Location Monitoring System to Prevent Falls of Cathodes in Industrial Electrolysis Facilities

Francisco Javier de la Calle Herrero, Alberto Gómez Blanco, Daniel F. García, and Rubén Usamentiaga

Abstract—**The current steel industry needs new efficient monitoring systems that to aid human operators in their tasks. One of the most dangerous steps in the electrolysis process is the moment in which the cathodes and the anodes are lifted from the cells and moved through the facility. This paper proposes a new inspection system to detect whether the cathodes can be lifted by the crane. The proposed system uses a camera that takes images of the rack of cathodes before they are lifted. The images are processed to detect incorrectly positioned cathodes that could generate a problem when lifted. The computer vision system used to process the images was tested on more than 5500 cathodes with 90% effectiveness on anomaly detection and 0.8% of detection errors. The results were then validated in a second industrial facility on more than 6000 cathodes providing even better results, proving the effectiveness and reliability of the system. The system has been also tested in terms of response time proving it suitable for real-time monitoring in a real facility.**

Index Terms—**Cathode fall, computer vision, electrolysis process, industrial safety, quality inspection.**

I. Introduction

The advances in the development of industrial environments has lead to faster and more efficient processes [2], most of them automated [3]. However, there are still some tasks performed by human operators, who are prone to mistakes due to fatigue. The aim of this paper is to propose an innovative system that can be used to automatically prevent faults in an industrial process which is usually the responsibility of human.

Electrolysis is a technique used to separate the elements of a compound using electricity. This process, used to produce materials such as aluminum, sodium or magnesium, requires two fundamental pieces to work as electrodes: anodes and cathodes. The factory involved in this research produces zinc using electrolysis.

Before the cathodes are installed in the electrolytic cell, they must be transported from the appropriate location. In many industrial processes, bridge cranes are used to lift and move heavy loads, including cathodes. Cathodes are usually placed on specially designed racks or pallets that can be easily lifted by cranes, or lifted directly by specially designed cranes that grab the cathodes and move them to and from the electrolytic cells. It is important to ensure that the cathodes are correctly placed and securely fastened to the crane to prevent them from shifting or falling during transportation. Then, they must be carefully placed in the electrolytic cell, properly aligned and spaced to maximize the efficiency of the process.

The cathodes are the parts in which the final product, zinc in this case, is obtained. During the electrolytic process, metal ions in the solution are reduced at the surface of the cathodes, forming a thin layer of pure metal. This layer of metal must be stripped from the cathodes mechanically. Therefore, the cathodes must be transported from the cells to the machine that strips the zinc from them. The machine involved has a rack to which the crane transports the cathodes ready for stripping and another rack from where the crane lifts the cleaned cathodes to transport them back to the cells and repeat the process. The other part of the process, involving the anodes, is out of the scope of this work.

The moment at which the crane lifts the cathodes from the racks is critical: a misplacement of the cathodes could cause them endangering to fall. Preventing cathode falling during transport is crucial to ensure the safety of workers and prevent damage to equipment. If the cathodes are not securely fastened during transport, they may shift or fall, causing injury to workers and damage to the cathodes or other equipment. In addition, if a falling cathode damages the electrolytic cell, it can cause delays in the production process and lead to significant financial losses. Therefore, it is essential to follow strict safety procedures and protocols when transporting cathodes to ensure that they are securely fastened and transported with care.

The detection of misplaced cathodes in the racks before the crane lifts them is crucial to prevent them from falling, ensuring the safety and efficiency of the factory. This task is usually performed by human operators, who check that each cathode is in the right cradle in the support beams of the rack. This paper proposes a computer vision system to detect any misplacement in this context. This system allows the human operator to review

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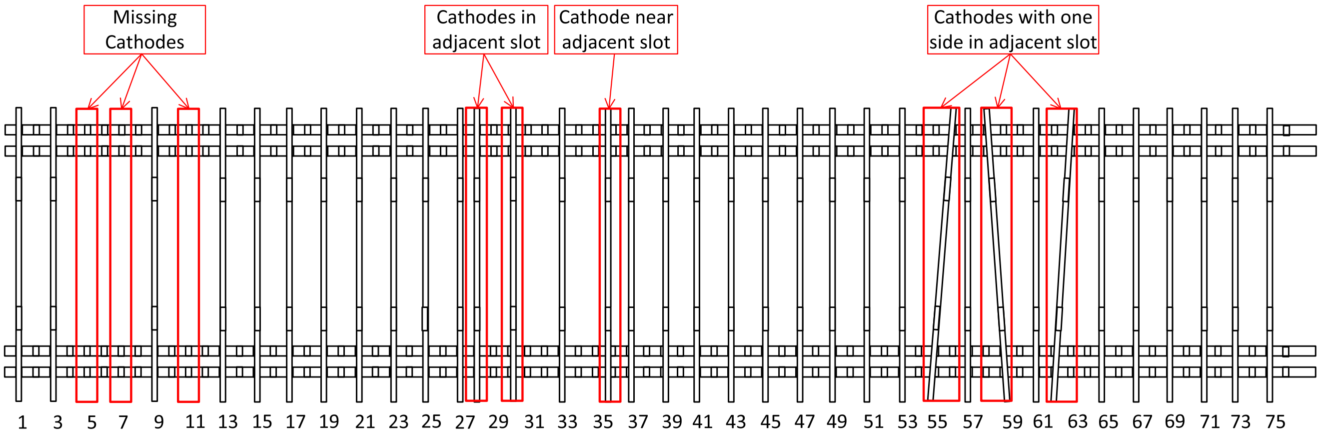


Fig. 1. Cathode placement fail examples.

the diagnosis of cathode positions from a safe distance and act only if a cathode needs to be moved [4].

