AUTOMATIC DETECTION OF DARK SHIP-TO-SHIP TRANSFERS USING DEEP LEARNING AND SATELLITE IMAGERY

Ollie Ballinger

University College London
Centre for Advanced Spatial Analysis

ABSTRACT

Despite extensive research into ship detection via remote sensing, no studies identify ship-to-ship transfers in satellite imagery. Given the importance of transshipment in illicit shipping practices, this is a significant gap. In what follows, I train a convolutional neural network to accurately detect 4 different types of cargo vessel and two different types of Ship-to-Ship transfer in PlanetScope satellite imagery. I then elaborate a pipeline for the automatic detection of suspected illicit ship-to-ship transfers by cross-referencing satellite detections with vessel borne GPS data. Finally, I apply this method to the Kerch Strait between Ukraine and Russia to identify over 400 dark transshipment events since 2022.

Index Terms— Deep Learning, YOLO, Ship Detection, Transshipment, Satellite Imagery

1. INTRODUCTION

A Ship-to-Ship Transfer (STS) operation involves the exchange of cargo between two or more vessels while at sea. Though STS are often conducted for legitimate reasons, they are also one of the primary vehicles for concealing the origins of goods for the purposes of smuggling, sanctions evasion, and other illicit ends [1]. "Dark" ship-to-ship transfers, in which one or more vessels involved turn off or manipulate their onboard Automatic Identification System (AIS) are of particular concern. Since the Russian invasion of Ukraine, sanctions evasion via dark transshipment has become so rife that the European Union banned access to EU ports for vessels which engage in ship-to-ship transfers if there is cause to suspect the cargo is of Russian origin [2].

There is a vast literature on the detection of ships using satellite imagery. The majority of these studies employ synthetic aperture radar imagery (SAR), which has a number of benefits for maritime surveillance including weather- and illumination-independent imaging [3, 4, 5, 6]. However, it is difficult to distinguish between different types of ship without optical information [7]. Though a number of studies employ object detection or segmentation models to detect ships in optical satellite imagery, none of them identify transshipment [8, 9, 10, 11, 12, 13, 14].

Conversely, there have been several studies that automatically identify transshipment using vessel positions extracted from AIS data [15, 16, 1]. Ship-to-ship transfers are identified by algorithmically linking together vessels that loiter near each other for extended periods of time [15, 1]. These studies have successfully shed light on illicit transshipment, mainly in the context of illegal fishing [17, 18]. However, dark ship-to-ship transfers cannot be identified by relying solely on AIS data, as AIS is deliberately disabled to avoid detection [19].

This study identifies dark transshipment using a three step procedure combining AIS data and satellite imagery. First, STS are identified in the AIS data by linking vessels that loiter together. The AIS data is then used to train an object detection model to identify STS in optical satellite imagery. Finally, STS detections in the satellite imagery are cross-referenced with AIS data to identify transshipment events that occur in the absence of AIS signatures.
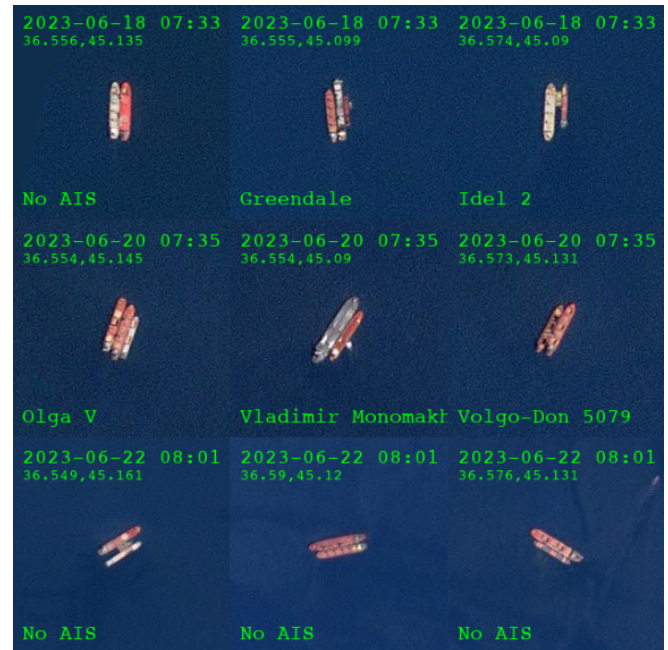

