Checking the coupling between overhead crane hook and steel ladle trunnion in Steelmaking Plant using convolutional neural networks

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Abstract.
Overhead cranes are equipment designed for the efficient and safe movement of large loads and are widely used in the industry. They play a very important role in logistics and production by allowing the flow of materials, machinery, and products from one location to another, whether within a factory, warehouse, shipyard, or any other industrial environment. These equipment have a simple mechanical structure, consisting of a main beam equipped with wheels that allow movement along tracks. A hoist is suspended under the main beam, which can also move along it, and is used to lift and lower loads. The element that couples the load to the lifting system varies according to the type of load. In this article, we explore the coupling system commonly used in the steel industry for handling steel ladles through overhead cranes, called hooks and bails. This study proposes the use of artificial intelligence (AI) and machine learning techniques, through computer vision based on convolutional neural networks to detect the coupling, segmenting both the hook and the bail and thereby determining the precise alignment of the assembly before lifting. This contributes to validating the operator's visual information, reducing possible human errors, and promoting greater safety for both the process and the people involved.

Keywords: ladle hoisting, ladle fall, steelmaking plant, deep learning.

1 Introduction

Overhead cranes are widely used in the industry, and their purpose is to move large loads efficiently and safely. They play a crucial role in logistics and production, allowing the transfer of materials, machines, and products from one location to another, whether within a factory, warehouse, shipyard, or any other industrial environment.

These devices have a simple mechanical structure, consisting of a main beam equipped with wheels that allow movement along tracks. A hoist is suspended under the main beam, which can also move along it and is used to lift and lower loads The element that performs the coupling of the load with the lifting system varies according to the type of load.

The proposed study is based on the context of overhead cranes operating in the steel industry, specifically in steelmaking processes. The transported load is steel in its liquid state through pots called steel ladles. The coupling system between the crane and the ladle is done by hooks and trunnions.

Steel ladles have a metal structure lined with refractory material, weigh approximately 150 tons, and can be loaded with up to 300 tons of liquid steel, bringing the total combined load to be handled by the overhead crane to around 450 tons. The operations of lifting and lowering the ladle require checking the coupling position of the hooks with the ladle trunnions. Only after this verification and correct alignment can the lifting or lowering movements be performed. The cranes are equipped with strategically positioned monitoring cameras focusing on the hooks, and it is the operator's responsibility to verify the coupling through their visual field and the cameras.

Operational safety is a primary concern. Operators of these devices must be adequately trained and follow strict safety procedures. This includes regular inspections, preventive maintenance, and the implementation of safety devices such as load limiters, emergency systems, among others. The proposal of this study is to perform automatic coupling detection, contributing to the validation of the operator's visual information. This way, possible human errors can be mitigated, bringing more safety to the process and people.

According to [1], the scenario in which these devices operate constantly experiences variations such as backgrounds, lighting, angles, and scales. Therefore, it is important to use appropriate methods and techniques to detect the hook in the image. Much of their work has achieved good performance in the area of target detection, especially with deep learning-based approaches.

The work of [2] proposed a solution based on machine vision and deep learning to address safety issues when the hook does not properly engage with the ladle trunnion, which is one of the hidden dangers during the lifting of the ladle by the crane. Techniques such as Mask Region-Based Convolutional Neural Network (Mask-RCNN) were introduced to segment the crane hook and find the bottom point of the hook contour. For recognizing the trunnion center point, a special color was painted on it. Thus, the determination of the coupling can be verified by calculating the angle between the horizontal line and the line connecting the bottom point of the hook and the trunnion center point. According to the experimental results of 100 test images, the average precision (AP) achieved using the mentioned segmentation methods can reach 92%/, and the performance of the safety judgment algorithm reached 96%/.

The work of [3] proposed an approach using another technique to obtain reliable matching between the crane hook and the ladle ear, using surface acoustic wave radio frequency identification (SAW RFID) localization. The SAW RFID tags are attached to the surface of the handle and the hook. The position of the bead is estimated through a geometric mapping approach with a special tag and reader antenna position, and the position of the hook is estimated by synthetic aperture approximation with the hook's motion pattern. Coupling is determined based on the relative position between the hook and the trunnion. The proposed method employs only two SAW tags and two reader antennas, facilitating routine installation and maintenance. Numerical simulation and physical experiments demonstrate that the proposed method works effectively.

The cited methods, although effective in determining coupling, are not easy to apply given the harshness of the environment. Thus, the proposal of this study is to work with images and deep learning techniques.

