATED WORK

In the field of trajectory classification, a plethora of works have focused on analysing the behaviour of the moving objects of interest. Most of the work in this domain employs Support Vector Machines (SVMs), Decision Trees (DTs), Bayesian Networks or Random Forests (RFs), or more recently Multi-layer Perceptrons (MLPs) as the primary classification algorithm, with various confidence rates and pre-processing techniques, according to the specific domain and use case they are applied to [5].

The data-sets used vary according to the availability to the researchers and the problems they are trying to solve. Several studies have used trajectories from Vessel Monitoring System (VMS) data to classify fishing activity [2, 11, 36, 37]. Huang et al. [11], for example, tackle the problem of fishing vessel type identification based only on VMS trajectories, extracting trajectory features that are used in machine learning schemes of XGBoost, in order to classify fishing vessels into nine types, achieving a classification accuracy of 95.42%. However, since the usage of AIS became compulsory for vessels and its positional transmission rate is much greater compared to the VMS, research studies have shifted towards the analysis of AIS data [17, 27, 35], making VMS studies obsolete.

Due to the fact that AIS data can be dense, often deemed as big data problems, a wide range of pre-processing methodologies exist in the literature. Some methods are trying to reduce the data-set by applying filters such as the type of gear as identified by AIS [33] while others are trying to limit or segment the geographical areas of interest [22]. More recent studies are employing hierarchical methodologies that segment the trajectories into small parts based on length, time or even behaviours (or points) of interest [3, 4, 6, 31].

The extracted features also vary according to the problem being examined and the chosen methodology. Most researchers use the coordinates, speed and direction as well as features extracted from these. Others, combined more features, such as the type of gear [12, 33] while others used the partitions of the trajectories themselves as features using techniques borrowed from text, image or video processing domains [3, 4, 6, 16].

Researchers have applied combinations of algorithms in order to achieve greater accuracy or faster results. For example, a combination of CB-SMoT [25] and DB-SMoT [28] was used in [22], trying to identify the moves and stops of fishing vessels in a specific area. The algorithms proved able to take into account the speed variation of the trajectory and the direction of the trajectory respectively, providing impressive combined results. Another combinational approach uses General Hidden Markov Models (GHMM) and Structural Hidden Markov Models (SHMM) paired with a Genetic Algorithm (GA) in an effort to classify trajectories of vessels [30]. Even though these approaches prove to be effective in most cases, they are also proving too demanding in time and processing power, making them hard to apply and optimize through hyper-parameter optimization in real life AIS datasets.

Recently, research in trajectory classification have performed many breakthroughs by employing auto-encoders [3, 6, 12, 19, 24] and adversarial frameworks [8, 29, 34]. Auto-encoders are based on clustering of trajectory segments in order to classify basic parts of a trajectory. Then these parts are combined into higher layer features that form longer trajectories, carrying aspects of their parts. They are unsupervised or semi-supervised techniques since the target of an auto-encoder is to be able to accurately re-create the training dataset, giving it the ability of self-validation. They show great promise when compared with classical supervised techniques but they deem further exploration in more domains.

Adversarial techniques, on the other hand, is mainly used in binary classification or abnormality detection problems. They are also unsupervised or semi-supervised techniques that often employ auto-encoders [8, 29]. They stem from game theory and they function by training one model per category, usually using different algorithms and methodologies for each category. Then an adversarial model is created by pitting each model against the other and comparing their confidence. These methods show great results, almost flawless in some use cases [29], but they do not function as well on multi-category problems.

3 METHODOLOGY

In this section, we present our proposed approach for the classification of vessel activities. 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).

3.1 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.

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 and the total vertical distance the vessel travels based on the minimum and maximum longitudes and latitudes respectively. Then, the distance each AIS position has travelled from the minimum longitude and latitude is calculated. Subsequently, the percentage of the total distance each AIS position has travelled so far from the minimum coordinate is measured. Each AIS position is placed inside a normalized bounding box or a surveillance space that is essentially an image representation. Finally, in order to make the pattern created by each trajectory more distinctive, a straight line between each temporally consecutive *pixel* or AIS position is drawn using the Bresenham's line algorithm [9]. 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.