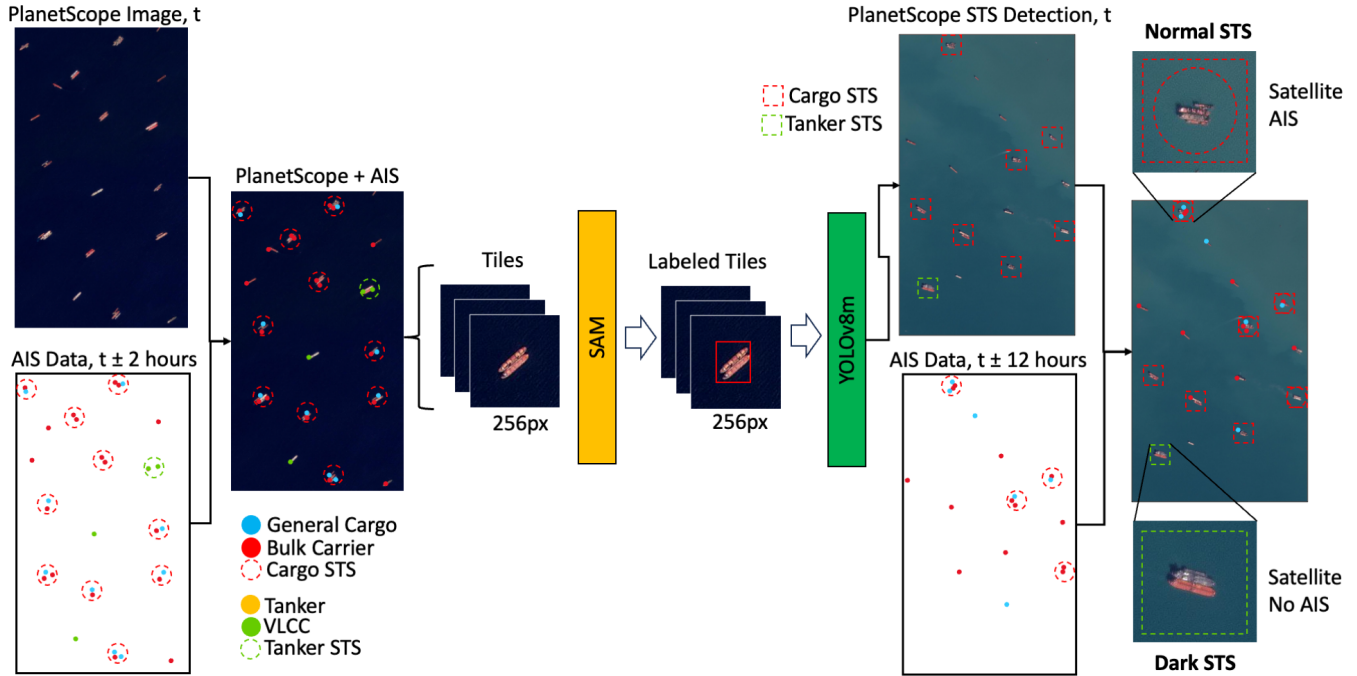**Fig. 1**. A sample of automatically detected dark STS

Fig. 2. Dark Ship-to-Ship Transfer Detection Pipeline

2. METHODOLOGY

Figure 2 details the methodology employed herein. First, AIS data are used to spatiotemporally locate ships in satellite imagery. Coupled with zero-shot segmentation via the Segment Anything Model, this yields a labeled dataset which is used to train a YOLOv8m object detection model [20, 21]. Finally, object detection is carried out on new satellite imagery, and cross-referenced with AIS data. Ship-to-ship transfers detected in satellite imagery but where fewer than two AIS signatures are present are considered to be dark STS.

