Development of computer vision informed container crane operator alarm methods

Abstract

Container crane operators' job is to unload or load containers from or to container ships at container terminals. They work in a harsh environment due to the prolonged work shift (four to six hours) and the restricted working area. After a long time of highly concentrated work, crane operators are highly likely to be exposed to discomfort and pain, and thus the probability of unloading a wrong container would increase to a large extent. To reduce the extra work, the operation cost, and the risk of cargo delay induced by the unloading of wrong containers, this study first develops a container color detection model to predict the color of the container being unloaded. The prediction results are then used to develop two crane operator alarm methods. Method 1 alerts the crane operator if the detected color of a container is not in compliance with the correct container color. Method 2 considers more comprehensive factors than method 1 by constructing a decision problem to decide whether to alert the operator considering the detected and the correct container colors. Both methods are compared to method 0, which does not use the alarm system and acts as the benchmark. The results of numerical experiments show that methods 1 and 2 are better than the benchmark method 0. Specifically, method 1 can save the expected annual total cost by about 82% compared to method 0, while method 2 performs better than method 1 and can save the expected annual total cost by about 85% compared to method 0. Extensive sensitivity analysis is also conducted to verify the methods performance and robustness.

Keyworks

Container crane operator; container color detection; crane operator alarm problem; container terminal management

1. Introduction

Multimodal transport is the foundation of modern logistics system involving multiple transportation modes such as rail carriers, aircraft, trucks, and vessels (Li et al., 2014, 2021; Wang et al., 2021). In the process, shipping containers (or containers for short) holding cargo need to be stored and transferred smoothly among different modes of transportation, and thus they are of standard types and sizes. 90% of them are general purpose containers with unified shape, surface material, and length according to the International Organization for Standardization (ISO) standard 668:2020 (ISO, 2020). It is common to see that a colorful collage of containers on vessels, in container terminals, and in depots. Their colors are mainly used for identification, either for different container types or company representations. In the first case, common colors are maroon for leasing containers belonging to leasing companies and white for one-way or reefer containers. In the second case, shipping container colors are chosen by shipping lines considering their brand colors for marketing and brand association goals. We list the common container colors and the related shipping lines as follows:

- Maroon: HMM, Zim Integrated Shipping Services
- Magenta: Ocean Network Express (ONE)
- Orange: Hapag-Lloyd
- Light yellow and dark yellow: Mediterranean Shipping Company (MSC)
- Light blue: Maersk Line
- Dark blue: CMA CGM, Wan Hai Lines, COSCO
- Green: Evergreen Marine Corporation
- White: COSCO

Container terminals, which are intermediate destinations of containers switched between different transportation modes, are strategically critical points of the complex global logistics network. Automation is the mainstream development trend of container terminals around the world, however, according to a report published by The International Transport Forum (2021), in 2021, fully automated container terminals do not exist, while about 53 container ports all over the world are automated at a certain degree. This only represents around 4% of global container terminal capacity. In addition, no terminal has completely automated quay cranes.

Container crane plays a vital role in container terminals, whose function is to load and unload containers from container ships. A container crane is operated by a container crane operator, who sits in a special operating cab above the hoist where the best view for carrying out the task is provided. A trolley is operated by the operator to lift or lower containers. The job of container crane operators requires concentration, precision, patience, and good hand-eye coordination. Container crane operators work in a challenging environment as the cab is small, and thus their movements are restricted. Moreover, a work shift of crane operator is usually four to six hours without a break. After such a prolonged period of repetitive while highly concentrated work, crane operators are highly likely to be exposed to discomfort and pain, resulting in deterioration of their work performance (Pau et al., 2016; Leban et al., 2017 and 2019). Therefore, the probability of unloading a wrong container from multiple stacked containers on a ship might increase. Consequently, the risk of cargo delay is increased and the terminal operational costs, from human, time, and economic perspectives, are also increased.

To address the issue, this study aims to make use of the varied shipping container colors to distinguish between different containers, so as to assist the work of container crane operators and reduce the port operational costs as well as the risk of container delay. To be more specific, two innovative container crane operator alarm methods are proposed, which are facilitated by a container color detection model realized by a popular computer vision library called OpenCV. Method 1 is based on a natural idea: a crane operator is alerted if the detected and the correct container colors are inconsistent. However, the container color detection model is not perfect, and thus the effectiveness of method 1 is adversely influenced. Therefore, method 2 aiming to minimize the total operational costs is developed, which considers more comprehensive situations than method 1. It is based on a decision problem considering more factors such as container wrongly unloading proportions, container color prediction accuracy rates, and three operational costs occurring in different situations: the cost of a false alarm when a correct container is being unloaded, the cost of a correct alarm when a wrong container is being unloaded, and the cost of a false alarm when a wrong container is being unloaded. A case study of the Hong Kong port and extensive sensitivity analysis are conducted to verify the effectiveness and robustness of the proposed models.

The remainder of this paper is organized as follows. Section 2 reviews two streams of studies related to the topic of this study. Section 3 develops the shipping container color detection model based on the OpenCV library. Section 4 studies the container crane operator alarm problem by developing a benchmark model and two innovative crane operator alarm models. Case study of the Hong Kong port and extensive sensitivity analysis are conducted in Section 5, where managerial insights are also provided.