The equipment used for the initial study will be an overhead crane in a steel mill that has a coupling system with the load as mentioned above. The coupling detection process will use an object detection technique with a machine learning algorithm model that will be YOLOV8 from Ultralitics [4]. The neural networks will be trained with a dataset of approximately 2000 images acquired through mobile devices. The target is to detect two objects, the hook and the trunnion of the ladle. This detection will be done on both sides of the ladle. For coupling detection, an algorithm will be developed to determine the correlation of the hook/trunnion position, a decision algorithm, using the region where the objects meet to calculate the distance and angle between them.

The contributions of this work are embedded in the context of process knowledge and increasing safety in handling liquid loads. Currently, this is a little-explored and underdeveloped topic but can bring immeasurable gains. The use of convolutional networks to perform coupling verification can prevent accidents and enable redundancy in coupling checks. Additionally, it can be part of a more complex system of autonomous cranes.

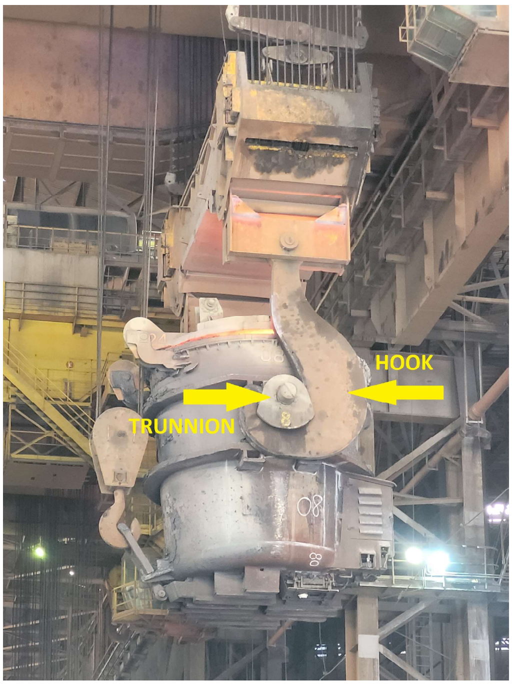

Figure 1. Steel ladle hoisting

2 Materials and Methods

This chapter will discuss the theoretical bases used in the development of the work. Such bases are necessary for the best use of the work and the understanding of the methods and steps described. Initially, the coupling process will be presented, followed by the coupling validation steps using the vision system.

2.1 Concepts

For ease of description, the coordinate system depicted in figure 2 has been established. The direction parallel to the ground and the surface of the lug is designated as X. The direction perpendicular to the ground and the surface of the lifting lug is designated as Y. Finally, the direction perpendicular to the surface of the lug is designated as Z. This coordinate system follows the right-hand rule.

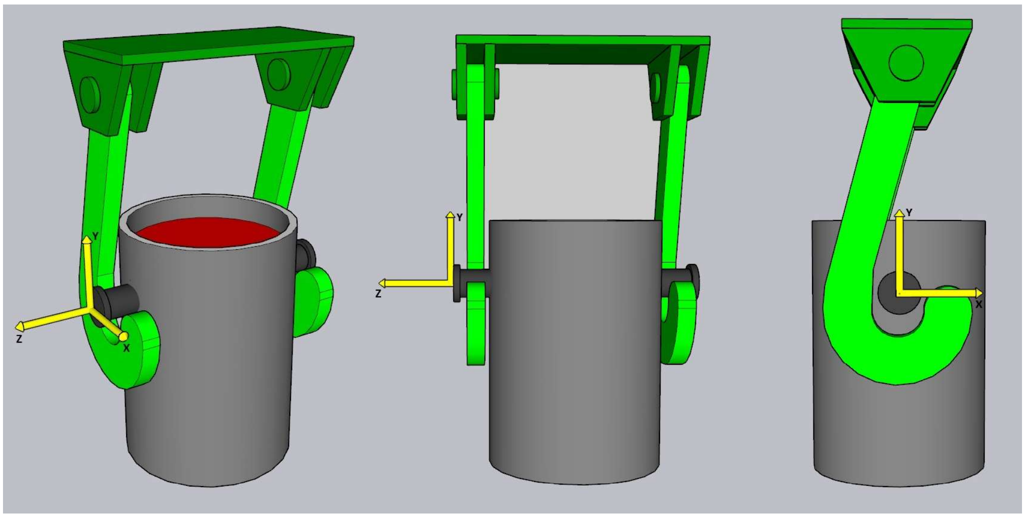

Figure 2. Coordinates definition and Images plans XOY / ZOY

After the trunnion and hook have been correctly coupled, a fixed point is defined as the origin of the system, the reference point R = (0,0,0). It is the difference in the distances between the center of the trunnion and the coupling cavity of the hook.

