5G Enabled Video Analytics for Detecting Container Seals in Port Operations

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***Abstract**: This article is focused on port control, logistics and remote automation, and aims at detecting the presence/absence of seals at cargo containers. The proposed use case is realized by developing a novel computer vision algorithm for the task at hand, enabled as far-edge computing services on board 5G connected Internet of Things (IoT) devices. The proposed service adopts key enabling technologies of the 5G ecosystem such Network Functions Virtualization (NFV) with MAnagement and Network Orchestration (MANO) support for (automated) lifecycle management of the various service components. The service and overall architecture can be deployed on commodity servers to facilitate interoperability across heterogeneous ports, at low cost. Our results, based on real datasets obtained from the Piraeus port operations illustrate that the subject computer vision approach can achieve up to about 94% accuracy for detecting the presence of absence of container seals.*

1 Introduction

European Ports and their day-to-day operations are key elements for the European economy and economic growth. About 74% of goods imported and exported into the European Union (EU) lands in at least one port before reaching its final destination. At the same time forecasted cargo volumes see an increase of about 57% by 2030 and double the current volumes by 2050. Such volumes introduce significant challenges for seaport operators especially when taking into consideration that almost all European ports along the TEN-T corridors currently operate almost at capacity level. To this end, it is of great importance to address operations at ports that are part of several work chains and thus can pose significant delays to subsequent/dependent operations, such as the loading/unloading phase of containers to/from vessels. Intelligent solutions based on the Physical Internet that require minimal investment and infrastructure requirements are key to the optimization of efficiency in container terminals.

Of particular importance, from the point of view of shipping companies, authorities and stakeholders is the seal-checking process of containers. Container seals are safely locking container doors and are installed right after container stuffing at the place of origin. Any attempt to access the contents of a container requires breaking the container seal. Container seal-presence check when entering/leaving container terminals verifies that container load remains intact during its stay at the terminal (and hence, is of paramount importance), proving to both shippers and customs authorities that the terminal has no liability in regards to container contents. This article focuses in the seal-checking use case in one of the busiest container terminals in Europe, the Piraeus Container Terminal (PCT) port in Greece. The Piraeus port is currently ranked 4th among the busiest European Ports of 2020 in terms of container throughput, and is presently moving about 5.5 million TEUs on an annual basis. In PCT, a mother vessel requires an average of 3000 stevedore moves for operation completion, e.g., for loading/unloading all containers that have either as final or intermediate destination the Port of Piraeus. The current seal-checking process requires human presence at the quay side and about 30 seconds per container to complete. Reducing this time by e.g., 3 seconds per container, results to 9000 seconds (or about 2.5 hours) reduction of vessel stay at the port and removes the need for human presence at an area with high safety risks. Attempts to introduce RFID technology in the past, either at seal or container level, has faced numerous barriers on behalf of container manufacturers, shipping lines and terminal operators mainly due to the infrastructure requirement and financial feasibility.

This paper will discuss 5G technologies enabling a computer vision analytics approach, to address this void, for automatic detection of the presence or absence of container seals as a far-edge computing service. In particular, the developed solution builds on the 5G network support for (automated) lifecycle management of the various service components, including both computing and communications/network resources. Leveraging but also further extending the operational scope of such capabilities, we develop a portable (far) edge computing service that on the one hand, integrates sensing, processing and communication functionalities, and on the other allows the remote and automated management and orchestration of the end-to-end computer vision analytics service; this includes a series of novel capabilities such as instantiating the service, (re-)configuring (computer vision) components, updating overall software, increasing bandwidth and/or resolution of inspection, etc.

Contributions

- We develop a holistic algorithmic methodology for the detection of container seals based on state-of-the-art computer vision techniques, and utilizing key enabling technologies of 5G networks.
- The proposed solution packs all necessary network and software components into Virtual Network Functions (VNFs) that can be orchestrated at scale and on demand to any compute node (or 5G-IoT device) based on opensouce could solutions and industry proven technologies.
- The proposed solution can be placed on commodity x86 servers and similar types of commercial off-the-shelf (COTS) hardware to facilitate interoperability across heterogeneous ports.
- We perform extensive analysis of our model from a real dataset obtained by PCT's daily port operations and find that our model can detect the presence/absence of container seals with about 94% accuracy.

The structure of the paper is summarized as follows: Section 2 references relevant computer vision techniques over a variety of applications and use cases. Section 3 details the selected computer vision methodology for the detection of container seals in port operations. Section 4 briefly discusses the 5G enablers used for the realization of the far-edge computing service, whereas the results are detailed in Section 5. Finally, Section 6 concludes the article.