Regarding speed, most common vessel types such as passenger, cargo or fishing vessels report a speed value between the range of 0 to 22 knots. To represent the speed values of each AIS position, this range was segmented to 2-knot increments with each increment corresponding to a different RGB color value in the final image. The 2-knot increment was chosen because we wanted a reasonable amount of color values while maintaining a relatively high number of increments. Furthermore, fishing vessels typically report a speed between 2 to 4 knots while fishing [14, 33] 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. 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 2 illustrates a trawling trajectory which has been transformed into an image.

More details on the trajectory image representation can be found in our previous works in [15, 16].

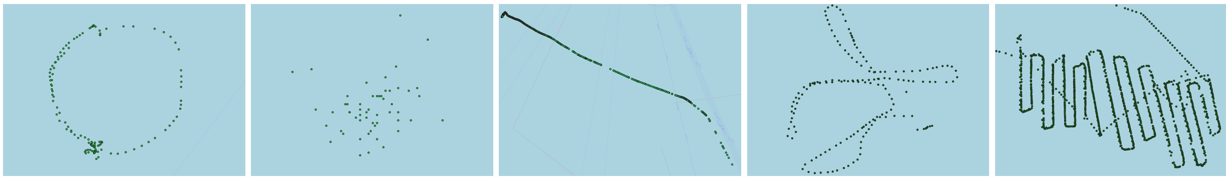
3.2 Convolutional Auto-encoder for Vessel Pattern Classification

An auto-encoder (AE) is an unsupervised neural network which is widely used for image reconstruction [32]. It is based on a single-hidden-layer feedforward neural network and is able to learn a compact representation of the input as a set of neural responses. An AE consists of an encoder and a decoder. The encoder encodes an input by mapping it to a hidden representation through a deterministic nonlinear function, and then the decoder reconstructs the input by mapping the hidden representation back to the original input space. More specifically, AE takes an input $x \in R^m$ and transforms it into a lower-dimensional hidden representation through a non-linear activation function $z = f(W_e x + b)$, where W_e and b are the weight matrix and bias vector of the hidden layer, respectively. The code z is then reversed mapped (decoded) using a function $\widetilde{x} = f(W_d z + b)$, where W_d is the decoder weight matrix and c is the decoder bias term. Each row of the weight matrix W_e corresponds to a feature. The AE encourages $\widetilde{x}$ to be as close as possible to x under a giver distance metric. In order to prevent learning degenerated features, the tied weight matrix $W_e = W_d^T$ is advocated. The objective of AE is to minimize the reconstruction error by minimizing a loss function.

Classic AE algorithms have often been limited to learning only low-level local structures such as lines and edges. Furthermore, they ignore the global structures and local connections of images, which in turn produce redundancy in the parameters. As a result, features are not able to gather sophisticated localised information within training. Thus, Convolutional auto-encoders (CAEs) [21] which constitute auto-encoder variants, extend the original patch-based models to cope with multidimensional images. Unlike patch-based methods, they preserve the relationships between neighbourhood and spatial information. CAE learn the optimal convolutional filters that minimize the reconstruction error and then these filters can be applied to any input in order to extract features. Thus CAEs are considered general purpose feature extractors as opposed to the AEs that completely ignore the 2D image structure. These semi-supervised CNNs are able to outperform fully supervised CNNs significantly in many applications [10]. In general, semi-supervised learning transfer knowledge from the labeled data to the unlabeled ones [7].

The CAE architecture is similar to classic AEs, except that the weights are shared. Given an input $x \in R^{m \times n}$, the output of kth feature map can be expressed as $z^k = f(x * W_e^k + b^k)$ where f is ReLU activation function and $*$ represents 2D convolution. The bias is processed per feature map [1]. Then the reconstruction is realized as $\widetilde{x} = f(\sum_{k \in M} z^k * \widetilde{W_d^k} + b_d^k)$ where $\widetilde{W}$ is 180° flipped weight matrix and M represents the group of latent feature maps [21]. Again, the objective of CAE is to minimize the reconstruction error by minimizing a loss function. The reconstruction error gradient is first back propagated and then the weights are updated using stochastic gradient descent.