2.1. Data

Two main sources of data are employed in this study. The first is data collected from a ship's Automatic Identification System (AIS), which encompasses vessel identification through unique International Maritime Organization numbers, real-time position data provided by GPS coordinates, and static details such as vessel dimensions and type. This information facilitates safe navigation, collision avoidance, and regulatory compliance in the maritime industry. AIS data were supplied by Lloyd's List Intelligence, and included over 1 million unique vessel positions spanning between January 1st 2021 and September 1st 2023.

The second data source is PlanetScope satellite imagery, which has a spatial resolution of 3 meters per pixel and a daily repeat cycle. Imagery was collected between January 1st, 2017 and September 1st, 2023. A cloud threshold of 0.7 was employed to discard cloudy scenes, resulting in imagery

available for 531 days (55% coverage). Both AIS data and satellite imagery were collected over the Kerch Strait anchorage (45°15'N, 36°30'E).

2.2. Identifying STS in AIS data

AIS data are first used to locate ships spatiotemporally in the satellite imagery and label them into one of four classes; **General Cargo:** A vessel capable of transporting a variety of goods with a capacity of up to 6,000 deadweight tons (DWT). **Bulk Carrier:** A ship designed to transport unpackaged dry bulk goods with a capacity exceeding 30,000 DWT. **Tanker:** A ship designed for the transportation of liquid cargoes with a capacity of up to 6,000 DWT. **VLCC (Very Large Crude Carrier):** A large tanker built for transporting crude oil with a capacity exceeding 100,000 DWT.

Then, transshipment is identified in AIS data by linking together ships that spend two or more hours within 500 metres of each other with a speed-over-ground below 1 knot. Depending on the type of ships involved in the transfer, the STS events are split into two categories; **STS Cargo** for transshipment involving dry cargo, and **STS Tanker** for transshipment involving liquid cargo (petroleum products).

This algorithm was applied to the full sample of AIS data, detecting over 12,000 ship-to-ship transfers in the Kerch strait since 2021, with more than half of these taking place since the Russian invasion of Ukraine.

2.3. Cross-referencing AIS and Satellite Imagery

For each satellite image, the AIS location with the highest temporal proximity to the timing of the satellite image for each ship is taken, with a maximum time difference of 2 hours. A spatial buffer of 500 meters is then taken to generate an image tile containing a single ship or transshipment event. Figure 3 illustrates the procedure of cross-referencing AIS tracks and PlanetScope imagery.

Fig. 3. Cross-referencing AIS and Satellite Imagery

Under normal circumstances, the agreement between the AIS data and the ships visible in satellite imagery is high enough that this procedure can not only localize the ship(s) in satellite imagery, but even the position of the AIS transponder on the bridge of the ship itself.

Once vessels have been located in the satellite imagery using the AIS data, the Segment Anything Model (SAM) developed by Kirilov et al. is employed to distinguish the ships themselves from the background [20]. High contrast between vessels and the background of open water enables efficient zero-shot segmentation. Segmentation masks are then converted to bounding boxes, and vessel information from the AIS data is used to label each image tile into one of six classes. Manual inspection of the result was conducted to ensure high quality. The class frequency distribution of the training dataset is reported in Table 1.

2.4. Object Detection

This labeled dataset is then utilized to train a YOLOv8m object detection model using an 80-20 train-test split [21]. The

Class	Frequency
General Cargo	11995
Bulk Carrier	1946
Cargo STS	2081
Tanker	3303
STS Tanker	637
VLCC	261
Total	**20223**

Table 1. Frequency Distribution of Ship Classes

model was trained for 50 epochs with a batch size of 128, and data augmentation techniques including mosaicking, random flips, and HSV color adjustments were employed. A Tesla P100 GPU with 16GB of memory was used for training, which lasted 3 hours and 17 minutes.

