Monitoring of the oxygen lance, in the steel fabrication process by LD conveter, using a Mask R-CNN deep learning network

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Abstract. A critical problem in the manufacture of steel by converting pig iron into a Linz-Donawitz (LD) converter is the accumulation of skull, a mixture of slag and steel, in the body of the lance used for oxygen injection. This accumulation of skull can cause serious problems, among them prevent the movement of the lance through the flanges located in the converters. Currently, in the steel industry, monitoring is done manually, based on an operator's experience. Traditional computer vision methods are not effective due to the hostile environment of the steelmaking process, due to its object detection algorithm. Problems such as light, smoke, and others, hamper the task of image recognition. To overcome these deficiencies, this article proposes a method to monitor and measure, in real time, the thickness of the skull on the lance using deep learning, more specifically a Mask R-CNN framework. Our method consists of installing a high resolution camera to monitor the lance in real time, sending images to a computer, equipped with a Mask R-CNN framework already trained to identify and measure the skull deposited on the lance. The results of the experiments performed show the feasibility of using the system to assist the operator in monitoring of lance skull.

Keywords: Linz-Donawitz converter, computer vision, convolutional neural networks, deep learning, Segmentation, Mask R-CNN.

1 Introduction

1.1 Steelmaking process in a Linz-Donawitz (LD) converter

Considered the fastest process in steelmaking, the LD process is the first part of the steelmaking process with oxygen. The process was first patented at "Linz" and "Donawitzed" in Austria.

In the manufacture of steel by converting pig iron into an LD Converter, the upper blowing basic oxygen oven (BOF) is equipped with a lance at the top of the converter. The lance injects oxygen into a surface of the liquid metal charge, a contact region called the impact zone. According to Shi [1], the function of oxygen is to oxidize elements such as carbon, manganese, silicon and phosphorus to refine the metallic charge and make the chemical composition, weight and temperature of the steel adherents to previously defined bands. With the oxidation reactions, which remove impuities, and the agitation of the converter's load due to blowing, an emulsion formed of CO and CO_2, metal droplets and slag (mixture of oxides constituted by the removal of impurities) is formed. This emulsion can cover the oxygen injection lance with the formation of a skull. The figure 1 shows the components of a steelmaking process in an LD converter.

1.2 Problems in the steelmaking process in an LD Converter

As reported by Filho and Barbosa [3], the slag oxidation product combines with the addition of CaO (calcium oxide) in the bath and flows over the metal oxide, part of this slag adheres to the spear forming a smudge. The formation of the smudge and its adhesion on the spear surface is inherent to the conditions of the process. The accumulation of shell on the surface of the boom increases its diameter and weight. We can see in figure 2 the

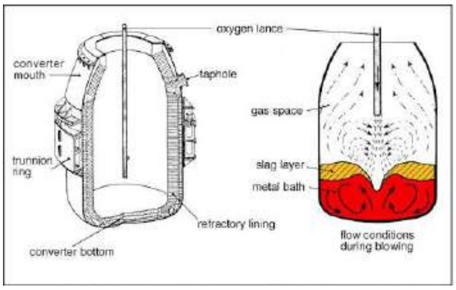

Figure 1. LD process components. (Adapted from [Sahu])

increase in the diameter of the lance with the grip of the skull.

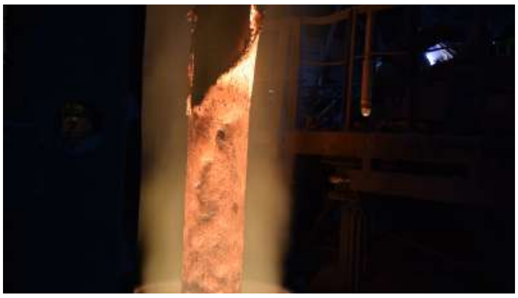

Figure 2. Night image of a lance covered with skull.