Computer vision techniques are often used to perform quality inspection tasks in many fields such as food, pharmaceutical, automotive, aerospace, railway and semiconductor [5]. It has become an essential tool for quality control in the metal industry, where it is used to detect defects in metal parts and ensure that they meet the required specifications and standards [7], [8]. These techniques can be applied in many stages of product manufacturing [6] and for other purposes, such as object detection for automatic guidance [9] or presence detection [10]. Furthermore, these techniques can enhance workplace safety by identifying potential hazards and alerting workers to take appropriate actions. In this paper computer vision techniques are applied to process monitoring.

Computer vision systems provides a unique advantage in industrial real-time monitoring and analysis of visual data as it can automatically detect certain situations and monitor the whole process in a hazardous environment without endangering human operators. Automatically preventing cathode falls using a computer vision system not only provides efficiency to the factory but also prevents material and human losses that may result from potential falls. In fact, this kind of system reduces the need for human operators to be near the electrodes and electrolytic cells, which can be a hazardous environment [11].

The rest of the paper is organized as follows: in Section II a description of the industrial context is given. Then, in Section III, the proposed system is described. Finally Sections IV and V give experimental results and conclusions.

II. Industrial Context

The electrolytic process in which the proposed system is developed uses electrolytic cells with 61 cathodes. These cathodes are lifted by a crane that leaves them in a rack for zinc stripping. The rack has two pairs of beams that support and move the cathodes one by one into the stripping machine. These beams have 122 slots for the 61 cathodes, labeled as odd and even slots. The cathodes are all placed either in the odd or the even slots, leaving an empty slot between each one. Therefore, the crane expects the cathodes to be placed in one of the sets of slots, odd or even. Correct placement of the cathodes in the slots is crucial to prevent falls when the crane lifts them.

The cathodes can be misplaced in several ways. In Fig. 1 several misplacements are shown in the first 76 slots of the rack, including from left to right: three missing cathodes in slots 5, 7 and 11, one cathode that should be in slot 29 placed in slot 28, one cathode that should be in slot 31 placed near slot 30, one cathode that should be in slot 35 placed near slot 36 and three cathodes that should be in slots 55, 59 and 63 placed correctly on one beam but wrongly on the other.

The aim of the system is to prevent cathode falls during lifting by detecting any of these misplacements. The first step then is to decide if the cathodes should be found in the odd or even slots of the beams; one cathode should be placed in every slot of the set. One of the given premises is that exactly 61 cathodes must be placed in the rack at a time. Therefore, if a cathode is not found in its designated slot, it must be located either in another slot, on the beam but not in a slot, or at an angle using two different slots on the two beans. In any of these cases, as shown in Fig. 1, a fall would occur when the crane tried to lift the rack.

The system must accomplish two main restrictions to be suitable in this context. Firstly, the cameras or sensors of the system must be placed in such a way that they can acquire the data from the rack while not affecting the industrial process. This is complex because the best perspective to acquire the images of the rack is from the perpendicular perspective, which is occluded by the crane while it is moving into position for lifting the cathodes. Secondly, the data acquisition must be fast enough not to slow down the production,

III. Proposed System

This section describes the proposed system including the camera placement, image acquisition and processing.

The system is composed of a camera that takes images of the racks and a computer that processes these images. After each image is processed, the system sends a report to the main control of the facility with the diagnosis of the rack so that a human operator can verify the diagnosis and take actions if

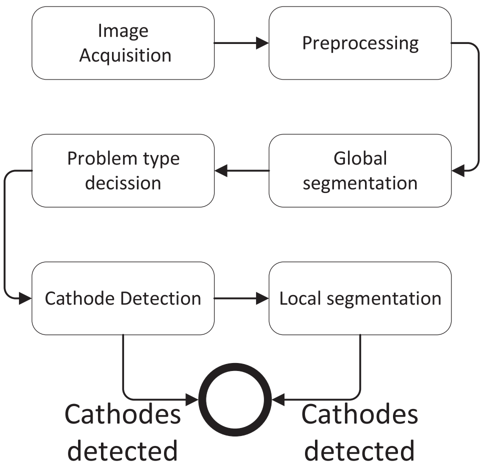


Fig. 2. Image processing steps.

needed. There must be two communication messages. First, the system receives a signal to acquire the image of the rack after the stripping machine has finished its work. Then, after the image is processed, the system sends the result to the main control in such a way that it can be viewed and understood easily. The results are represented by an array of ones and zeros where a 1 is defined as a well-placed cathode and 0 as a wrong-placed or missing cathode.