2. Literature review

Two streams of studies related to the current research topic are reviewed in this section: container crane operator management and detection tasks of shipping containers. Considering the harsh working environment of container crane operators, a series of studies have been done to assess the fatigue and discomfort encountered by crane operators in their daily work. A container crane simulator environment with two pressure-sensitive mats placed on the seat pan and backrest was created by Pau et al. (2016) to monitor the variations in seat-body interface pressure of a crane operator during his/her regular work shift of 4 hours. Based on the performance of eight professional operators, it was found that the backrest pressure was low and constant, while the seat pan pressure increased by 10% over the simulated shift. The results indicated that as work progressed, crane operators' discomfort increased, and they would modify their posture to reduce the stress on the buttocks. A container crane simulator environment was also used by Leban et al. (2017) to analyze the trunk sway of container crane operators during the 4-hour work shift. The results obtained from 16 crane operators suggested that in the progress of one work shift, there was a linear increase in both amplitude and velocity of sway, indicating that the fatigue of the crane drivers increased. Leban et al. (2019) further investigated the changes in postural strategies of container crane operators by analyzing the trend of in-chair-movement (ICM) during a 4-hour shift to present their discomfort and fatigue in a container crane simulator environment. The results obtained from 16 crane operators showed that there was a significant increase in ICM after 45 to 60 minutes from the beginning of a work shift, indicating that the crane drivers' discomfort and fatigue increased by a certain extent.

The existing literature on detection tasks of shipping containers is extensive and focuses particularly on container code identification. Container code printed on the back of a shipping container is the unique identifier of a container, which has 15 alphanumeric characters indicating its country, size, and type according to the ISO6346 standard (ISO, 1995). Although the techniques of text identification are well developed, correctly identifying container code is not a trivial task due to the degradation of container images caused by uneven illumination, background variation, and smear, etc.

Generally, the procedure of container code identification contains two steps: text region locating and text recognition, while denoising and filtering are used throughout the process to improve accuracy. Traditionally, container code identification is mainly achieved by rules generation. For example, He et al. (2004) proposed a container code extraction method based on template matching by first generating standard templates with standard align modes from the collected images. Then, new images were matched with the standard templates to achieve automated container code extraction. Considering the domain knowledge that the color of container code is usually black or white, Kim et al. (2006) proposed a container code recognition system which regarded the areas that were not black or white as noises. Edge detection was then applied to extract the code area. Individual characters were extracted by an 8-directional contour tracking method, and then ART2-based self-organizing supervised learning algorithm was used for text identification.

With the fast development in massive data collection and storage as well as computation power, deep learning (DL) based methods are becoming increasingly popular in recent years for container code identification. Mei et al. (2016) developed a framework combining convolutional neural network (CNN) and template matching for single character recognition, and the characters were combined and verified using verification rules according to domain knowledge. Verma et al. (2016) proposed an end-to-end pipeline solution to container code identification. In particular, to reduce the interference of varied noises, noisy text regions were first removed by an adaptive score arrogation algorithm. Then, text localization was realized by Resnet and U-net, and text recognition was achieved by convolutional recurrent neural network (CRNN). Online training was realized in a container code recognition system developed by Liu et al. (2018), which consisted of context detection and recognition modules based on computer vision and DL models. To increase recognition accuracy, container images were collected from cameras in three views: top view, right view, and left view. A scene text detector based on CNN was first used for text localization, and then Google Tesseract engine based on long short-term memory (LSTM) network was used for text recognition. In addition to container code identification, other popular detection tasks of shipping containers include container cargo inspection for goods discrimination (Che et al., 2018) and empty container damage recognition (Klöver et al., 2020).

The studies reviewed above show that container crane operators are prone to fatigue and discomfort due to the prolonged working period, repetitive working contents, and the restricted working area. Consequently, their cognitive efforts to guarantee safe and effective movement of containers are reduced, especially after a long period of work. On the other hand, although there are extensive studies on detection tasks of shipping containers, especially the container code identification, to the best of the authors' knowledge, there is no existing study on container color detection and no alarm system to alert container crane operators regarding their wrong container unloading actions based on the results given by container detection models. Although container code identification can be helpful to inform the crane operator if a wrong container is being unloaded, accurate container code identification can be difficult. For example, in traditional models, container codes in 29 out of the 950 images cannot be correctly segmented out and thus be recognized in He et al. (2004). When DL models are adopted, the overall code detection accuracy is only 93.4% and the code recognition accuracy is only 93% in Liu et al. (2018). As a container code contains several digits, misidentification of any digit would cause recognition error. Moreover, the computation burden of DL models can be very high, and thus is hard to be applied when the computation power is limited, or real-time recognition is required. Therefore, this study innovatively adopts computer vision technology for container color detection, and the results are then used to assist in alerting the crane operator if a wrong container is being unloaded, so as to reduce the extra work induced and the total expected annual costs.

