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Detection and segmentation of pig iron slag scrapers using Mask R-CNN for wear control

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Abstract. The steel industry presents a vast list of problems and opportunities for improvement, ranging from the factory floor to levels of business management. Operating procedures are revolutionized every day to decrease failures, create reliable parameters and increase equipment reliability, and with the continuous and accelerated advance of innovations in industrial processes, computer vision is increasingly present and is necessary for the automation of new systems or of systems that need an update in their way of operating. This project aims to segment and detect, through convolutive neural networks, the shovels of the slag scrapers in pig iron pans in a Kambara Reactor of a steel plant. Aiming at detecting the wear of the shovels to control their use and replacement using Mask R-CNN for instance segmentation and pixel count for wear control.

Keywords: Computer vision, shovel, steel, wear control.

1 Introduction

Today, steel is the essential raw material for most sectors, being used from large industrial equipment to appliances, civil construction and vehicles. And, according to the Statistical Yearbook 2019 of the Instituto Aço Brasil [1], the world production of crude steel was 1.8 billion tons, with Brazil contributing 35.4 million tons, equivalent to 2% of the world's total production. According to the same report, Espirito Santo was in 3rd place in the regional distribution of crude steel production, contributing with 20.6% of the total national production.

The production flow of a steel mill includes:
- Receipt, preparation and storage of raw materials;
- Manufacture of sinter, coke and pig iron;
- Production of liquid steel;
- Transformation of liquid steel into slabs and hot rolled coils;
- Shipment of finished products in a multimodal system.

In the production of liquid steel, it is necessary to remove sulfur from pig iron from blast furnaces, this process is called desulfurization, and according to Kirmse [2]: “The presence of sulfur in steel alloys is a constant, this is undesirable in virtually all cases. In rare exceptions your presence is required. The quality requirements for several steel applications have resulted in sulfur levels below 50 ppm (parts per million) and due to market issues, practically all companies have been striving to meet this demand. Steel products with low sulfur levels have been reflected in better market values due to the quality gains in the mechanical strength requirements in the application”.

One of the ways to perform desulfurization is using the KR station (Kambara Reactor), and one of the steps in that station is the scraping of the slag. The slag is a mass of impurities that is suspended over the pig iron, due to its lower density. Removing the slag is the same as removing these impurities.

In the KR of a steel mill, the slag is removed by scrapers (Skimmers) operated by two control switches, via the operating room through cameras (Figure 1).

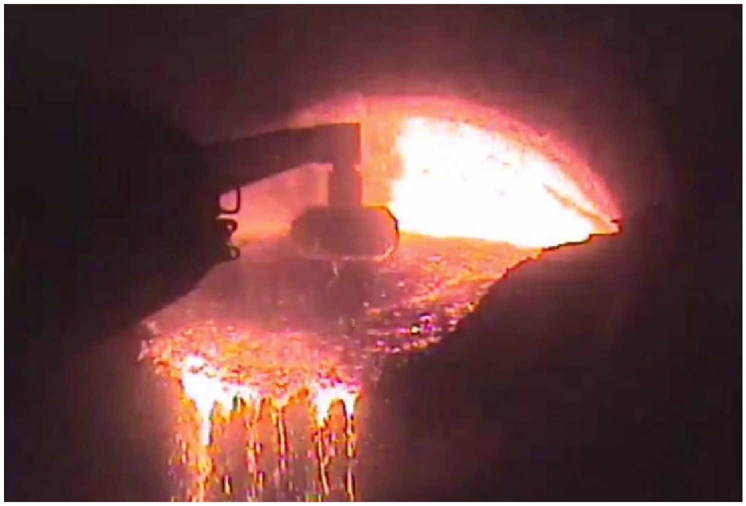

Figure 1. View of the operator during scraping

The Skimmer is controlled by an operator to perform the following movements:

- Advance;
- Retreat;
- Spin;
- Immersion;
- Submersion.

At the end of the Skimmer we have a shovel, made of refractory material, which comes in direct contact with the slag, and consequently with the liquid pig iron, to drag it towards the edge of the pan, removing the impurities from the pig iron.

With the constant use of the scraper, the refractory material of the shovel suffers natural wear due to friction with the slag and pig iron that are at high temperatures. Thus, after a few days of operation, the shovel needs to be replaced due to wear.

The highlight of this operation is due to the fact that it is the operator who decides when to change the shovel based on his experience, having no standardization or measurable method of measuring the shovel. It can lead to an unnecessary exchange, which increases the total cost of the operation, or the use of the shovel with very high wear, generating a risk of damage to the Skimmer.