The operation of the system is based on the premise that in each rack, before the crane lifts the cathodes, 61 cathodes must be well-placed in their intended slots. Following this premise, if the system cannot find a cathode in each slot, there might be a problem in that rack that can produce a cathode falling or a missing cathode, which reduces the efficiency of the facility.

In Fig. 2 the image processing steps are shown following a classic pipeline of computer vision techniques [12]. These steps will be described in the following subsections.

A. Image Acquisition

The industrial context establishes the limitations in camera placement and image acquisition. The best way to place the camera to obtain the least distorted image of the cathodes is directly above them in a perpendicular position. This would be the same position where the crane should be located to lift the cathodes. Based on this, there are two options for placing the camera: on the crane itself or above it.

The first option implies several disadvantages in terms of maintenance. If the camera were located on the crane, it would be moving with it, even when the crane was leaving the cathodes in the electrolytic cells. This could produce damage to the camera due to the proximity to the electrolytic cell, reducing its durability. In addition, the camera would need further maintenance to keep it clean in order to obtain clear images.

The second option implies that the camera should be able to obtain images from a long distance with enough resolution to distinguish each cathode. This is the best option as the camera is placed in a location that is less prone to vibrations, changes in position, and dirt.

Illumination conditions are a key factor in image acquisition so they should be constant at all times. In this kind of environment this is very difficult due to environmental light, keeping in mind that the factory is in production 24 hours 7 days a week, and the size of the area of interest. Therefore, the selected camera should be able to adapt its parameters in such a way that the acquired image maintains its features under different illumination conditions. The selected camera is a MOBOTIX Mx-M73A-RJ45 which is capable of acquiring images with a dynamic exposure time that meets the challenges of these illumination conditions providing similar images at all times. The camera is fixed to the factory ceiling pointing perpendicularly at the rack at 10.5 meters. This camera is designed for video-surveillance, which makes it cheaper than computer vision cameras, reducing the cost of the system significantly.

The features of the acquired images should be constant so the same conditions for processing them are maintained in different illumination scenarios. The exposure time must be changed dynamically to keep the images constant, adapting to changing illumination. Therefore, several images are acquired automatically changing the exposure time so that the brightness of the acquired image converges to an optimal value. In this way, the images acquired at different times of day or in different periods of the year will be similar. In addition, this makes the system adaptable to facilities with different illumination conditions.

B. Preprocessing

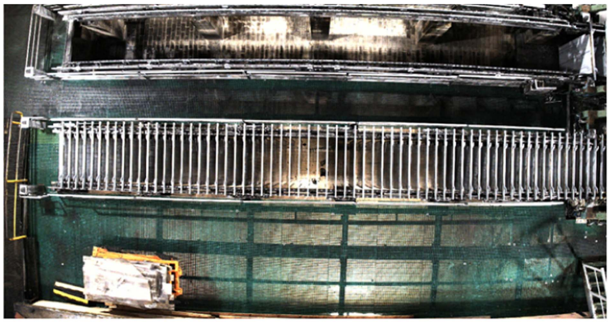
The first step in the image processing method is to rectify the image and translate it to real world coordinates. In order to rectify the image the camera must be correctly calibrated [13]. Image rectification provides an image in which the cathodes can be easily measured and located once the image is translated to real world coordinates. This is extremely important because, as explained in Section II, the system must check not only that the cathodes are present, but that they are in their intended position.

Calibrating a pinhole camera involves determining the intrinsic and extrinsic parameters of the camera to correct for any distortions in the images it acquires. The intrinsic parameters are related to its internal characteristics, such as focal length, principal point, and image sensor size, while the extrinsic parameters refer to the position and orientation of the camera with respect to the 3D world.

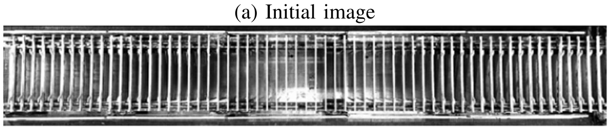
The aim of the calibration procedure is to estimate the intrinsic and extrinsic parameters of the camera from a set of images of a calibration target with known 3D coordinates. The relationship between the 3D coordinates of the calibration target, X, and the 2D image coordinates, x, is expressed in (1), where s is a scaling factor, K is the camera intrinsic matrix, R is the rotation matrix representing the camera orientation, t is the translation vector representing the camera position and $[R|t]$ is the extrinsic matrix that combines the rotation and translation parameters.

$$s \cdot x = K \cdot [R|t] \cdot X \tag{1}$$

The intrinsic matrix, K, is defined in (2), where f_x and f_y are the focal lengths in the x and y directions and c_x and c_y are the



(a) Initial image



(b) Image after preprocessing

Fig. 3. Preprocessing of the image.