3. Shipping container color detection model

We first search container figures of the colors of concern from Google Images[1]. We require that one container is contained in one image, and it occupies the image's main part. This requirement aims to improve the detection accuracy, which can be easily achieved in practice by adjusting the position, angle, and focal length of the cameras. Container color detection is based on OpenCV[2] which is an opensource computer vision library. The color space (i.e., a way to represent the color channels in an image) used by OpenCV is HSV, or hue, saturation, and value, which represents the color, greyness, and brightness, respectively. Especially, hue determines the color seen by naked eyes, saturation represents color purity, and value shows how bright the white light shines on the color. The hue range is [0, 179], the saturation range is [0, 255], and

[1] https://www.google.com/imghp?hl=en
2 https://opencv.org/

the value range is [0, 255]. The color detection model contains two steps: Step 1: HSV range extraction, and Step 2: color and contour detection, which are resented as follows.

Step 1: HSV range extraction

For each color of concern, we randomly select 20% of images from all the images collected for benchmarking (which we call them by benchmark image set), with the aim to specify its HSV ranges. The remaining 80% of images constitute the validation set. Then, for each benchmark image, HSV of ten random points of the container is detected. Finally, the maximum and minimum H, S, and V among all selected points in these benchmark images are chosen as the basic ranges for H, S, and V. The finally adopted range for H (which determines the specific color) is almost identical to the basic range, while the ranges for S and V (which represents color purity and brightness, respectively) are extended from the basic ranges considering the influences of sunlight, shade, and depigmentation. One exception is white, whose H value ranges from 0 to 173 in the benchmark image set because of shade and reflection as it is highly likely to be influenced by sunlight and the surrounding objectives. Therefore, for color white, we fix H and S to 0 and set the range for V to [0, 255] based on experience, and regard it as the default container color in Step 2. The colors of concern, the number of benchmark images, and the detected and adopted HSV ranges are shown in Table 1.

Insert Table 1 here

Step 2: color and contour detection

The HSV range of each color of concern is then used to detect the colors of the shipping containers in images of the validation set. The procedure is shown in *Procedure 1*. One thing that needs to be mentioned is that we impose judgements on the pixel ratio (i.e., the ratio of the number of pixels within a color's HSV range and the total number of pixels in the image) of the largest or the second largest color detected to reduce the influence of background, light, and interference colors, which might confuse similar colors (e.g., light blue and dark blue). The detection accuracy of each color, except for the default color 'White', is presented in Table 1. It can be seen that the overall accuracy is 94.74%. We further examine the predicted colors of each color of concern in the validation set in Table 1. Especially, 'row accuracy' shows the detection accuracy ratio for each color of concern, and 'column accuracy' shows for each predicted color, the possibility that the predicted color is the real color.

Procedure 1. Shipping container color and contour detection

Input: An image with one shipping container as the main part; HSV ranges of the colors of concern
Output: The color and area of the shipping container in the image

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Step 1   Read the image from its input file. Use Gaussian blur to reduce image noises. Turn the
         original image to HSV color space.
Step 2   Initialize color_ratio_list = [] and container_color = None
         for each color c of concern:
             Turn the pixels falling in the color's HSV range to value 1 while others to value 0.
             Calculate the ratio of the pixels of value 1 and the pixels of the whole image which is
             denoted by ratio_c. Add ratio_c to color_ratio_list.
Step 3   Choose the largest ratio from color_ratio_list denoted by max_ratio_c, and the
         corresponding color is denoted by max_c.
Step 4   if max_c != 'White':
             if max_ratio_c >= 0.25:
                 Set container_color = max_c, find the contour of the largest area in color max_c, and
                 outline the minimum circumscribed rectangle.
             else:
                 Set container_color = 'White'.
         else:
             Choose the second largest ratio from color_ratio_list denoted by max2_ratio_c, and the
             corresponding color is denoted by max2_c.
             if max2_ratio_c >= 0.1:
                 Set container_color = max2_c, find the contour of the largest area with color max2_c,
                 and outline the minimum circumscribed rectangle.
             else:
             Set container_color = 'White'.
Step 5   Output container_color and the minimum circumscribed rectangle (if any).
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4. Container crane operator alarm problem

Currently, the most widely-used container stowage plan is the bay-row-tier system, where a container's stowage space number is a string of six digits with each two digits representing bay, row, and tier from front to back (GDV, 2022). The operators are instructed by the stowage space numbers to unload the containers to their allocated trucks. The unique container slot specified by the six-digit stowage space number can be easily mistaken by the operators due to carelessness, especially when they are tired and irritable after long hours of boring work (Pau et al., 2016; Leban et al., 2017 and 2019). For example, suppose that a light blue container with the stowage space number 531412 should be unloaded, but it is likely that a dark blue container with the number 531212 which is next to the light blue container is unloaded instead by the operator as he/she mistakes the row number. If the mistake is not alerted to the operator, the cost to rectify the mistake after unloading the container can be high.