The model's overall F1 accuracy is 97%, and an mAP50 of 99% indicating a high degree of accuracy in identifying the six classes of vessel in satellite imagery. Figure 4 reports training diagnostics, and Figure 5 displays a normalized confusion matrix showing high class-wise accuracy in the test set.
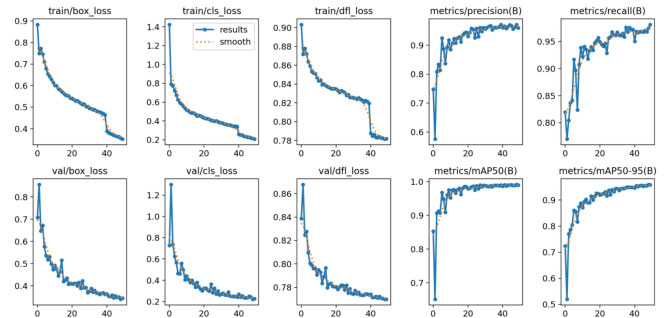

Fig. 4. YOLOv8m model diagnostics

The trained model is not only highly accurate but light weight: at just 52MB (25.8m parameters) and with an inference speed of 2.179 ms per tile, it can search 115 km^2 per second. As such, it can be deployed without significant compute resources and analyze new imagery in near real time as it becomes available.

3. DARK SHIP-TO-SHIP TRANSFER DETECTION

To detect dark ship-to-ship transfers, the object detection model is first used to locate STS in satellite imagery. Once a transshipment event has been located, the surrounding 500m area is searched for AIS signals within 12 hours on either side of the satellite image. Because STS involves a minimum of two ships, searches which return less than two distinct vessel identities are classified as dark ship-to-ship transfers. In total, there were 402 dark ship to ship transfers identified in the

Fig. 5. Normalized class-wise confusion matrix

Fig. 6. Dark STS involving Vladimir Monomakh

Kerch Strait between 2021 and September 2023. Each one could involve the potential exchange of millions of dollars' worth of cargo.

Figure 6 shows an example of an automatically detected dark STS. A transshipment event was detected in satellite imagery, but the corresponding location showed AIS transmissions from a single vessel in the 24 hours on either side of the satellite image. The one present AIS signal is from Vladimir Monomakh, a Very Large Crude Carrier owned by Russia's state oil company Rosneft with a length of 250 meters and a carrying capacity of 827,996 barrels [22]. However, another even larger vessel is clearly visible in the satellite imagery. Vladimir Monomakh also experiences a draught change of 0.6 meters approximately two hours after this satellite image was taken, suggesting that the vessel lost significant weight.

Following Russia's invasion of Ukraine, G7 countries instituted a price cap of $60 per barrel for Russian crude oil, meaning that Vladimir Monomakh would be carrying roughly $49 million worth of oil when at capacity. However, on the date of the transfer visible in Figure 6 the world price of brent crude was $78 per barrel. As such, circumventing the price cap would increase the sale price of the ship's cargo by around $14 million. The world price of brent crude peaked at $94/barrel in September 2023, increasing the value of this incentive to $28 million.