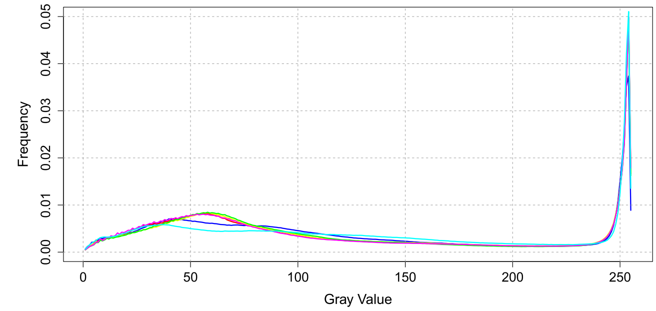


Fig. 4. Gray values histogram in images.

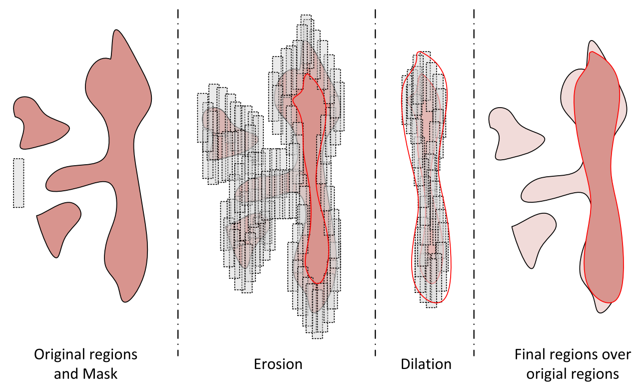


Fig. 5. Schematic representation of opening operation pipeline.

coordinates of the center point.

$$K = \begin{bmatrix} f_x & 0 & c_x \\ 0 & f_y & c_y \\ 0 & 0 & 1 \end{bmatrix} \tag{2}$$

To estimate the camera parameters, the intrinsic and extrinsic matrices that minimize the error between the observed image coordinates, x, and the predicted coordinates obtained using the 3D coordinates, X, and camera matrices must be calculated. This can be done using a nonlinear optimization such as Levenberg-Marquardt.

Once the camera is calibrated, the estimated parameters can be used to rectify the image. The rectification process involves calculating a set of homography matrices that map the distorted image coordinates to the rectified image coordinates. The homography matrix, H, can be calculated as (3), where R_1 and R_2 are the rotation matrices that align the epipolar lines of the rectified image, and t_1 and t_2 are the translation vectors that move the camera to the rectified position.

$$H = K \cdot [R_1|t_1] \cdot R \cdot [R_2|t_2]^{-1} \cdot K^{-1} \tag{3}$$

The rectification homography can be applied to the original image using image warping, which involves mapping each pixel (u, v) in the original image to its corresponding pixel (u', v') in the rectified image using the homography matrix H (4).

$$[u', v', 1] = H \cdot [u, v, 1] \tag{4}$$

Once the pixels are mapped, the pixel values from the original image are interpolated into the rectified image to obtain the final rectified image.

After the preprocessing, the Region Of Interest (ROI) can be easily extracted in order to avoid the influence of environmental conditions in the surroundings. During the process, the image is also transformed into gray-scale. Fig. 3 shows the preprocessing result.

C. Global Segmentation

In order to determine whether the cathodes are correctly positioned, the first step is to extract the cathodes from the image. In this first step, a global segmentation of the image is performed in order to avoid the influence of the different illumination conditions in different parts of the image.

First, the histogram of gray values of the images should be studied in order to check if a binary threshold is suitable for extracting the foreground of the images, the cathodes. In Fig. 4 the histogram of six different images obtained at different times and on different days is shown. In this Figure two areas can be easily described as the ones in which the gray values are clustered, around the values 50 and 250. These two areas correspond to the background and the foreground of the image, making it suitable for a binary thresholding technique.

The segmentation limit is calculated dynamically for each image as follows. First, the relative histogram of the gray values is determined. Then, relevant minima are extracted from the histogram, to be used as parameters for a thresholding operation. In order to reduce the number of minima, the histogram is smoothed with a Gaussian. The mask size is enlarged until there is only one minimum in the smoothed histogram. Then, the threshold is set to the position of this minimum.

The result at this point is shown in Fig. 7(a), with the extracted regions shown in red.

As can be seen in Fig. 7(a), the cathodes are correctly extracted but the result is very noisy. In order to remove the noise extracted as foreground, an opening operation is performed

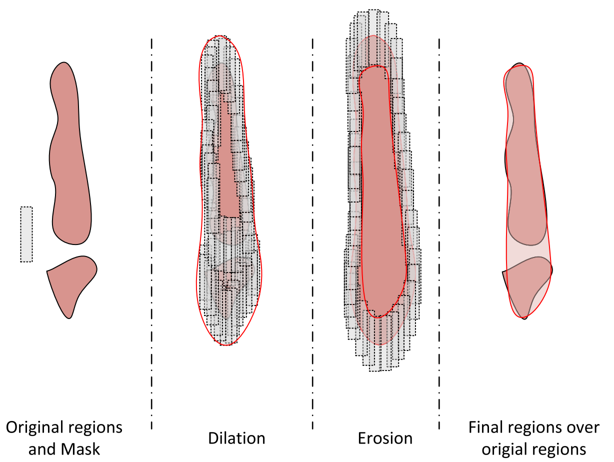


Fig. 6. Schematic representation of closing operation pipeline.