It is important to highlight that the flat boom measures 40 cm and the duct through which the boom passes 80 cm. For this reason, the increase in the casing on the lance becomes a critical problem, as it makes it difficult to move the lance in the operations of introducing and removing the interior of the converters as they pass through the duct, known as the "lance shirt", depending on the amount of skull deposited on the lance, it can stick to the passage duct causing serious problems. The figure 3 shows the moment when the lance grasps the passage duct due to the skull deposited on its surface.

Figure 3. Image of a lance covered with skull clinging to the passage duct.

According to Filho and Barbosa [3], currently, in the steel industry, the monitoring of excess skull deposited on the lance is done by an operator who analyzes the images on a monitor. This operator is given an enormous responsibility to decide the right moment to stop the process for removal of the lance skull. A wrong decision can lead to serious problems such as loss of productivity, increased costs and operational insecurity. It can even damage the lance structure if the operator does not make the decision at the right time.

2 Related works

To improve the efficiency of measurement Ayres et al. [4] proposed a method to measure of the skulll deposited on the lance using traditional computer vision. Your article cites three events inherent to the rustic environment of the process that made measurement difficult. Sparks of light falling near the lance are momentarily detected as edges, which generally results in measurements of thickness greater than the actual one. Another complicating factor is the low luminosity of the measurement region that induces the system to measure more or less than the actual measurements. Finally, the smoke that crosses the region where the measurement is made, obfuscating the edges of the lance, generating noisy attenuations for larger and smaller diameters of the real.

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Wu et al. [5] proposed a new image segmentation algorithm, with which the iron pellets superimposed on the image can be well separated and thus the size distribution of green iron pellets (PSD) can be measured online with good accuracy. The proposed algorithm first identifies the markers of each pellet directly from the gray scale image by a method of double morphological reconstruction; then, a circle scanning method is proposed to divide the overlapping pellets and measure the diameter of each segmented pellet. His method obtained an accuracy of 94.3, compared to the results of manual sieving.

This article proposes a method to monitor and measure, in real time, the thickness of the shell on the lance using deep learning, more specifically convolutional neural networks (CNN). This is divided as follows: in section 3 the theoretical foundation is presented where the major pillars of knowledge were addressed and defined. In section 4 the developed system is presented. Section 5 presents the analysis of the data and results of the project's implementation.

3 Theoretical foundation

This section briefly describes the Mask R-CNN presented by He et al. [6], framework used in the implementation of the system proposed in this article.

3.1 Mask R-CNN

Before describing the Mask R-CNN it is important to mention some frameworks that boosted advances in object detection and semantic segmentation as Fast R-CNN presented by Girshick [7], Faster R-CNN presented by Ren et al. [8] and Fully Convolutional Network presented by Long et al. [9]. They are intuitive, flexible and robust frameworks, in addition to fast training and inference time.

One of the main stages of Mask R-CNN is semantic segmentation, which combines classic computer vision tasks in object detection. Its objective is to classify individual objects and locate each one using a bounding box and semantic segmentation, where the objective is to classify each pixel in a fixed set of categories without differentiating object instances. This challenging task requires a complex method to obtain good results.

Mask R-CNN extends Fast R-CNN by adding a branch to predict segmentation masks in each region of interest (RoI), parallel to the existing branch for classification and boundary box regression (figure 4). The mask branch is a small FCN - Full Conection Network applied to each RoI, providing a segmentation mask pixel by pixel. Mask R-CNN is simple to implement and train, given the structure of the Faster CNN framework, which facilitates a wide variety of flexible architecture projects. In addition, the mask branch adds only a small computational overhead, allowing for a quick system and quick experimentation.

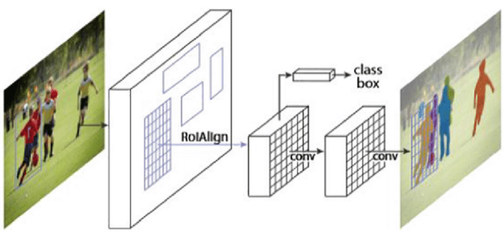


Figure 4. The MASK R-CNN structure for instance segmentation.