2 Related Work

The video (or image) analytics task at hand is a classic computer vision task, which can be seen either as a straightforward classification task (i.e., images containing seals or not) or an equivalent object detection task (i.e., detect if the image contains a seal and where). There is a variety of approaches which have been successfully employed to tackle such problems, ranging from classic mathematical computer vision tools such as template matching [1], feature/keypoint descriptors and pertinent matching algorithms [2, 3, 4], to the state-of-the art approach of deep learning, particularly convolutional neural networks [5, 6]. References in the cited works point to an ample variety of successful real-world applications of these methods, with examples covering both image classification and object detection. Each of the aforementioned tools has its advantages and disadvantages; the successful application of each one of these general methods requires special effort and further customization to the specific task at hand and choosing one method over the others is usually a tradeoff. We provide further details of our approach in the next section.

3 Computer Vision Analytics

In Figures 1 to 4 we provide examples of non-sealed versus sealed containers. Seals are marked by red bounding boxes.

Figure 1. Unsealed Container

Figure 2. Unsealed Container

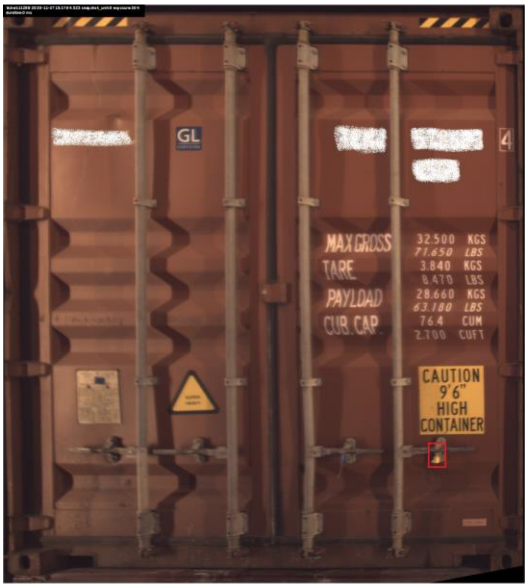

Figure 3. Sealed Container

Figure 4. Sealed Container

In general, seals are located in the lower-right quarter of the cotainer, placed in dedicated positions on the vertical bars or horizontal bar handles of the back side of a container. Given the fact that the images are taken from slightly varying distance and angle, and that bar and handle locations may also vary from one container to another, seals may be located virtually anywhere in the lower-right quarter of the image.

Rather than employing a deep learning based approach we have chosen to develop a custom algorithm utilizing mathematical computer vision tools, for the following reasons. As previously mentioned, the task at hand may be seen as either a classification task or an equivalent seal detection task. In the first case, a cropped part of the image (i.e. its lower right quarter) would be fed directly to a classification scheme (such as a convolutional network) and the output would be a binary variable corresponding to a "sealed" or "non-sealed" label. As can be seen from the Figures, such an approach essentially aims to classify a quite large image, rich in shape (e.g. letter characters), edge (e.g. shadows) and texture (e.g. rust, stickers, etc.) features by the existence or inexistence of a very small pattern in it. Despite their widely-celebrated merits, deep learning approaches have been shown to be heavily prone to unexplainable (and hence very difficult to remedy) errors in such occasions [7]. Attempting to build a seal detection scheme seems more promising; however, any pertinent deep learning approach would require large amounts of properly annotated images, something that is both tedious and extremely time consuming. Thus, we have opted for a more classical approach, whose details and advantages we discuss in this and the following sections.

By careful examination of sample images, we have chosen a collection of representative seal images (like the ones indicated by the red boxes in Figures 3 and 4) which we used as templates to be searched and matched within a given image. The developed algorithm essentially searches the image for templates matching one (or more) of the representative ones. If a match is found, the algorithm returns a bounding box around the matched segment of the image, and the container is labeled as sealed. If no matching is found, the image is labeled as unsealed. In detail, the algorithm works as follows.

1) The input image is cropped around its lower-right quarter. A noise reducing, edge-preserving bilateral filter is applied to the cropped image. Subsequently, we calculate the edges of the image, and an opening/closing smoothing filter is applied on the edges.
2) We repeat the steps of (1) for the seal image.

3) We perform a basic template matching on the edges by using simple matching measures including correlation coefficients and normed square differences [1].
4) If a matching is found, we perform an additional check using to reduce false positives; The histogram of oriented gradients (HOG) feature vectors of the seal image and the matched image area are computed and their Pearson correlation coefficient is computed. A significant correlation (>0.5) declares the image sealed and the algorithm is terminated by returning the seal location in terms of a bounding box. Otherwise, we repeat steps 2-4 for the next seal image.
5) If no matching is found, the image is declared non-sealed.