We study the container crane operator alarm problem (CCOAP for short hereafter) by assuming that when the operator is unloading a wrong container, alerting the operator that a wrong container is being unloaded can be realized by taking the relationship between the color of the container being unloaded (which can be predicted by the container color detection model proposed in Section 3) and the color of the container that should be unloaded (which is known) as well as the costs associated with different actions into account. To be more specific, for each container being unloaded, it can be wrong or correct, and the operator can be alerted or not. Given perfect information, only when a wrong container is being unloaded should the operator be alerted. However, judging whether the container being unloaded is a correct container based on the correct and the predicted colors is a complex process: in addition to the correct container color, we do not know the actual container color; Instead, we only know the predicted container color (which might be inaccurate). A detailed illustration of the three types of colors and the four possible cases are summarized in Figure 1 and are further explained in the next paragraph.

Insert Figure 1 here

A natural and basic idea is that if the predicted and correct colors are inconsistent, the operator is alerted. In this case, if the prediction is accurate (which means that the actual color and the predicted color are identical, and is different from the correct color), it is sure that a wrong container is being unloaded by the operator. However, the prediction can be inaccurate, that is, the actual color and the predicted color are not identical. Under this condition, it is unknown whether the actual color is the correct color. Therefore, the container being unloaded might be the right container but predicted to be a different color. It can also be a wrong container of a different actual color than the correct color or a wrong container other than the correct one but with the same actual color. Moreover, even if the predicted and correct colors are consistent, it is also possible that the prediction is inaccurate (which means that the actual color and the predicted color are not identical, and thus the actual color is different from the correct color) and a wrong container is being unloaded. If the prediction is accurate (which means that the actual color and the predicted color are identical, and they are the same as the correct color), the container being unloaded might also be wrong (a container other than the correct container but with the same color of the right container) or is indeed correct. In such various cases, the cost of alerting the operator regarding unloading a wrong container in CCOAP can be varied: if a right container is being unloaded and the operator is not alerted, this is an ideal case with zero cost. Alternatively, if the operator is alerted, there is a container double check cost. If a wrong container is being unloaded, both alerting and not alerting the operator can incur costs. The CCOAP is proposed and addressed in this section.

The CCOAP aims to decide whether to alert the operator if a certain color of the container being unloaded is detected. Consider a set of shipping container colors of interest K with each color denoted by k. Suppose that in reality, a total of M containers are to be unloaded (e.g., in a year) at the port. The proportion of containers to unload that are of color k is α_k, and among all containers of color k, the proportion that is wrongly unloaded in daily operation (where a wrong container of the same or a different color is unloaded) is β_k. Denote the actual (which is unknown in the crane operator alarm system, otherwise it can be used directly instead) color of the container being unloaded by $\bar{k}$, and the color of the container detected by the shipping container color prediction model is $\hat{k}$. Given the actual color $\bar{k}$, the probability of predicting it to be color $\hat{k}$ is $\hat{P}_{\bar{k}\hat{k}}$. $\hat{P}_{\bar{k}\hat{k}}$ can be derived from the validation set as shown in Table 1, and $\sum_{\hat{k}\in K} \hat{P}_{\bar{k}\hat{k}} = 1$, $\bar{k} \in K$. The five events in CCOAP are summarized in Table 2.

Insert Table 2 here

We further consider three costs in this problem, which are identical to all colors of interest: c_1, which is the cost of false alarm (i.e., the operator is alerted but he is actually unloading the correct container; the operator has a double check and then disables the alarm for the container), i.e., the cost of container color checking by the operator; c_2, which is the cost if a correct alarm is sent to the operator and the operator corrects the mistake (i.e., the operator is alerted and he/she checks the container by himself/herself and finds that indeed the wrong container is being unloaded; therefore, he/she places the container back to the ship, and then goes to unload the correct one); c_3, which is the cost of the inconsistency between the correct container to be unloaded and the container being unloaded while not alerting the operator (i.e., the operator is unloading a wrong container, but he/she is not alerted; the wrong container is found out by the port only after it is already in the port). Obviously, we have $c_3 > c_2 > c_1$. Suppose the color of the correct container is $\tilde{k}$. The CCOAP can be divided into four scenarios based on whether a correct container is unloaded (i.e., $A=1$ or $A=0$), and whether to send an alarm (i.e., $E=1$ or $E=0$). The cost associated with each scenario can easily be derived as shown in Table 3, which applies to both method 1 and method 2. In both methods, what we know is the correct container color $\tilde{k}$ and the detected container color $\hat{k}$, and the actual container color $\bar{k}$ is unknown.

Insert Table 3 here

The CCOAP can be addressed by the following three methods. In particular, method 0 is the benchmark which is the current approach adopted by the Hong Kong port, where no system is used to alarm the crane operators. Method 1 is based on a natural idea, which alerts the crane operator if the correct and the detected container colors are inconsistent. However, it does not take the inaccuracy of the container color detection model into account. Therefore, method 2 is further proposed, which is based on a decision problem considering more comprehensive factors such as container wrongly unloading proportions, container color prediction accuracy rates, and three operational costs occurring in different situations. Details of the three methods are given as follows.