In this research work, input images were scaled to the fixed size of 64×64 pixels. Training was conducted for 15 epochs with a batch size of 8. Rectified Linear Unit (ReLU) was chosen as the activation function due its reduced likelihood of vanishing gradients and its efficient computation. In order to prevent model overfitting data



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

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

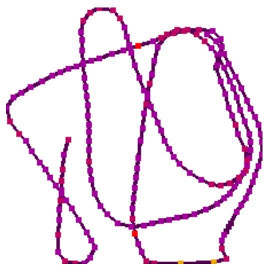


Figure 2: Example of a trawling trajectory that has been transformed into an image.

augmentation is employed, which increases the amount of training data [26]. Thus, data augmentation was performed during training, leveraging several multi-processing techniques. Specifically, the transformations employed included random rotation of the images, horizontal flips and width/height shift. Data augmentation improved the generalization and enhanced the learning capability of the model. The encoding part of the auto-encoder contains the convolutional and max-pooling layers to decode the image. The max-pooling layer is used as a downsampling strategy which decreases the sizes of the image by using a pooling function. The decoding part contains convolutional and up-sampling layers. The up-sampling layers are utilized to reconstruct the sizes of the image. In other words they act opposite of the pooling function. The last convolutional layer activates the softmax function. The softmax layer is specifically used in order to compute the probability of each classes. As a loss function the binary_crossentropy is used which computes the cross-entropy loss between true labels and predicted labels. Finally, the optimization method called Adam [13] is utilized during compilation which finds the minimum of the objective (error) function making use of its gradient.

4 EXPERIMENTAL EVALUATION

4.1 Dataset Description

The 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 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 [18]. Each AIS record consists of 10 attributes as described in Table 1.

The vessels have been monitored for one month period starting on March 1st, 2020 and ending on March 31st, 2020. Vessels transmit

Table 1: Dataset Attributes

Feature	Description
ship_id	unique identifier for each ship
lat, lon	the longitude and the latitude of the current ship position
ship_type	AIS reported ship-type
speed	Speed over ground in knots
course	Course over ground in degrees with 0 corresponding to north
heading	Ship's heading in degrees with 0 corresponding to north
destination	AIS reported destination
navigational_status	identifier regarding vessel's activity
timestamp	the time at which the message was received (UTC)

their position and their navigational status[2] in pre-defined time intervals. When vessels travel at high speeds, the frequency can get as high as one message every two seconds, while the lowest frequency can get as low as one message every 3 minutes when the vessels are not moving. The navigational status is manually entered in the dataset by the vessel's crew. It constitutes an identifier regarding the vessel's activity (e.g. a value of "1" indicates that the vessel was anchored when the message was received).

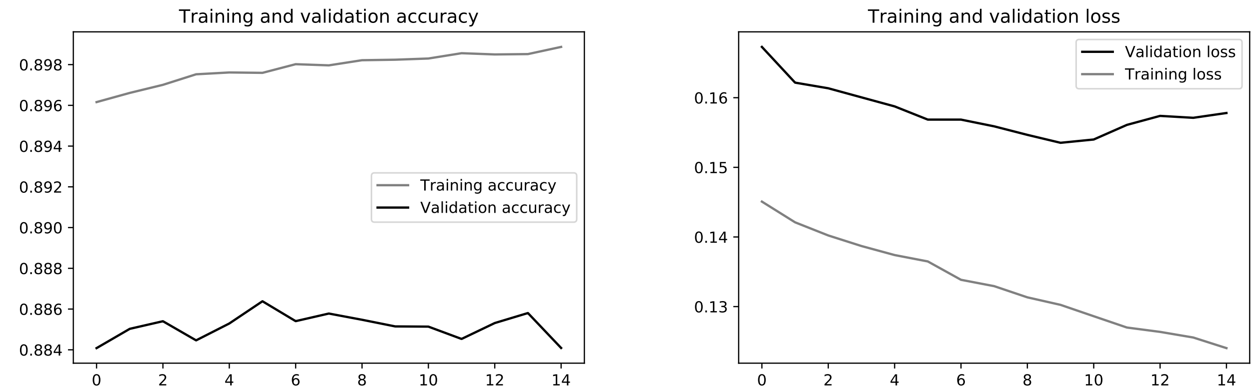
4.2 Convolutional Auto-encoder Evaluation