over the regions in the image. The opening operation is shown schematically in Fig. 5. The operation consists of an erosion followed by a dilation using the same mask. First, the mask is moved following the contour of the regions, eliminating the area that intersects with it. This is called an erosion. Then, the same mask is moved again following the contour of the resulting regions, generating a new area for the region. This is called a dilation. In this case, the mask should be a vertical rectangle in order that any region that is not strictly oriented as the mask is removed but the ones that follow the same orientation, the cathodes, are maintained. The size of the mask is calculated as $0.55 \cdot W \times 0.1 \cdot H$, W and H being the width and the height of the cathodes respectively.

The result at this point is shown in Fig. 7(b), with the extracted regions shown in red.

In Fig. 7(b) not only are the regions of the cathodes extracted, but most of the noise has been removed, including other factory structures which were extracted, such as the beams of the rack. The opening operation successfully eliminated the noise but it also eliminated some parts of the cathodes, which had been poorly extracted by the thresholding as can be seen on both sides of the image, in which the cathodes are cut in several regions. In order to recover the cathodes as a single region, a closing operation is performed. The closing operation is the inverse of the opening operation, performing the same actions in reverse order: a dilation followed by an erosion. The outcome is that nearby regions can merge into a single region based on the mask used while regions without nearby neighbors remain the same size. Fig. 6 is an example of a closing operation. The size of the mask is calculated as $0.75 \cdot W \times 0.16 \cdot H$, W and H being the width and the height of the cathodes respectively.

The result at this point is shown in Fig. 7(c), with the extracted regions shown in red.

After the closing operation each cathode is extracted as a single region in most cases but there are still some zones extracted which are not part of a cathode, as can be seen in the middle of the image in Fig. 7(c). This is why a second opening is performed using a larger mask, which should eliminate these areas while respecting the cathodes. The result at this point is shown in Fig. 7(d), with the extracted regions shown in red.

D. Problem Type Decision

Once the foreground of the image is extracted (the cathodes), the system detects whether the cathodes are in the odd or even slots of the rack. Two sets of target regions are generated for the odd or even problem, the two are shown in Fig. 9.

The intersection between the two sets of target regions and the extracted regions is performed. The proportion of the area of the target regions that intersects with the extracted regions is calculated, and a proportion of odd and even targets is obtained. If the proportion obtained of one of the targets is more than double the other, that set of target regions is used to look for the cathodes. In the example of Fig. 7(d), the proportion of even targets is 78.66% and of odds is 1.32%, so the targets to be used are the even ones.