Note that the algorithm essentially performs seal detection; Based on the results of this detection the image is labeled as sealed or non-sealed; besides the class label, the output of the algorithm contains also the location of the seal in the image, if the image contains a seal. The algorithm was implemented by making extensive use of the OpenCV computer vision library. As detailed in the next sections, the algorithm was built by experimenting on a dataset of about 4,000 images. It has been tested on a separate, previously unseen and unused dataset of 2,000 images, resulting in an overall detection accuracy of 93.55%.

4 5G Enabled Video Analytics with NFV-MANO Support

This section describes 5G technologies enabling the discussed computer vision approach (Section 3) for automatic detection of the presence or absence of container seals as a far-edge computing service. In this framework, we present the overall architecture of our end-to-end solution, including both hardware and software components. The end-to-end edge computing service is composed of commercial off-the-shelf (COTS) hardware and open-source platforms, to expedite deployment and potentially facilitate interoperability across heterogeneous ports. The envisioned video analytics service will be deployed on novel 5G enabled Internet-of-Things (IoT) devices (c.f., 4.2) positioned at selected areas of interest within the Piraeus port, to automate the container seal detection process. In the sequence we present the architecture and respective devices that are used for our in lab testing at the ICCS 5G testbed.

4.1 MANO (ETSI MAnagement and Network Orchestration)

The adoption of NFV is considered as one of the enablers for a fully softwarized 5G architecture, that allows significantly higher flexibility for network service providers to instantiate and monitor services, configure and update them, commonly known as day0 to day2 operations of management and network orchestration [13].

Particularly, the MANO platform that is exploited for the container seal use case is based on Open Source MANO (OSM) release nine [8], an ETSI-hosted software stack aligned with ETSI NFV. The main platform is divided in three main components; the Virtualized Infrastructure Manager (VIM), which controls and manages the resources of an Network Function Virtualization Infrastructure (NFVI), i.e., the 5G-IoT devices that will host the VNFs and perform the video analytics tasks; the Virtual Network Function Manager (VNFM) taking care of the instantiation of VNFs, configuration, modification and termination of VNF instances, i.e., activating/deactivating/modifying the far-edge computing service; and the NFV Orchestrator (NFVO), which orchestrates the allocation of resources (compute, storage, networking, etc.) under the control of (potentially) different VIMs and manages the lifecycle of network services. This architecture will allow the instantiation of the container seal detection service, at scale, towards any 5G-IoT device under the control of the MANO platform, e.g., distributed at several sites of interest within the port premises.

The VIM exploited by the MANO platform for the container seal detection use case includes several components based on a subset of services offered by Openstack [9] (Victoria release). Other VIM solutions are also available e.g., OpenVim [10]. OpenStack is an opensource cloud operating system that controls large pools of compute, storage, and networking resources, i.e., the NFVIs, all managed and provisioned through APIs with common authentication mechanisms. The VIM orchestrator will be the interface towards the NFVI devices, i.e., the 5G-IoT nodes, that will host the VNFs (software applications that deliver network and computer vision service functions) and deliver the respective solution for facilitating the far-edge computing service of container seal detection. The VIM tool is controlled by the OSM to facilitate the MANO system, taking care also of the VNFM and VNFO services given the pool of NFVI nodes and the set of VNFs. For more details regarding the 5G-MANO stack please refer to [13] and references therein.

4.2 5G-IoT Device

The designed portable 5G-IoT edge device is composed of three main components: a generic compute node (that hosts the virtualized network and video analytics functionality) such as the NVIDIA Jetson Kit [11]; a high-resolution camera for data capturing (i.e., the input video feed for the analytics model of the container seal use case) and a 5G interface to establish communication with the backend system for visualization, database management, streaming of ultra-high-definition (UHD) videos etc. The prototype in-lab testing equipment of the 5G-IoT device as designed and tested at the ICCS 5G testbed is depicted in Figure 5.

Figure 5: 5G-IoT device components.

For the in-lab testing at ICCS we employ the 4G/5G stack of the OpenAirInterface platform following the Non-standalone (NSA) option of 5G technology [12]. USRP Software Defined Radio (SDR) devices are employed for the cellular connection, e.g., through B210 or N310 [14], and establish the high bandwidth connection necessary for the transmission of the UHD video streams. Upon migration to the port premises, the device will be placed at the quay side cranes in PCT, to enable the detection of presence/absence of container seals. The overall architecture is illustrated in Figure 6.