In order to evaluate the CAE performance, several commonly used classification metrics were adopted: Accuracy (ACC), Precision, Recall, and F1-score. *Accuracy* indicates how well a classification algorithm can discriminate the classes of the trajectories in the test set [20]. As shown in Equation (1), *ACC* can be defined as the proportion of the predicted correct labels (true positives + true negatives) to the total number of labels (N).

$$Accuracy(ACC) = \frac{|Correctly\ Labeled\ Examples|}{N} \tag{1}$$

Precision is the proportion of predicted correct labels to the total number of actual labels while *Recall* is the proportion of predicted correct labels to the total number of predicted labels. Recall is also known as sensitivity or the True Positive Rate (TPR). The F1-score consists of the harmonic mean of precision and recall, where

[2] https://help.marinetraffic.com/hc/en-us/articles/205426887-What-kind-of-information-is-AIS-transmitted-2020-04-06



(a) Accuracy **(b) Loss**

Figure 3: Training and validation accuracy/loss

precision is the average precision in each class and recall is the average recall in each class, as illustrated in Equation (2).

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \tag{2}$$

In order to provide good-quality representations of vessel activities to the model, 200 representative images (see Section 3.1) from each class were selected. The resolution of the images is set to 64×64. The dataset was randomly split into 80% and 20% for training and testing respectively and contain trajectory images of the different vessels. The trajectories were segmented into equally-sized temporal-window trajectories of $8h$ in length. This particular temporal-window was selected because the mobility patterns of the vessels require some time to form [14]. During a one-hour window, for instance, the anchored pattern as described in Section 3 will most probably not have fully formed. The Keras package and a TensorFlow backend were employed along with the Python programming language for training the CAE model.

Table 2 illustrates the classification results of CAE model.

Table 2: Accuracy results of CAE model

Precision	Recall	F1-score	Accuracy
94%	94%	94%	89%

The results suggested that the CAE model achieved an overall accuracy of 89%. A recall of 94% is able to guarantee that the different vessel mobility patterns would be accurately identified/reconstructed with a high probability. In addition, a high precision value of 94% indicates that there is a small chance that classes will be misclassified. Finally, a F1-score of 94% means that False Positives and False negatives were minimized. In addition, we visualize the accuracy and loss of the model during their training (in every epoch) in Figure 3a and Figure 3b respectively. CAE demonstrated a smooth training process during which the accuracy gradually increased and the loss decreased. Moreover, it can be observed that the accuracy of both training and validation did not deviate much from one another, a phenomenon that can also be observed for the training and validation loss, indicating that the model did not overfit.

5 CONCLUSION AND FUTURE WORK

In this work we presented an approach for trajectory classification which employs a convolution auto-encoder model. The aim of our approach is to move one step forward of our previous works [15, 16], where various CNN supervised models were utilized for trajectory classification, and to provide a semi-supervised classification of vessel mobility patterns. The performance of the proposed methodology was evaluated on a real-world dataset and demonstrated an F1-score of 94% and an overall accuracy of 89%.

This research work should be considered as a work in progress. As a future work, on the one hand, we aim at improving the overall accuracy and effectiveness of the model and to perform more experiments. On the other hand, our goal is to investigate several semi-supervised or unsupervised techniques in order to develop a model that is able to recognize labels in the data with limited or no a priori knowledge and re-train itself at an online manner. Finally, further research will be conducted to compare the classification performance of CAEs and CNNs.

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