Vladimir Monomakh was identified as having conducted 22 dark STS in which it had its own AIS turned on, but was detected in satellite imagery with another ship that had its AIS turned off. There are also a significant number of dark STS in which there are no AIS signals at all, but one of the ships present closely resembles Vladimir Monomakh.
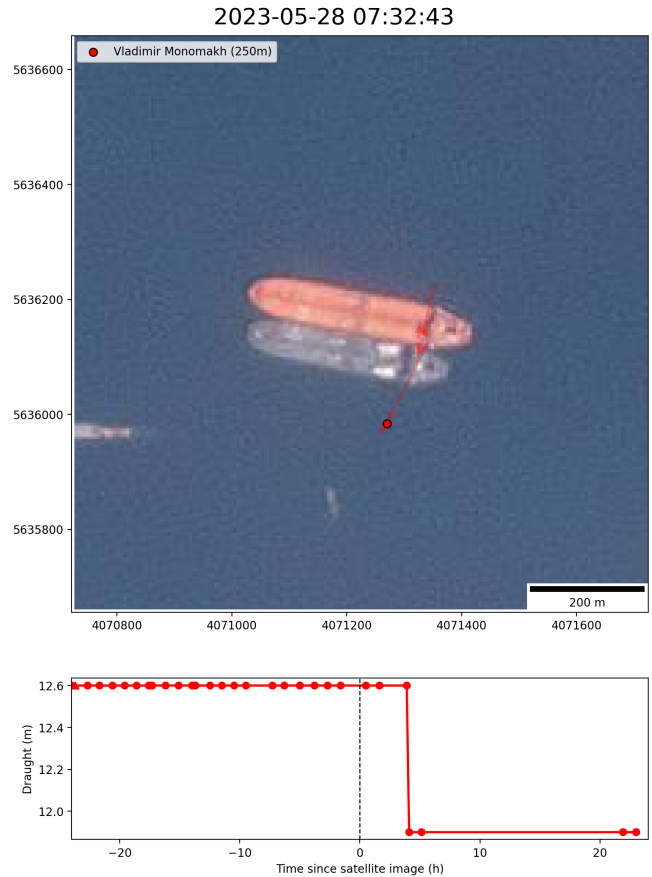
4. CONCLUSION

There are a number of avenues for further research. The most obvious would be to expand the geographical coverage of the training data to improve out of sample performance. Another impactful extension of this research would be to conduct capacity estimation. This can be done straightforwardly, as there is a roughly log-linear relationship between ship length and carrying capacity, and the diagonal of a bounding box is a close approximation of a ship's length.

This study pioneers the application of deep learning techniques for the identification of dark Ship-to-Ship Transfers (STS) in satellite imagery, addressing a crucial gap in maritime surveillance. Leveraging a combination of Automatic Identification System (AIS) data and PlanetScope satellite imagery, the proposed methodology successfully detects dark STS events, where vessels manipulate or disable their AIS for illicit purposes. The results reveal over 400 dark transshipment events in the Kerch Strait between 2022 and September 2023, underscoring the prevalence of such deceptive maritime activities. The demonstrated efficacy of this approach signifies its potential for enhancing maritime security and facilitating timely intervention in illicit shipping practices.

5. REFERENCES

[1] Nathan A. Miller, Aaron Roan, Timothy Hochberg, John Amos, and David A. Kroodsma, "Identifying global patterns of transshipment behavior," vol. 5.

[2] European Comission, "11th package of sanctions," .

[3] Shunjun Wei, Xiangfeng Zeng, Qizhe Qu, Mou Wang, Hao Su, and Jun Shi, "HRSID: A high-resolution SAR images dataset for ship detection and instance segmentation," vol. 8, pp. 120234–120254.

[4] Muhammad Yasir, Wan Jianhua, Xu Mingming, Sheng Hui, Zeng Zhe, Liu Shanwei, Arife Tugsan Isiacik Colak, and Md Sakaouth Hossain, "Ship detection based on deep learning using SAR imagery: a systematic literature review," vol. 27, no. 1, pp. 63–84.

[5] Siyuan Zhao, Zenghui Zhang, Weiwei Guo, and Ying Luo, "An automatic ship detection method adapting to different satellites SAR images with feature alignment and compensation loss," vol. 60, pp. 1–17, Conference Name: IEEE Transactions on Geoscience and Remote Sensing.

[6] Siyuan Zhao, Ying Luo, Tao Zhang, Weiwei Guo, and Zenghui Zhang, "A domain specific knowledge extraction transformer method for multisource satellite-borne SAR images ship detection," vol. 198, pp. 16–29.

[7] Zhonghua Hong, Ting Yang, Xiaohua Tong, Yun Zhang, Shenlu Jiang, Ruyan Zhou, Yanling Han, Jing Wang, Shuhu Yang, and Sichong Liu, "Multi-scale ship detection from SAR and optical imagery via a more accurate YOLOv3," vol. 14, pp. 6083–6101, Conference Name: IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing.