The cameras will be positioned only in the XY plane, since the trunnion has a mechanical system that serves as a guide for the hook, as can be seen in figure 3, dispensing with an alignment check in the YZ plane. It is very difficult to attach cameras to the overhead crane and have complete images of the hook and trunnion viewed in the XY plane. Therefore, the coordinates will be checked by means of 2 cameras, which will be positioned at strategic fixed points where the overhead crane lifts the pans.

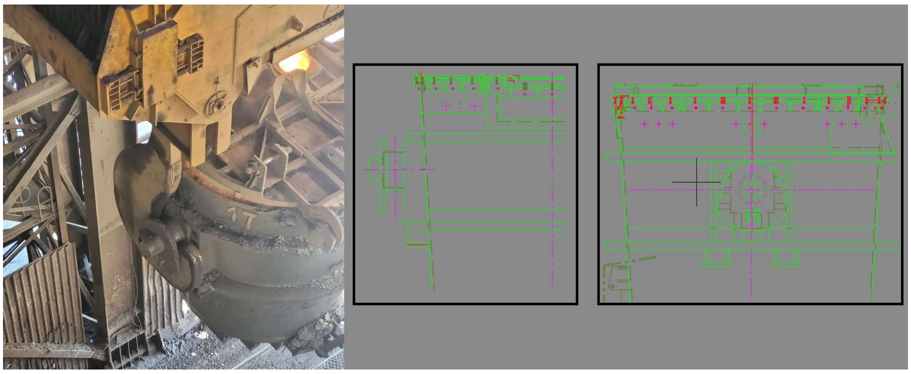

Figure 3. Trunnion guide for hook alignment

2.2 Analysis of the lifting procedure

Due to the numerous daily movements of the ladle and the overhead crane, they end up varying in three-dimensional space. These positional deviations make it difficult to align the trunnion with the hook. This section analyzes the lifting operating procedure and the conditions for reliable alignment of the hook handle within the spatial scope.

The procedure for approaching the hook with the pan until it is lifted can be seen in Figure 4. Initially, the operator of the rolling point lowers the hook and aligns its tip towards the center of the trunnion. Then, he approaches it until the tip of the hook touches and presses the trunnion into the mechanical alignment guide mentioned in chapter 2.1. At this stage, the alignment on the Z axis has been achieved; otherwise, the operator must repeat the steps mentioned. With the tip of the hook in contact with the trunnion, the operator makes an arc movement while maintaining contact with the trunnion, thus ensuring that the Z alignment is not lost.

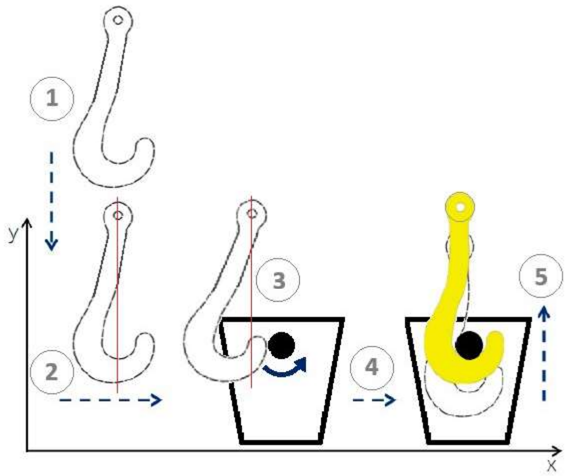

Figure 4. Trunnion guide for hook alignment

Due to the small contact pressure, from a certain angle the hook will tend to return to its original alignment in a pendulum movement and at this point it will be properly aligned with the trunnion. If this pendulum movement is not sufficient or there is some gripping at the hook joints, the tip of the hook may coincide with the center of the trunnion and thus unbalance the pan during the lifting movement and cause an accident. If the alignment is correct, the operator can begin lifting.

2.3 Hook and Trunnion Detection Method

Industries are often required to store data from their processes. This data is essential for system optimization and other data-related analyses. However, data collection in real industrial applications involves well-known challenges, such as sampling time issues, missing data, outliers, operating conditions, accuracy, and so on [5]. For this development, several steps will be required, such as data acquisition, input data selection, choosing the model to be applied, training, and validation of the chosen model.