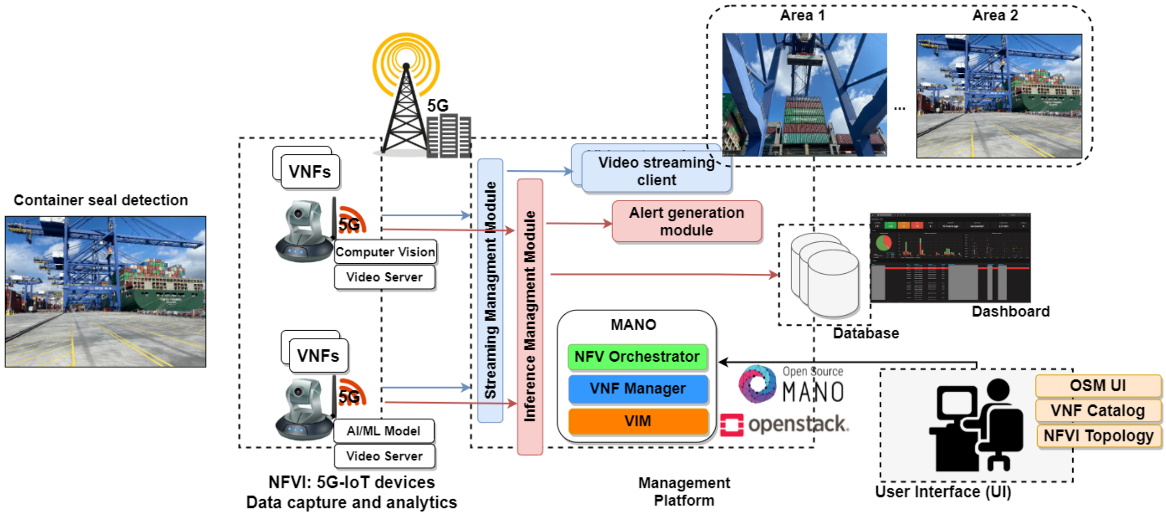

Figure 6: NFV-MANO enabled far edge computing architecture overview.

The instantiation process of a set of VNFs has the following workflow. Initially the user (administrator) interfaces a User Interface (UI), where the VNFs to be deployed are selected by a catalogue of supported services. The VNFs will bring all the necessary components for the analytics tasks to the 5G-IoT devices (software packages, libraries, etc.) as discussed in Section 3. When the user instantiates the service, the VNF descriptions are sent to the underlying VIM for preparing and configuring the physical infrastructure that will host them, i.e., the 5G-IoT nodes. These services will configure network interfaces, features regarding the virtualization technologies for the underlying physical resources (Virtual machines, Containers, Bare metal, etc.) as well as all software related services/components that need to be instantiated at the device for container seal detection analytics. The streaming management module (Figure 6) handles all video data transmitted by the 5G-IoT devices at the backend system enabling real-time monitoring of the operation, whereas the inference management module will receive the inference of analytics services from the IoT device, interface with the database (and respective dashboards) and alert generation module, e.g., container seal missing from the subject container.

For the overall deployment at PCT premises the required investment is minimal since it does not require special cameras and the cost of the compute node is less than the one of a standard user PC. At the same time, MANO capabilities lower the operational costs related to physical access to the device or downtime for maintenance.

5 Experimentation and Results

5.1 Dataset and Setup

A total amount of about 4,000 images, roughly 2,500 sealed and 1,500 non-sealed was used to select the representative seal patterns, and to build and tune the parameters and thresholds of the algorithm. The resulting algorithm was tested on a separate, previously unseen dataset consisting of 1,000 sealed and 1,000 non-sealed images.

5.2 Results

We visually inspected the output of the algorithm for each image of the test set, and manually measured correct versus incorrect seal detections. The confusion matrix of the resulting seal detection scheme is given in Figure 7.

	Actual Sealed	Actual Non-Sealed	**Accuracy**
Classified as Sealed	921	50	94.85%
Classified as Non-Sealed	79	950	92.35%
Recall	92.10%	95.00%	
	Overall Accuracy:	93.55%	

Figure 7: Confusion matrix of the proposed computer vision approach for the detection of container seals.

6 Conclusion

We have built a computer vision algorithm achieving high accuracy in detecting the existence of container seals in images of container back sides. For reasons mentioned above, we have opted to build the algorithm using mathematical computer vision tools, rather than deep learning. Contrary to deep learning approaches, the developed algorithm has the advantage that each of its steps is perfectly explainable, thereby facilitating further experimentations and improvements. Furthermore, by (optionally) tightening the algorithms' decision thresholds, the algorithm can be exploited as a reliable tool for annotating large amounts of images, thereby facilitating the use of deep learning-based object detection techniques. The overall service targets the far-edge computing vertical with NFV-MANO support for automation for ports: port control, logistics and remote automation. 5G enabling technologies have been considered based on open source solutions, COTS hardware and industry proven technologies to facilitate cross-knowledge sharing with heterogeneous ports or any other third party interested.

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