Method 0: Do not alert, i.e., do not use the system. This is a benchmark model. The annual cost will be

$$C^0 = c_3 \sum_{k \in K} M \alpha_k \beta_k \ . \tag{1}$$

Method 1: Alert if the detected color of a container is not $\tilde{k}$, i.e., $\hat{k} \neq \tilde{k}$, and not alert otherwise. The expected (fixed) cost for this single container, denoted by $C^1_{\tilde{k}}$, is

$$C^1_{\tilde{k}} = (1-\beta_{\tilde{k}})(1-\hat{P}_{\tilde{k}\tilde{k}})c_1 + \beta_{\tilde{k}} \sum_{\bar{k} \in K} \alpha_{\bar{k}} \left[(1-\hat{P}_{\bar{k}\tilde{k}})c_2 + \hat{P}_{\bar{k}\tilde{k}} c_3 \right]. \tag{2}$$

The explanation of Eq. (2) is as follows. Given the condition that the color of the correct container is $\tilde{k}$, the probability of unloading a wrong (or right) container is $\beta_{\tilde{k}}$ (or $1-\beta_{\tilde{k}}$). If a right container is unloaded but the operator is alerted because of the inaccuracy in color detection, the cost is $(1-\hat{P}_{\tilde{k}\tilde{k}})c_1$. If a wrong container is unloaded whose color is $\bar{k}$ (may or may not be $\tilde{k}$ which is the right container color, i.e., $\bar{k}=\tilde{k}$ or $\bar{k}\neq\tilde{k}$) with the possibility $\alpha_{\bar{k}}$. Then, the cost would be $\sum_{\bar{k}\in K}\alpha_{\bar{k}}\left[(1-\hat{P}_{\bar{k}\tilde{k}})c_2+\hat{P}_{\bar{k}\tilde{k}}c_3\right]$, where the first part in the square brackets is the cost of the correct alarm as the predicted container color is not $\tilde{k}$ and the second part is the cost of no alarm as the predicted color is $\tilde{k}$. A more detailed explanation of the above analysis is shown in Table 4.

Insert Table 4 here

Therefore, the total cost of unloading one container using method 1 can be calculated by summing the costs of all scenarios, which is $C_{\tilde{k}}^1$. Then, the annual cost C^1 will be

$$C^1=\sum_{\tilde{k}\in K}M\alpha_{\tilde{k}}C_{\tilde{k}}^1. \tag{3}$$

Method 2: Whether to alert the operator if the detected color of the container being unloaded is $\hat{k}$ and the correct container color is $\tilde{k}$ is determined by the following decision problem. Denote $D_{\hat{k}\tilde{k}}=\{0,1\}$ by the decision space of whether to alert the operator. Let $d_{\hat{k}\tilde{k}}=1$ mean that the operator is alerted and $d_{\hat{k}\tilde{k}}=0$, otherwise. We consider the problem from the perspective of the correct container color $\tilde{k}$. For any container that is being unloaded, its predicted color is $\hat{k}$. If the right container whose color is $\hat{k}$ is unloaded, as we have $\hat{k}=\tilde{k}=\bar{k}$ in this case, the probability would be $(1-\beta_{\tilde{k}})\hat{P}_{\tilde{k}\hat{k}}$; if a wrong container is being unloaded, its color can be any color of concern, i.e., $\bar{k}\in K$ with the probability $\beta_{\tilde{k}}\sum_{\bar{k}\in K}\alpha_{\bar{k}}\hat{P}_{\bar{k}\hat{k}}$. Note that in this case, the actual container color $\bar{k}$ might be the same as or different from the correct container color $\tilde{k}$. Then, the expected cost for operating the containers whose correct color is $\tilde{k}$, denoted by $C_{\tilde{k}}^2$, is

$$C_{\tilde{k}}^2=\sum_{\hat{k}\in K}\min_{d_{\hat{k}\tilde{k}}\in\{0,1\}}\left\{d_{\hat{k}\tilde{k}}\left[(1-\beta_{\tilde{k}})\hat{P}_{\tilde{k}\hat{k}}c_1+\beta_{\tilde{k}}\sum_{\bar{k}\in K}\alpha_{\bar{k}}\hat{P}_{\bar{k}\hat{k}}c_2\right]+(1-d_{\hat{k}\tilde{k}})\beta_{\tilde{k}}\sum_{\bar{k}\in K}\alpha_{\bar{k}}\hat{P}_{\bar{k}\hat{k}}c_3\right\} \tag{4}$$

where the first part in the curly brackets is the cost of an alarm (while unloading a right container [the first part in the square brackets] or a wrong container [the second part in the square brackets]) and the second part is the cost of no alarm (while unloading a wrong container). A more detailed explanation of method 2 is given in Table 5.