Dataset

The dataset was produced using images obtained by mobile devices and fixed cameras from the warehouse monitoring system. This provides a reasonable variability in angles and lighting conditions. The extraction of frames from the videos was performed using an algorithm created in Python and using the image hash as a criterion for differentiating them, [6]. Image hashes tell whether two images look nearly identical. There are several hashing algorithms such as average, perceptual, difference, and wavelet. In this case, we used the average hash on the image. After applying some image separation criteria such as variability, lighting, images without information, among others, approximately 2,000 qualified frames were obtained.

Preprocessing

In the data preprocessing stage, the Roboflow tool [7] was used to mark two classes: hook and trunnion.

In addition to marking, this tool offers several features and filters such as: image auto-orientation, resizing, data augmentation, among others. However, they were not used because this processing can later be performed directly from YOLO. Data separation was used in 80% for training and 20% for validation. A dataset was not reserved for testing, as the images that will be used to evaluate the model will come directly from the cameras in real time.

Model

The object detection models used in this study were YOLOv8 or "You Only Look Once version 8". It is an evolution of the YOLO series, known for its efficiency and speed in real-time detection. This model uses a unique approach, dividing the image into grids and displaying the bounding boxes along with the class probabilities, allowing for faster and more accurate detection. This model is pre-trained with the COCO dataset [8], which contributes to its generalization ability and performance in various object detection tasks. According to [9], YOLOv8 stands out compared to Mask R-CNN and Faster R-CNN mainly due to its efficiency and speed, being a one-stage model that performs detection and classification in a single step, which significantly reduces inference time. In addition, it maintains high accuracy in complex environments when compared to Mask R-CNN. YOLOv8 is also more scalable and suitable for real-time applications and devices with limited resources, while Mask R-CNN and Faster R-CNN, being two-stage models, require more computational power [10].

Training and validation of the model

Training a neural network model requires a large number of images as input, since small amounts of data make it difficult to verify its generalization and robustness. The greater the number and types of images, the greater the robustness of the learning. However, since the crane hook and trunnion are industrial equipment that do not allow random operation and also simulations of pan tipping due to incorrect coupling, the images used were in normal operation of these equipments. The model used was YOLOv8n and the hyperparameters tested in combinations: Epochs 20 and 50; Batch 16 and 32; optimizers SGD , Adam and also by automatic determination.

2.4 Coupling Determination Algorithm

In addition to object detection, shown in the previous section, it is essential for this system to have a simple and robust algorithm to determine whether the ladle hook and trunnion are correctly coupled. For this purpose, a judgment algorithm based on angle and distance was designed, which can be easily calculated.

The algorithm that will determine the correct coupling needs to obtain the xyxy coordinates from the baudboxes generated by YOLOV8 object detection, figure 5. These coordinates will serve as a reference to determine the coupling position, which is the meeting of the central coordinate of the trunnion with the coordinate of the fitting position of the trunnion on the hook.

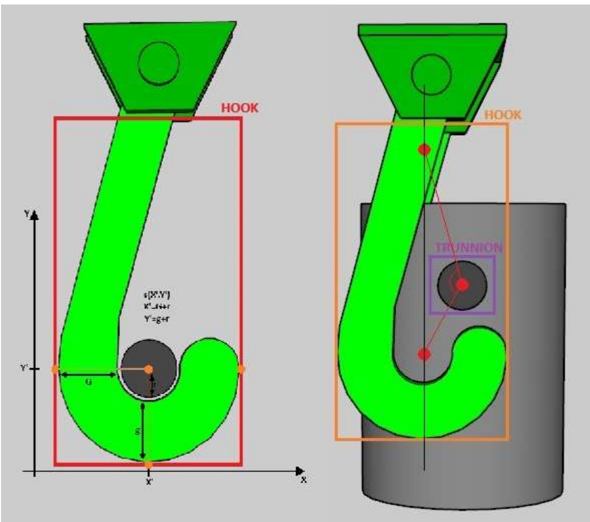

Figure 5. BaudBox coordinates

By determining the trunnion's fitting coordinate in the hook and also the central coordinate of the trunnion pin, it is possible to calculate the angle between the line connecting the two points. It can determine whether the hook and trunnion are correctly aligned and also measure the distance between the points using a pixel x millimeter calculation.

The flow of the judgment algorithm is as follows:

1) Determine the trunnion's fitting coordinate in the hook. To do this, it is necessary to know the hook's dimension and have the baudbox coordinates as a reference.

2) Determine the coordinate of the center of the trunnion pin.