As shown in table 1, the Mask R-CNN surpasses all previous results of a unique model of the art in the task of instance segmentation in the competition using the COCO dataset, data set with the objective of advancing the state of the art in object recognition, presented by Lin et al. [10], including the highly designed entries from the 2016 competition winner. As a by-product, our method also excels in the COCO object detection task. In ablation experiments, we evaluate several basic instantiations, which allows us to demonstrate their robustness and analyze the effects of the main factors.

Table 1. Comparison of Mask R-CNN with the state of the art in instance segmentation.

	backbone	AP	AP50	AP75	APs	APm	APl
MNC Dai et al. [11]	ResNet-101-C4	24.6	44.3	24.8	4.7	25.9	43.6
FCIS Li et al. [12] + OHEM	ResNet-101-C5-dilated	29.2	49.5	-	7.1	31.3	50.0
FCIS+++ Li et al. [12] + OHEM	ResNet-101-C5-dilated	33.6	54.5	-	-	-	-
Mask R-CNN	ResNet-101-C4	33.1	54.9	34.8	12.1	35.6	51.1
Mask R-CNN	ResNet-101-FPN	35.7	58.0	37.8	15.5	38.1	52.4
Mask R-CNN	ResNeXt-101-FPN	37.1	60.0	39.4	16.9	39.9	53.5

Mask R-CNN models can run on a GPU for about 200ms per quador, and training using the COCO dataset takes one to two days on a machine with 8 GPUs. The fast training and testing speeds, together with the flexibility and precision of the structure, will benefit and facilitate future research on instance segmentation.

The system proposed in this article, its application and the results obtained are described below.

4 System design and proposed algorithm

To capture the images, a camera was placed in a location at the same height as the upper section of the lance passage duct, in order to collect images of the boom at the entrance and exit of the duct, as can be seen in figure 5 . For further analysis, videos were captured at a rate of 23 frames per second, with a resolution of (1920x1080) pixels. After the images were collected, an algorithm was developed using Mask R-CNN, to segment and obtain the measure of the spear thickness in centimeter.

Figure 5. Hardware components of the proposed system

To compose the training, validation and test bases, images of the captured videos were generated at a rate of 23 frames per second. Each image, from the training and validation base, was demarcated in the region of the spear determined for monitoring, for this purpose the VGG Image Annotator (VIA) was used, an image annotation tool that can be used to define regions in an image and create textual descriptions of these regions.

In the formation of our system, we used as a base the Mask R-CNN network already trained with the Coco dataset, combining the backbone Resnet-101, responsible for the most generic characteristics, training only the head of the network, a Full Network Connection, part responsible for the most specific characteristics, method known as transfer of learning.

CNN have some parameters whose values are defined before the learning process starts, they are called hyperparameters. There are several hyperparameters in a CNN, table 2 show some hyperparameters and their values that have been used.

Table 2. Parameters used for network training

Parameters	Valor	Description
Number of epoch	10	Number of training epoch
Steps for epoch	100	Number of samples per epoch
Images of GPU	2	Number of images processed by GPU
Learning rate	0.001	Network learning rate
Minimum confidence	0.9	Ignore trust detection less than 0.9

The graph in figure 6 shows the loss curves (training and validation) by number of seasons during the training stage. As detailed in the table above, 10 times were used for training.