Insert Table 5 here

As method 2 is based on a decision problem where $d_{\hat{k}\tilde{k}} = 1$ represents sending an alarm to the crane operator and $1 - d_{\hat{k}\tilde{k}}$, otherwise, $d_{\hat{k}\tilde{k}}$ is also incorporated in the expression of $C^2_{\tilde{k}}$. Then, the annual cost C^2 will be

$$C^2 = \sum_{\tilde{k} \in K} M \alpha_{\tilde{k}} C^2_{\tilde{k}} . \tag{5}$$

5. Numerical experiments

The CCOAP is implemented by first inputting the color of the correct container that should be uploaded to the crane management system, which is also accessible by the crane operator. In addition, a camera should also be put at a proper position in the top of each crane to take photos of the container being operated and then detect the actual color of the container. Then, a decision system based on the CCOAP is used to decide whether to alarm the crane operator based on the actual and detected container colors and the performance of the shipping container color detection model. The CCOAP involves three types of parameters: a) port specific parameters (M, $\alpha_{\bar{k}}$ for $\bar{k} \in K$, and $\beta_{\bar{k}}$ for $\bar{k} \in K$), b) port operational cost parameters (c_1, c_2, and c_3), and c) color prediction model related parameters ($\hat{P}_{\overline{k}k}$ for $\bar{k} \in K$), whose values can have a significant impact on the effectiveness of the problem. We first use the Hong Kong port as a case study to validate the performance of the three methods proposed to address the CCOAP. Then, extensive sensitivity analysis is conducted to further validate the performance and robustness of the three methods to address the CCOAP and generate managerial insights. The results of the case study and the sensitivity analysis are presented in Table 10.

5.1 Case study of the Hong Kong port

According to the port container throughput statistics provided by the Hong Kong Marine Department (2022), the total container throughput (including those from seaborne and river) at the Kwai Tsing Container Terminals (KTCT) was 14,456,000 TEUs (short for twenty-foot equivalent units) in 2020 and 14,580,000 TEUs in 2021, and the average TEUs was $14,518,000$ over the two years. TEU is an inexact unit of cargo capacity itself, and different sizes of containers can have different TEUs, while most of them are of 20 TEUs and 40 TEUs. According to the estimate of Budget Shipping Containers (2022), about two-thirds of shipping containers are 40ft containers, and the number of actual shipping containers will be broadly 60% of the TEU value. Therefore, we roughly set $M = 9,000,000$. As the numbers of containers in each color $\bar{k}$ loaded and unloaded are unknown at the Hong Kong port, we assume that $\alpha_{\bar{k}}$ is identical to the ratio between the collected images of each color and all the collected images (except for the benchmark color white) as shown in Table 1. As containers in similar colors (e.g., light blue and dark blue) are more likely to be mistaken, we classify these colors into three error levels from I to III. Level I includes color green, which have no similar color; level II includes container colors maroon and magenta, and light blue and dark blue, which has one similar color for each of them; level III includes container colors orange, dark yellow, and light yellow, which has two similar colors for each of them. For colors in levels I to III, we set $\beta_{\bar{k}} = 0.02$, $\beta_{\bar{k}} = 0.05$, and $\beta_{\bar{k}} = 0.10$, respectively. For the prediction of each color, $\hat{P}_{\bar{k}\bar{k}}$, $\hat{P}_{\tilde{k}\tilde{k}}$, and $\hat{P}_{\tilde{k}\hat{k}}$ can all be derived from Table 1, as all of them show the probability of predicting the color shown by the first subscript to the color shown by the second subscript. We present $\alpha_{\bar{k}}$, $\beta_{\bar{k}}$, and $\hat{P}_{\bar{k}\bar{k}}$ for each color of concern $\bar{k} \in K$ in Table 6.

Insert Table 6 here

We set port operation related parameters $c_1 = 1$, $c_2 = 5$, and $c_3 = 100$ for the following reasons. The actions taken by the operator regarding c_1 include double checking the container and disabling the alarm while without any operation on containers (as this cost is induced by wrong color prediction while a correct container is being unloaded), and thus we set it to one unit of cost. The actions taken by the operator regarding c_2 include double checking the container, putting it back, and going to the right container (where this cost is induced by correct color prediction while a wrong container is being unloaded). We impose two units of cost to the latter two actions, respectively, and thus c_2 is 5 units of cost. The actions taken by the operator regarding c_3 can be much more complex as the wrong container has already been moved to the container yard due to inaccurate color prediction: the wrongly unloaded container needs to be found and then re-loaded to a truck, and in this process several other containers onto it need to be unloaded to enable its operation and then loaded back. Then, the wrongly unloaded container should be sent to the original place. The crane should also be driven to the place where the right container should be unloaded. Therefore, it is highly likely that the consignee of this container cannot receive the goods in time. In addition, a lot of human and time resources are consumed in the whole process, which might further cause delays in other port operations. Taking all of these issues into account, we give a large value to c_3 at 100 units.

Given the above basic parameter setting, the costs associated with methods 0 to 2 are shown in Table 10. It clearly shows that under the given parameter settings, more than 80% of the costs can be saved by the proposed crane operator alarm method 1 and method 2 compared to the benchmark method 0. To be more specific, the improvement of method 1 over method 0 is 81.59% from 60,354,000.0 to 11,109,978.5, and the improvement of method 2 over metho 0 is 84.97% from 60,354,000.0 to 9,071,394.1. Moreover, method 2 in which whether to alert the operator is solved by a decision problem is better than method 1 as the improvement of method 2 over method 0 is higher than that of method 1 over method 0.

5.2 Sensitivity analysis

Extensive sensitivity analysis is conducted in this subsection considering different scenarios of the ratios of containers in each color of concern (i.e., α_k) and the container wrongly unloading proportions for each color of concern (i.e., β_k) at a port, port size, and container color detection model accuracy rate.