Using a very worn shovel, it is necessary to submerge the Skimmer further towards the pig iron, which may damage other components that cannot come into direct contact with the material at high temperature (such as the body of the spear or the head of the shovel). The time in the scraping process also increases, since the operator must operate with more caution and the material dragged is less due to the reduced area of the shovel.

By making the exchange before necessary, the cost of the scraping operation increases, since it is necessary to purchase more shovels to replace the stock for continuous use.

Due to these factors, and considering that image processing is increasingly present in industries, it has a large number of possible applications for several problems, as in Spong et al. [3] who present several basic digital image processing techniques, and according to Bourchardt and Pezzin [4] commenting on the computational interpretation in image processing and also according to Pérez and Bueno [5], exposing the feedback from control systems by image, a solution that aims to inform the operator of the actual shovel wear for the correct replacement moment, removes human flaws, extends the life of the Skimmer components and reduces the cost of unnecessary shovel changes.

This project aims to present a method for segmenting and detecting the shovels of the slag scrapers via image processing using a convolutive neural network in order to inform the operator of the correct time for changing the shovels.

2 Related works

The R-CNN Method (Regions with CNN features) proposed by Girshick et al. [6] for object identification, has the architecture shown in figure x1, in which: (A) uploads an image, (B) extracts the proposals from regions, (C) calculates the resources of each proposal a convolutional neural network and by last (D) classifies each region in a specific class.

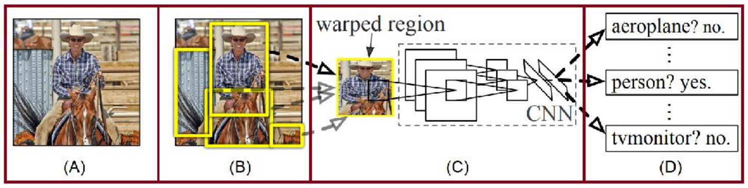

Figure 2. The R-CNN Structure [6]

The architecture of Faster R-CNN by S. Ren et al. [7] introduces the Region Proposal Network (RPN) technique on R-CNN, which increases the speed and execution of the detection algorithm with several applications, some of which are seen in D. Wang et al. [8] which presents the use of the technique for detecting dairy goats in surveillance video, in Q. Yang et al. [9] for recognition of feeding behavior for pigs housed in groups and in C. Cao et al. [10] for detecting small objects.

The FCN (Fully Convolutional Network) by J. Long et al. [11], unlike convolutional neural networks, uses pixel by pixel operation and simultaneously simplifies and accelerates learning and inference, improving accuracy when transferring pre-trained classifier weights.

Developed by Facebook AI Research [12] and published in 2017, the Masked Region based Convolution Neural Networks, or Mask R-CNN is a neural network for Instance Segmentation.

It uses the Faster R-CNN architectures and Fully Convolutional Network (FCN), for object detection (figure 3) and semantic segmentation (figure 4) respectively, joining the two techniques to perform Instance Segmentation (figure 5).

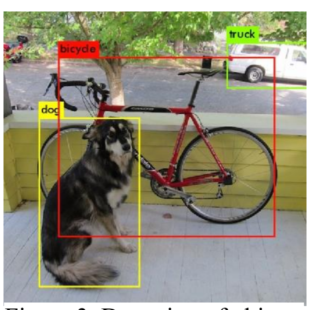

Figure 3. Detection of objects in the image [7]

Figure 4. Semantic segmentation [11]

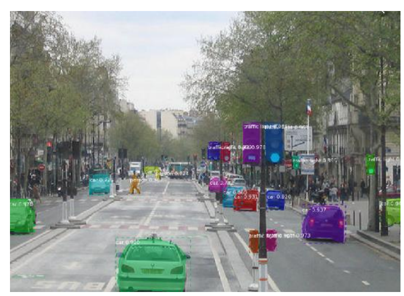

Figure 5. Instance segmentation [12]

According to Abdulla [13], the steps of the semantic segmentation of the Mask R-CNN can be better visualized through figure 6, where:

- Classification: There is a balloon in this image;
- Semantic Segmentation: These are all the pixels of the balloons;
- Object detection: There are 7 balloons in this image;
- Instance segmentation: There are 7 balloons in this image and these are the pixels belonging to each one.