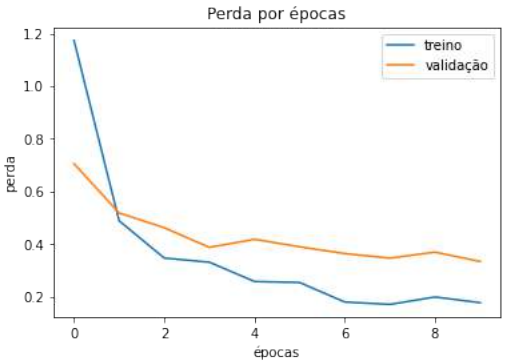


Figure 6. Smoothed curves for training and validation

In the next section we will analyze the performance of the system in monitoring the lance through images taken from the test base. In addition to generating a video with the performance of the system and publish in youtube (Sahu [13]).

5 Results

The main objective of the system is not to allow the lance, which cleans to measure 40 cm, to be taken by the casing to the point of grasping the boom passage duct, whose diameter measures 80 cm. To measure the diameter of the lance in the images, the system uses the pixel x cm ratio. The system create of 3 strips according to the criticality of the lance diameter measurement: green for diameter up to 50 cm, yellow with diameter between 51 and 60 cm and red above 60 cm. To analyze the results, some images and their respective measurements made by the system are presented. The figure 7 shows a clean lance, measuring 40 cm, low criticality attributed by the system.

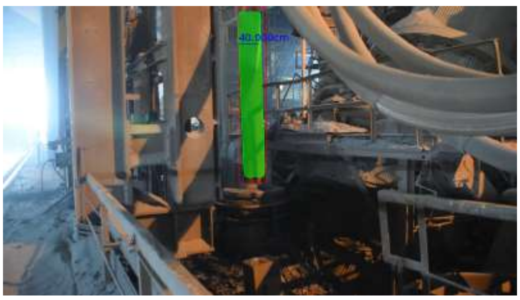


Figure 7. Clean lance, without deposited shell, measured by the system

A complicating agent of image measurement reported by Ayres et al. [4] is low luminosity. This can induce the system to measure diameters smaller or larger than the real ones. However, the Figure 8(a) shows the original image and the Figure 8(b) show the segmentation and correct measurement of the system in a night scene with low luminosity, measuring 50.189 cm and assigning the average criticality, yellow color. Another complicating agent for measurement mentioned is smoke, which, due to noisy attenuations, induces the system to measure larger and smaller diameters of the real. The figure 9(a) shows the spear taken by smoking with difficult visibility. However, the Figure 9(b) shows that neither smoke nor low visibility influenced the segmentation and measurement of the system, attributing 42,532 cm, yellow, medium critically.

Finally, the figure 10(a) shows the lance taken by the incandescent shell, while the figure 10(b) shows the segmentation of red color, as the diameter measurement reached 74,146, maximum criticality, reaching almost 80 cm, the passage duct measurement. In addition, in this situation the system emits an audible alert.

(a) Lance image in a low light setting. (b) Lance image in a low light setting measured by the system.

Figure 8. Lance image in a low light setting.

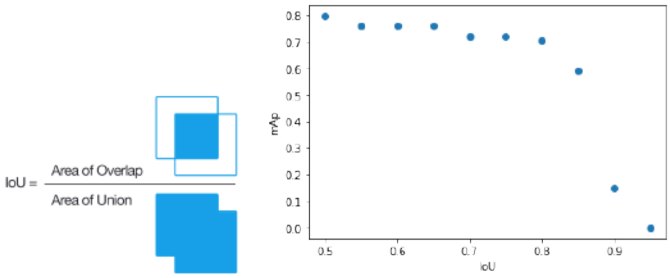
(a) Smoke-covered lance image. (b) Smoke-covered lance image measured by the system.

Figure 9. Smoke-covered lance image.

(a) Image of the lance covered by the smudge. (b) Image of the lance covered by the shell measured by the system.

Figure 10. Image of the lance covered by the smudge.