5.2.1 SA1: different container ratios and wrongly unloading proportions

SA1 considers ports with similar size as the Hong Kong port while using the same container color detection model, i.e., we keep M, c_1, c_2, c_3, and $\hat{P}_{\bar{k}\bar{k}}$ (and $\hat{P}_{\tilde{k}\tilde{k}}$ and $\hat{P}_{\tilde{k}\hat{k}}$) unchanged and consider different cases for $\alpha_{\bar{k}}$ and $\beta_{\bar{k}}$, $\bar{k} \in K$. As the ratios of containers in different colors operated annually by a port are unknown, in

Section 5.1, we assume that the ratio is the same as the ratio of the collected images in each color as shown in Table 1, and that the wrongly unloading proportion is related to the three error levels related to color similarity. SA1 considers different ratios of container colors or wrongly unloading proportions under the given settings. To be more specific, for the ratios of container colors in SA1-1, we consider three cases: case 1. all colors have the same ratio; case 2. the more similar colors of a container color, the larger its ratio; case 3. the more similar colors of a container color, the smaller its ratio. In particular, in case 2, we assume that each color in level I/II/III weights one/two/three. In case 3, we assume that each color in level I/II/III weights three/two/one. Container ratios in the three cases are presented in Table 6. Regarding container wrongly unloading proportions in SA1-2, we consider three cases: case 1. all colors have the same mistaken ratio; case 2. the more similar colors of a container color, the slightly larger its wrongly unloading proportion; case 3. the more similar colors of a container color, the much larger its wrongly unloading proportion. Container wrongly unloading proportions in the three cases are presented in Table 7. To make readers better understand the change trend in parameters, we visually show the parameter values in Figure 2 where the colors are ranked by levels.

Insert Table 7 here

Insert Figure 2 here

Method performance in SA1-1 and SA1-2 is shown in Table 10. As shown by case 2 and case 3 of SA1-1 in Table 10, when containers of color with more similar color(s) have a smaller ratio among all containers operated annually by a port, the expected annual total cost decreases. Meanwhile, the cost saving of method 2 compared to the benchmark method 0 also decreases while that of method 1 compared to method 0 increases. This is because method 1 only alerts operator when the predicted and correct container colors are inconsistent. Therefore, alarm error increases as the ratios of container colors with more similar colors increase, and thus the cost saving of method 1 over method 0 decreases. In contrast, method 2 focuses on minimizing the total cost while considering more comprehensive cases regarding the predicted and correct container colors, and thus it is more sensitive to the changes in container color ratios than methods 0 and 1. Therefore, the cost saving of method 2 over methods 0 and 1 increases.

A similar pattern is shown in Table 10, indicating that method 2 is more sensitive to the changes in the prediction errors of container colors with more similar color(s). From case 1 to case 3 of SA1-2, container wrongly unloading proportions increase in container colors with more similar colors. The expected annual total cost increases as expected. There is only a minor change in the cost saving ratio of method 1 at no more than 0.4%, while this ratio increases from 81.66% to 89.10% (7.44%) of method 2. The cost saving of method 2 over method 1 also increases. The results of SA1 show that method 2 is the most suitable when there are larger ratios of container colors with more similar colors and when their wrongly unloading proportions increase.

5.2.2 SA2: different port sizes and cost

SA2 considers ports with different sizes and thus operational costs, i.e., different values for M, c_1, c_2, and c_3 while keeping other parameters unchanged. As Hong Kong port ranks at the back of the top 10 container ports over the world in recent three years (World Shipping Council, 2022), we deem it as a large container port, with $M = 9{,}000{,}000$, $c_1 = 1$, $c_2 = 5$, and $c_3 = 100$. In SA2, we consider container port sizes in four cases: case 1. small container port, case 2. medium container port, case 3. large container port, and case 4. very large container port, with M from small to large. We further assume that c_1, c_2, c_3 are positively correlated to M. The settings of these four parameters in the four cases are shown in Table 8. To make readers better understand the change trend in parameters, we visually show the parameter values in Figure 3 where the colors are ranked by levels.

Insert Table 8 here

Insert Figure 3 here

Method performance in SA2 is shown in Table 10. It can be seen that as port size increases, the expected annual total cost increases accordingly as higher cost of port operation is needed. Table 10 shows that in small and medium ports, the performance of method 1 and method 2 is quite similar. However, in large ports and very large ports, method 2 significantly overperforms method 1, and the cost saving ratios increase as port size increases. In particular, method 2 is more sensitive than method 1 with the increase in port size: when port size increases from small to medium, from medium to large, and from large to very large, 5.62%, 4.96%, and 3.50% more expected annual total cost can be saved by method 2 compared to method 0. In contrast, although 5.62% more expected annual total cost can be saved by method 1 over method 0 when port size increases from small to medium, the cost saving of method 1 is not sensitive when port size increases from large to very large and from medium to large. The results of SA2 show that both method 1 and method 2 are suitable to be applied in small and medium ports, and method 2 is the most suitable to be applied in large and very large ports.