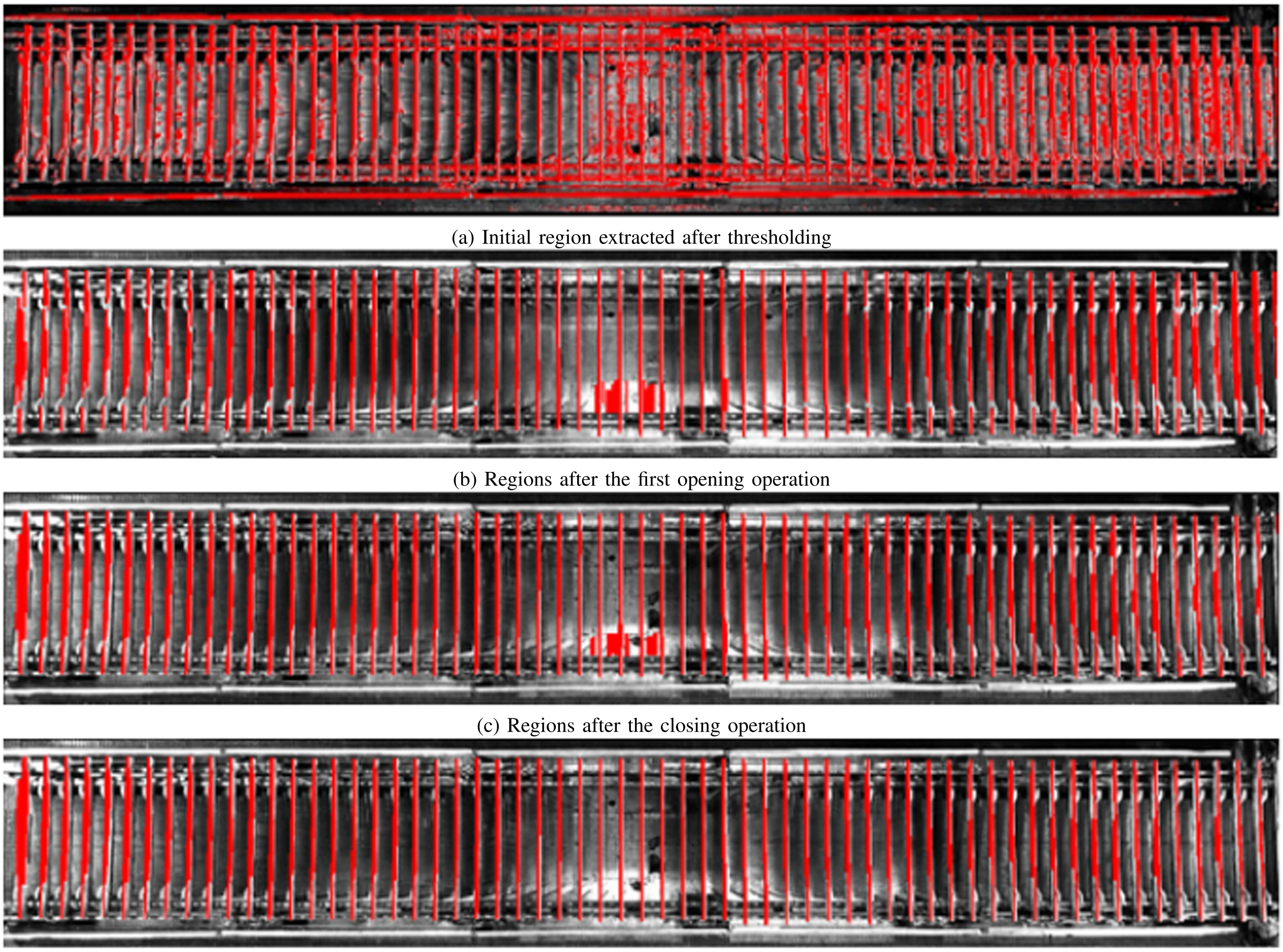
E. Cathode Detection

Once the extracted and the target regions are obtained for each image, the next step is to detect the cathodes in the target regions. To do so the extracted regions are separated into connected components, with one region per cathode. The result may present several problems. There may still be some noise in the image that has not been deleted in previous steps and some cathodes may have been detected as several unconnected regions. These two situations can be seen in Fig. 9(a). This figure uses a different image than previous figures in order to better demonstrate the problem.

To mitigate these errors, two actions are performed. First the regions whose their centers are closer than 39 millimeters in the horizontal axis, which is 1.5 the width of a cathode (26 millimeters), are grouped, putting the regions that represent a cathode into a single region. Next, the regions that do not represent a cathode are removed. These regions probably represent light reflections on the sides of the cathodes. In order to eliminate these regions, all regions whose length is less than 755 millimeters, half the real length of a cathode (1 510 millimeters) is eliminated. The result can be seen in Fig. 9(b) in which each cathode is represented in a different color.

Now, the regions are cleaned of noise and grouped into the regions that represents each of the extracted cathodes.The intersection between the extracted regions and each of the target regions is calculated. For each target, the proportion that its intersection represents is calculated. If a target region is over an established proportion value, a cathode has been detected in that target region, that is a cathode detected in a slot of the rack. This value is calculated empirically as 80% from a set of labeled images used as a training set for developing the algorithm.

At this point, most of the cathodes that are in their slots have been detected, but others some have not. This situation is shown in Fig. 10, in which three correctly positioned cathodes are not detected. This is called a False Positive (FP) because it provides a diagnosis with 3 failures while in fact all the cathodes are correctly placed.



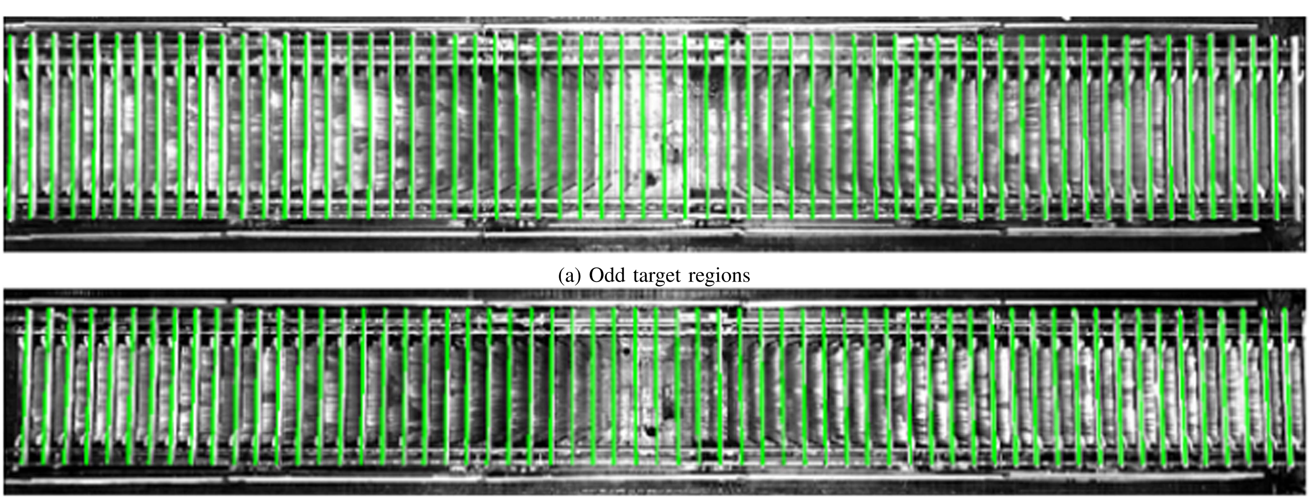
(a) Initial region extracted after thresholding