To do the calculation of AP for object detection, we would first need to understand IoU - Intersection over union. The IoU is given by the ratio of the area of intersection and area of union of the predicted bounding box and ground truth bounding box, as shown 11(a) . To compute mAP (mean Average Precision), of the proposed method, a set of tests with 27 images was used. The mAp for the IoU was computed in a range of 0.5 to 0.95, with steps of 0.05. The figure 11(b) shows the graph showing the mAPs for each IoU. The average mAp, presented below, can be calculated by adding the mAp of each IoU. mAP: IoU=0.50:0.95 = 0.5962962962962963



(a) Intersection over Union. (b) Graph showing the mAPs for each IoU.

Figure 11. IoU (Intersection over union) and Average Precision and mAP for Object Detection.

6 Conclusion

In this article a method is presented to monitor and measure, in real time, the thickness of the skull on the lance using deep learning, more specifically Mask R-CNN framework. This method consists of building a system that monitors the lance in real time through images, assisting the operator in deciding when to stop the lance for maintenance. Another possibility is the integration of this system with another system to carry out automatic lance maintenance. Unlike tools that use traditional visual computing, which has difficulties with external agents such as low light and smoke, the tool presented showed quite satisfactory results in the measurement of the lance skull even in scenarios with these external agents. The results of the experiments performed show the feasibility of using the system to assist the operator in monitoring the skull on the lance. As future work from this, we can use YOLOv3, presented by Redmon and Farhadi [14], a very promising framework for object detection.

References

[1] Shi, C., 2004. Steel slag—its production, processing, characteristics, and cementitious properties. *Journal of Materials in Civil Engineering*, vol. 16, n. 3, pp. 230–236.

[Sahu] Sahu, K. LD STEEL MAKING PROCESS, year = 2018, url = https://www.ferrophysical.com/2018/07/ld-steel-making.html, urldate = 2020-03-10.

[3] Filho, E. A. & Barbosa, A. A., 2015. Dispositivos automatizados de remoção de cascaão nas lanças dos convertedores ld.

[4] Ayres, L. M., Salarolli, P. F., Batista, L. G., Salcides, I. R., Bernades, N. D., Contarato, R. B., Furtado, H. S., Cuadros, A. M., & Almeida, G. M., 2018. Measurement of thickness of oxygen lance skull in ld converters using artificial vision. In *2018 13th IEEE International Conference on Industry Applications (INDUSCON)*, pp. 1123–1127. IEEE.

[5] Wu, X., Liu, X.-Y., Sun, W., Mao, C.-G., & Yu, C., 2019. An image-based method for online measurement of the size distribution of iron green pellets using dual morphological reconstruction and circle-scan. *Powder Technology*, vol. 347, pp. 186–198.

[6] He, K., Gkioxari, G., Dollár, P., & Girshick, R., 2017. Mask r-cnn. In *Proceedings of the IEEE international conference on computer vision*, pp. 2961–2969.

[7] Girshick, R., 2015. Fast r-cnn. In *Proceedings of the IEEE international conference on computer vision*, pp. 1440–1448.

[8] Ren, S., He, K., Girshick, R., & Sun, J., 2015. Faster r-cnn: Towards real-time object detection with region proposal networks. In *Advances in neural information processing systems*, pp. 91–99.

[9] Long, J., Shelhamer, E., & Darrell, T., 2015. Fully convolutional networks for semantic segmentation. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 3431–3440.

[10] Lin, T.-Y., Maire, M., Belongie, S., Hays, J., Perona, P., Ramanan, D., Dollár, P., & Zitnick, C. L., 2014. Microsoft coco: Common objects in context. In *European conference on computer vision*, pp. 740–755. Springer.

[11] Dai, J., He, K., & Sun, J., 2016. Instance-aware semantic segmentation via multi-task network cascades. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 3150–3158.

[12] Li, Y., Qi, H., Dai, J., Ji, X., & Wei, Y., 2017. Fully convolutional instance-aware semantic segmentation. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 2359–2367.

[13] Sahu, K., 2020. Monitoramento do cascão da lança.

[14] Redmon, J. & Farhadi, A., 2018. Yolov3: An incremental improvement. *arXiv preprint arXiv:1804.02767*.