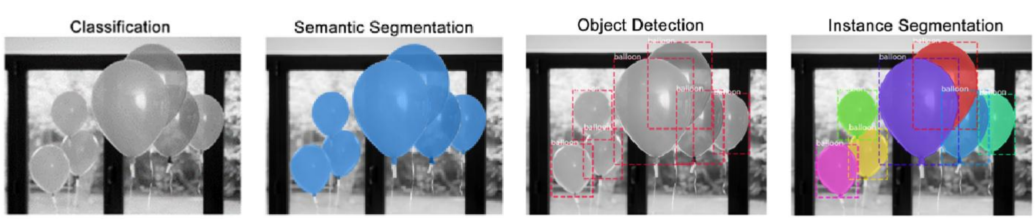

Figure 6. Segmentation process steps [13]

3 Methodology

In this project, Mask R-CNN was used in the images provided to the Skimmer operator to detect the Skimmer's shovels.

3.1 Google Colaboratory (Colab)

For the development of the algorithm, the platform used was Google Collaboratory (Colab), which according to Google itself, is a product that allows the user to write and execute python code through the browser and is especially suitable for machine learning, analysis of data and education.

Also according to the company, Colab is a service hosted on Jupyter Notebook that does not require configuration to be used, in addition to providing free access to computing resources, including GPUs (Graphics Processing Unit).

Using the free access of the platform the types of GPUs vary, and there is no way to choose which type of GPU the user will be able to connect to, however the available GPUs generally include the following models:

• Nvidia K80s;
• Nvidia T4s;
• Nvidia P4s;
• Nvidia P100s.

3.2 Microsoft COCO: Common objects in context

The initial training of our neural network used the weights already trained with the Microsoft COCO dataset, developed by T.-Y. Lin et. al [14] in the basic network of Mask R-CNN. Tests were carried out with random initial weights to detect the shovels, but there were no results.

Therefore, when using the transfer of learning from the COCO dataset, we obtain the initial weight that already segments several usual objects, being necessary only to inform one more class for detection and segmentation of the Shovels before training the new neural network.

3.3 VIA (VGG Image Annotator)

To include yet another object class, it is necessary to manually segment some reference images to obtain sufficient data in order to train the network.

This segmentation was performed manually with the images of the scraping process, using the VIA program (figure 7). In this program, the user manually selects the area of the object he wants to segment and provides a JSON file at the end with the anchors of the images indicating the location of the marked objects.

Figure 7. VIA (VGG Image Annotator)

3.4 Training and inference

Following the guidelines of Mask R-CNN, training was performed with the scraper images. 80 images were used, 60 images for training and 20 for validation.

Using the Region Proposal Network (RPN), from the Faster R-CNN architecture, the image is analyzed to find areas that contain objects. The regions that the RPN scans are called anchors, and distributed in boxes across the image area. After training, the object is detected in the image (Figure 8), represented with the name *"raspador"* during the tests. In the next step, a mask is generated to segment the region and in the final step we get to the Instance Segmentation (Figure 9).

Figure 8. Shovel detection

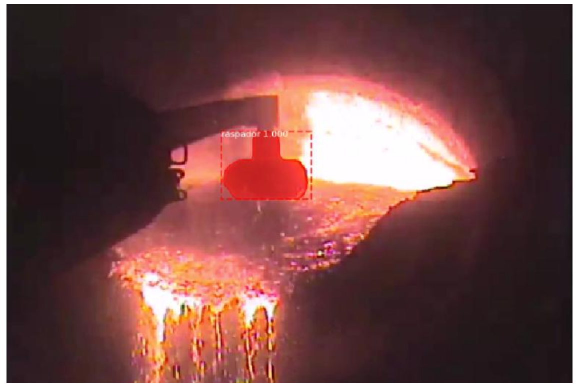

Figure 9. Shovel segmentation

With the use of the COCO dataset for learning transfer, it was possible to obtain satisfactory results, accurately segmenting all the scrapers tested after training the neural network, below is the figure 10 with the values of loss and validation in each period in which the network was trained.