[8] Christina Corbane, Laurent Najman, Emilien Pecoul, Laurent Demagistri, and Michel Petit, "A complete processing chain for ship detection using optical satellite imagery," vol. 31, no. 22, pp. 5837–5854, Publisher: Taylor & Francis _eprint: https://doi.org/10.1080/01431161.2010.512310.

[9] Mesut Kartal and Osman Duman, "Ship detection from optical satellite images with deep learning," in *2019 9th International Conference on Recent Advances in Space Technologies (RAST)*, pp. 479–484.

[10] Bo Li, Xiaoyang Xie, Xingxing Wei, and Wenting Tang, "Ship detection and classification from optical remote sensing images: A survey," vol. 34, no. 3, pp. 145–163.

[11] G. Máttyus, "NEAR REAL-TIME AUTOMATIC MARINE VESSEL DETECTION ON OPTICAL SATELLITE IMAGES," vol. XL-1-W1, pp. 233–237, Conference Name: WG I/4, III/4, IC IV/VIII, VII/2
ISPRS Hannover Workshop 2013 (Volume XL-1/W1) - 21 – 24 May 2013, Hannover, Germany Publisher: Copernicus GmbH.

[12] Nadia Proia and Vincent Pagé, "Characterization of a bayesian ship detection method in optical satellite images," vol. 7, no. 2, pp. 226–230, Conference Name: IEEE Geoscience and Remote Sensing Letters.

[13] Guang Yang, Bo Li, Shufan Ji, Feng Gao, and Qizhi Xu, "Ship detection from optical satellite images based on sea surface analysis," vol. 11, no. 3, pp. 641–645, Conference Name: IEEE Geoscience and Remote Sensing Letters.

[14] Fei Wu, Zhiqiang Zhou, Bo Wang, and Jinlei Ma, "Inshore ship detection based on convolutional neural network in optical satellite images," vol. 11, no. 11, pp. 4005–4015.

[15] Kristina Boerder, Nathan A. Miller, and Boris Worm, "Global hot spots of transshipment of fish catch at sea," vol. 4, no. 7, pp. eaat7159, Publisher: American Association for the Advancement of Science.

[16] A. A. Masroeri, Aulia Siti Aisjah, Vedanta Agam, May Pradenta, and Muh Arif Samudya, "Analysis of fuzzy logic systems types 1 and 2 in identifying of IUU fishing and transshipment: a case study in indonesia's vulnerable waters," vol. 972, no. 1, pp. 012060, Publisher: IOP Publishing.

[17] Rui Saito, Yoshioki Oozeki, Kenji Takasaki, Tsutomu Saito, Shinji Uehara, and Masanori Miyahara, "Transshipment activities in the north pacific fisheries commission convention area," vol. 146, pp. 105299.

[18] Shailender Kumar, Harshit Muhal, Ishan Chaudhary, and Kirti Dabas, "Identification of IUU transshipment activity using AIS data," in *2022 3rd International Conference for Emerging Technology (INCET)*, pp. 1–7.

[19] Pierre Bernabé, Arnaud Gotlieb, Bruno Legeard, Dusica Marijan, Frank Olaf Sem-Jacobsen, and Helge Spieker, "Detecting intentional AIS shutdown in open sea maritime surveillance using self-supervised deep learning," pp. 1–12, Conference Name: IEEE Transactions on Intelligent Transportation Systems.

[20] Alexander Kirillov, Eric Mintun, Nikhila Ravi, Hanzi Mao, Chloe Rolland, Laura Gustafson, Tete Xiao, Spencer Whitehead, Alexander C. Berg, Wan-Yen Lo, Piotr Dollár, and Ross Girshick, "Segment anything," .

[21] Joseph Redmon, Santosh Divvala, Ross Girshick, and Ali Farhadi, "You only look once: Unified, real-time object detection," pp. 779–788.

[22] British Petroleum, "Approximate conversion factors," .