(b) Regions after the first opening operation

(c) Regions after the closing operation

(d) Regions after the second opening operation

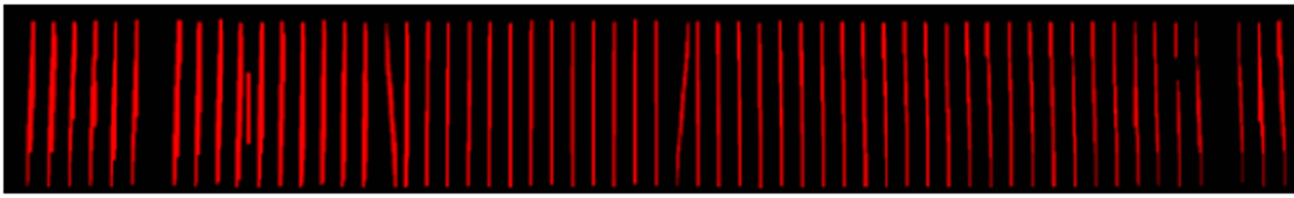
Fig. 7. Extracted regions during global segmentation.



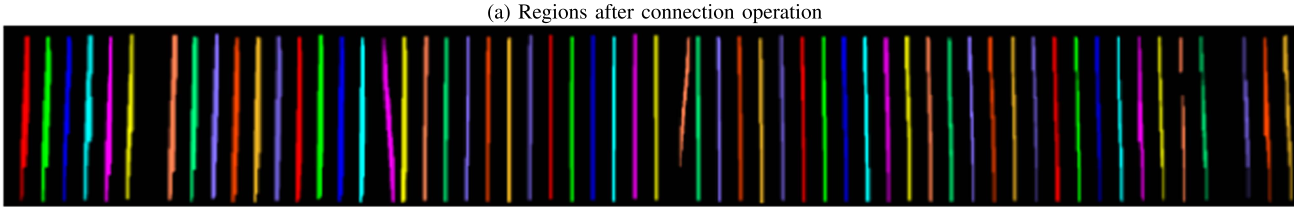
(a) Odd target regions

(b) Even target regions

Fig. 8. Target regions for odd or even problems.



(a) Regions after connection operation



(b) Final regions representing cathodes. Each color represents one different region.

Fig. 9. Regions representing the cathodes.

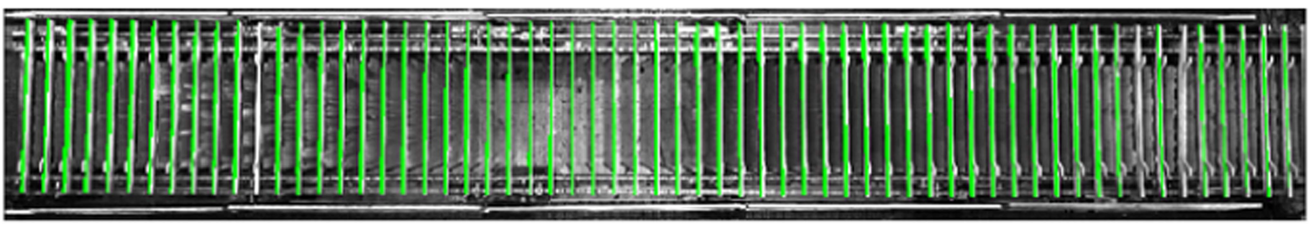


Fig. 10. Cathodes detected. Three false positives can be seen in the image.

After this step the cathodes already detected pass to the final result. The target regions in which a cathode is not detected pass through a second step of detection.

F. Local Segmentation

During the previous steps of the process, most cathodes were found correctly in their intended target regions, but there are still some target regions in which nothing was detected. Among these target regions without a cathode there are some in which there is a correctly placed cathode and other in which there is nothing or an incorrectly placed cathode. The aim of the second segmentation is to distinguish between these two groups.

The same segmentation procedure is used but now, the histogram of gray values is obtained locally for each cathode. The region of interest for each cathode goes from the previous to the next slot. There is always a free slot between two adjacent target regions as the problem is defined as odds or evens as explained in Section III-D.

Once the segmentation is done, a sequence of opening and closing operations is performed using a rectangular mask. The mask is defined to follow the orientation of the target region as this is also the orientation of any cathode which is correctly placed in its intended slot.

First an opening operation is carried out with a small mask to eliminate small areas of noise. The size of the mask is calculated as $0.20 \cdot W \times 0.066 \cdot H$, W and H being the width and the height of the cathodes respectively.

When most of the noise has been removed, before eliminating the rest of the noise segmented between cathodes, the different regions in which the same cathode is detected are joined to prevent them from being eliminated. A closing operation is applied to join those regions. The mask in this case is calculated as $0.2 \cdot W \times 0.4 \cdot H$, W and H being the width and the height of the cathodes respectively.