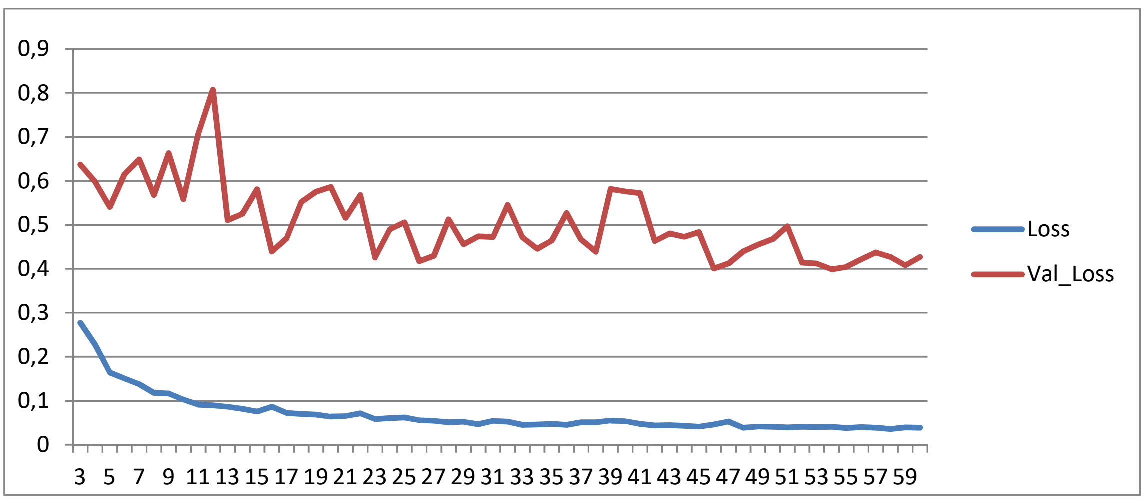

Figure 10. Network training

3.5 Measurement and comparison

After identification and segmentation, each pixel is counted, so we can compare the number of pixels that each shovel had before being replaced by wear, creating a parameter between the average pixel of the last exchanges, as shown in figure 11. And, with this value obtained, we can compare it with the pixels of a new shovel to obtain a standardization when changing the shovel (Figure 12).

Figure 11. Shovel before replacement

Figure 12. Shovel after replacement

4 Conclusions

Analyzing the results obtained by counting the pixels of the Skimmer shovel, we can create a maximum wear pattern allowed for its use.

The next steps of the project will be to collect data from the shovels that will be exchanged in the future to verify their actual measurements and the number of pixels of them before exchanging, creating a parameter between the average pixel of all shovel s in their last scraping and accompanied gradual wear.

With this we can define the exact moment of the exchange, not losing in quality and speed in the scraping of the slag nor increasing the expense with the early exchange without the real need.

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References

[1] Instituto Aço Brasil. *Anuário Estatístico 2019*. Rio de Janeiro, 2019.

[2] O. J. Kirmse. "Estudo do comportamento metalúrgico do reator kambara através de modelagem física". Universidade Federal de Ouro Preto, 2006.

[3] M. W. Spong, S. Hutchinson and M. Vidyasagar. *Robot Modeling And Control Image Processing*. 1. Edition. New York: JOHN WILEY & SONS, INC, 2006.

[4] E. F. Bourchardt and M. Z. Pezzin. "Identificação de veículos utilizando técnicas de visão computacional". UNESC, 2012.

[5] M. A. Peréz and M. Bueno. "3D Visual Servoing Control for Robot Manipulators Without Parametric Identification". *IEEE Latin America Transactions*, 2015.

[6] R. Girshick, J. Donahue, T. Darrell, and J. Malik. "Rich feature hierarchies for accurate object detection and semantic Segmentation". *Conference on Computer Vision and Pattern Recognition (CVPR)*, 2014

[7] S. Ren, K. He, R. Girshick, and J. Sun. "Faster R-CNN: Towards realtime object detection with region proposal networks". *Neural Information Processing Systems (NIPS) Conference*, 2015.

[8] D.Wang, J. Tang, W. Zhu, H. Li, J. Xin and D. He. "Dairy goat detection based on Faster R-CNN from surveillance video". *Computers and Electronics in Agriculture*, n. 154, pp. 443–449, 2018.

[9] Q. Yang, D. Xiao and S. Lin. "Feeding behavior recognition for group-housed pigs with the Faster R-CNN". *Computers and Electronics in Agriculture*, n. 155, pp. 453–460, 2018.

[10] C. Cao, B. Wang, W. Zhang, X. Zeng, X. Yan, Z. Feng, Y. Liu, Z. Wu. "An Improved Faster R-CNN for Small Object Detection". *IEEE Access,* 2019.

[11] J. Long, E. Shelhamer, and T. Darrell. "Fully convolutional networks for semantic segmentation". *Conference on Computer Vision and Pattern Recognition (CVPR)*, 2015.

[12] K. He , P. Dollar, R. Girshick and G. Gkioxari. "Mask RCNN". *IEEE International Conference on Computer Vision (ICCV)*, 2017.

[13] W. Abdulla. "Splash of Color: Instance Segmentation with Mask R-CNN and TensorFlow". Matterport Engineering Techblog, 2018.

[14] T.-Y. Lin, M. Maire, S. Belongie, J. Hays, P. Perona, D. Ramanan, P. Dollar, and C. L. Zitnick. "Microsoft COCO: Common objects in context". *European Conference on Computer Vision (ECCV)*, 2014.