5.2.3 SA3: different container color prediction accuracy rates

For the container color detection model proposed in this study, it might have different accuracies when applied to different ports due to the quantity and quality of the container figures collected for model construction. Its accuracy can also vary at the same port because of the influence of strong sunlight and heavy rains. SA3 takes these factors into account by setting different accuracy rates of $\hat{P}_{\bar{k}\tilde{k}}$, $\hat{P}_{\tilde{k}\tilde{k}}$, and $\hat{P}_{\tilde{k}\hat{k}}$. The following cases are considered. In case 1, a container color detection model with 100% accuracy is used. For other cases, for color green which has no similar color, we assume that its prediction is 100% accurate. For colors with similar color(s), we assume that the color detection model only mis-predicts the color to its similar color(s) with equal probability. In cases 2, 3, and 4, a container color detection model has 100% accuracy for color green of error level I and 90%, 80%, and 70% for $\hat{P}_{\bar{k}\bar{k}}$ if color $\bar{k}$ is in error levels II and III, and for $\hat{P}_{\tilde{k}\tilde{k}}$ and $\hat{P}_{\tilde{k}\hat{k}}$ if color $\tilde{k}$ is in error levels II and III. The details are presented in Table 9. Method performance in SA3 is shown in Table 10.

Insert Table 9 here

Insert Table 10 here

Table 10 shows that as the wrong prediction rates for container colors with more similar color(s) increase, the expected annual total cost of method 0 remains unchanged as it is nothing to do with the color prediction model, while that of methods 1 and 2 increases. Moreover, the cost savings of method 1 and method 2 compared to method 0 decrease, as their performance is adversely influenced by the increase in the inaccuracy of the color prediction model. Especially, such influence is more obvious in method 1, where the cost saving over method 0 decreases from 82.30% to 78.85% (-3.45%), compared to the influence on method 2, where the cost saving over method 0 decreases from 85.25% to 83.38% (-1.87%). Therefore, it can be seen that method 2 is the most robust against the increase in the inaccuracy of the container color detection model.

6. Conclusion

Multimodal transport plays a key role in global modern logistics, and it is facilitated by standard shipping containers which can be smoothly transferred among different transportation modes. When container ships arrive at the container terminal, containers are unloaded from the vessel one by one to trucks. This task is accomplished by crane operators, whose job is to load and unload containers to and from vessels by operating container cranes. The working environment of crane operators can be harsh due to the prolonged working period, repetitive working contents, and the restricted working area. Consequently, they are prone to fatigue and discomfort, and the probability of unloading a wrong container from a vessel is expected to increase with the progress of a work shift. To reduce the extra work and expected annual costs brought about by the issue, this study innovatively uses the color of shipping containers as an indicator of alerting crane operators for unloading a wrong container. We consider eight widely-used container colors, namely maroon, magenta, orange, light yellow, dark yellow, light blue, dark blue, and green, and the container color is predicted by a popular computer vision library called OpenCV. After obtaining the distribution of the prediction accuracy of the colors of concern, three methods are developed to address the container crane operator alarm problem. To be more specific, method 0 is a benchmark where no alarm is performed. Method 1 alerts the crane operator if the predicted container color is inconsistent with the color of the container that should be unloaded. Method 2 is based on a decision problem to decide whether to alert the crane operator with the aim to minimize the expected annual costs.

In numerical experiments, the case study of Hong Kong port is first conducted to verify the effectiveness of the proposed methods. The results show that method 1 can save the expected annual total cost by about 82% compared to method 0, while method 2 can save the expected annual total cost by about 85% compared to method 0. Then, extensive sensitivity analysis is conducted considering different scenarios of the ratios of containers in different colors and their wrongly unloading proportions, port sizes, and container color prediction accuracy rates. The results show that 1) method 2 is the most suitable when there are larger ratios of container colors with more similar colors and when their wrongly unloading proportions increase; 2) both methods 1 and 2 are suitable for small and medium ports, and method 2 is the most suitable for large and very large ports; 3) method 2 is the most robust against different accuracy rates of the container color detection model. Therefore, it can be concluded that overall, method 2 is the most superior as it is the most comprehensive and flexible one which considers factors such as container wrongly unloading proportions, container color prediction accuracy rates, and three operational costs occurring in different situations and is in the form of a decision problem. The proposed container color detection model and the following crane operator alarm methods are expected to improve port efficiency and save port operation costs.

There are several future research questions that can be further studied. First, the current container color detection model is relatively rough, as it directly detects the color of each pixel of a figure containing a single container without initial figure processing to increase the color detection efficiency. For example, the surface of a container is not flat, and this feature can magnify the influence of light and reflection and thus reduce the color detection accuracy. Therefore, in future research, such feature can be considered in the color detection model by developing proper figure processing methods or revising the color detection algorithms. In addition, figure denoising algorithms can also be applied to reduce the influence of strong sunlight, heavy rains, and frog. Second, the values of costs c_1, c_2, and c_3 are set based on assumption considering the actions associated with these costs. In order to obtain more precise values, they can be measured by practical operational costs at port in future research, such as by calculating the product of the time spend by the operators at the port to accomplish the related tasks and their wage. Alternatively, they can be measured by conducting surveys and interviews on operators at port to know more about how many efforts and how much time they need to apply to finish the corresponding tasks.

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