3) Determine a third reference coordinate on the same axis as the hook's fitting coordinate.

5) With the three coordinates defined, it is possible to calculate the angle between the trunnion and hook, where 180° represents the alignment between them.

6) The distance calculation is done through the trunnion's fitting coordinate in the hook and the center of the trunnion pin.

In this experiment, the angle threshold is set to 180° based on the shape of the hook and the shell. When the angle calculated by the algorithm is less than 180°, we can check whether the hook and the shell journal are not correctly aligned, and when the angle is greater than 180°, it is found that there is alignment. After checking the angle, the algorithm also checks the distance between the points, where a distance of 0 mm indicates that the coupling is complete.

2.5 Results

The trained model that achieved the best performance was the combination of 20 epochs, Batch 16 and Adam optimizer. It is worth mentioning that in the automatic determination of the optimizer, performed by the YOLOv8 algorithm, in all combinations the one used was AdamW and it did not prove to be superior to Adam in this case. The results are shown in Figure 6.

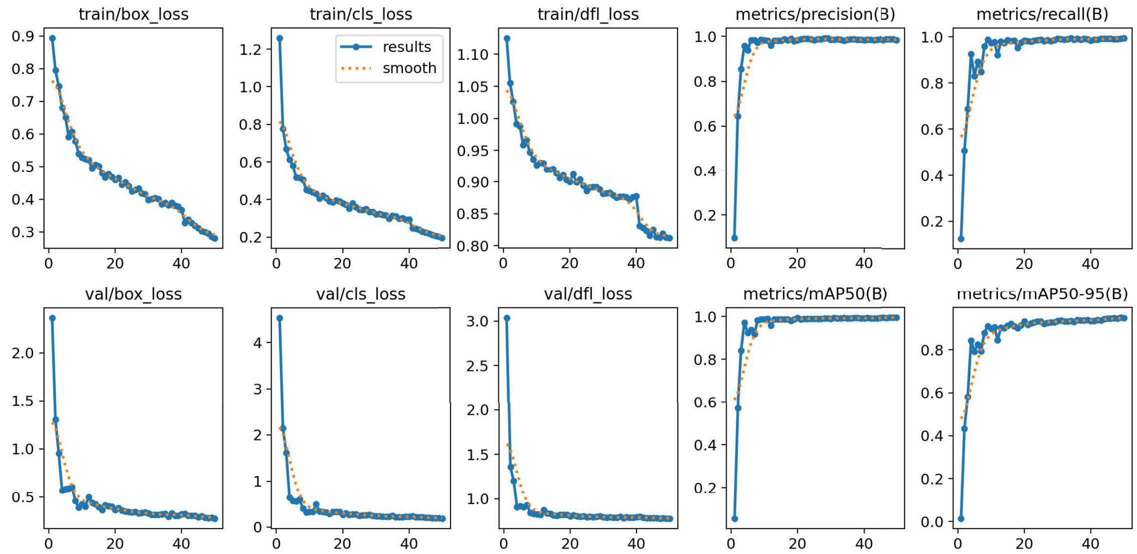

Figure 6. Training and validation results

After testing with real images of an overhead crane performing ladle freezing operation, the feasibility of the applied method was validated, as can be seen in Figure 7. These images were recorded from a steel plant in Brazil. It can be seen that the hook and trunnion can be completely identified, and the precise lowest point of the hook can be correctly found, thus the proposed method can be applied to real production sites.

3 Conclusions

This study demonstrated the feasibility and effectiveness of using convolutional neural networks for automatic detection of coupling between hooks and trunnions in overhead cranes within the steel industry. By implementing deep learning techniques, it was possible to develop a system capable of accurately segmenting and identifying the

Figure 7. Algorithm results

components involved in the lifting process of steel ladles. The results obtained with the YOLOv8 model, trained with a varied and robust dataset, showed high precision in detecting and validating the coupling, significantly contributing to operational safety and reducing human errors.

Moreover, the use of convolutional neural networks in the industrial environment opens up new possibilities for applying artificial intelligence in critical processes where safety and accuracy are paramount. The developed system not only validates the operator's visual information but also provides an additional layer of safety that can prevent accidents and optimize workflow.

Future research can focus on integrating this system with automated crane controls, further enhancing efficiency and safety in industrial processes. The implementation of more advanced machine learning algorithms, such as recurrent neural networks or hybrid models, can improve the predictive and adaptive capacity of the system, making it more robust to environmental and operational variations. Expanding the dataset with images under different lighting conditions and angles can also contribute to the model's generalization and robustness.

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