At this point, most of the cathodes have been detected as a single region, but there is still some noise to be removed. A second opening operation is carried out. The size of the mask is calculated using $0.57 \cdot W \times 0.79 \cdot H$, W and H being the width and the height of the cathodes respectively. This mask is extremely big in order to eliminate any possible light reflection that could have been segmented and enlarged into a bigger region by the previous operations. However, as some of the cathodes regions may have been divided in two or more regions, a final closing is needed to join them. The last closing uses a mask which is $0.2 \cdot W \times 0.2 \cdot H$, W and H being the width and the height of the cathodes respectively.

Now, the regions must be be classified into cathodes that are well placed and those that are not. This is done with a Knowledge Base with well placed 4411 cathodes and 122 cathodes that are not correctly placed or are missing. These numbers describe an imbalanced classes problem, which can be addressed using several techniques including under-sampling and over-sampling in order to make it suitable to construct machine learning models [14]. However, the aim here is to evaluate the separability of the classes using simple rules that could be tuned if the conditions of the cathodes change without needing to retrain an existing model.

Of the 44 features extracted from the regions in the Knowledge Base (in which the well placed cathodes are the *Negative* class while the missing or incorrectly placed cathodes are the *Positive* class) three of them are relevant to the possible separability of

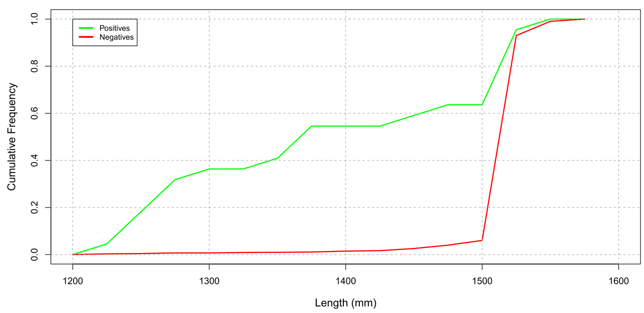


Fig. 11. Length distribution of the regions.

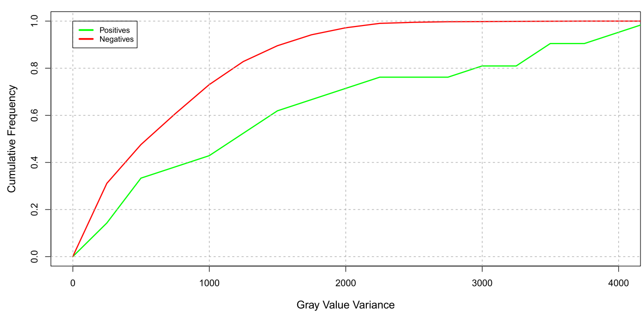


Fig. 12. Gray value variance distribution of the regions.

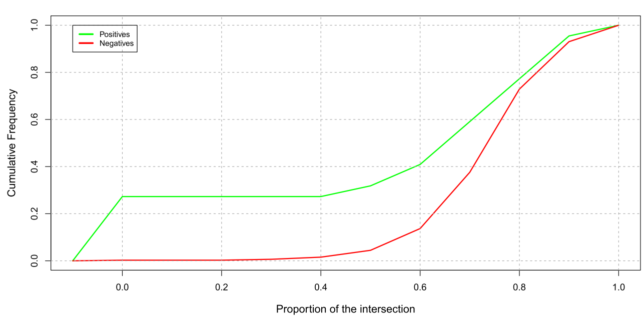


Fig. 13. Proportion of the intersection distribution of the regions.

the classes that can be obtained with them: length of the region, gray value variance and intersection proportion. The Length of the region is defined in (5), where R is a region defined by its bounding box defined by its left top corner (x_1, y_1) and right bottom corner (x_2, y_2). The variance of the gray level of the region is defined in (6), where R is a region, p a pixel from R with the gray value $g(p)$ and F the plane ($F = |R|$). The proportion of the intersection is defined in (7), where R is the region and T the target region.

The cumulative distribution function of the values of these features for the regions are shown in Figs. 11, 12, and 13.

$$Length\ (R\ (x_1, y_1, x_2, y_2)) = y_2 - y_1, \forall R \tag{5}$$

$$Variance = \frac{\sum_{p \in R} \left(g(p) - \frac{\sum p \in R(g(p))}{F} \right)^2}{F}, \forall R \tag{6}$$

$$Intersection\ proportion = \frac{|R \cap T|}{|T|}, \forall R, T \tag{7}$$

TABLE I
Datasets Description

Set	Racks without errors	Racks with errors	Well placed cathodes	Problematic cathodes
Dev Set	47	38	4454	121
Test Set 1	32	9	2113	14
Test Set 2	20	13	1631	75
Test Set 3	20	14	1731	27
Total Test	72	36	5475	116

According to the distributions shown in Figs. 11, 12, and 13, three thresholds can be established to separate the two classes. Fig. 11 shows that an instance can be classified as *Positive* if its *Length* is less than 1400 mm. Fig. 12 shows that an instance can be classified as *Positive* if its Variance is more than 3 000. Fig. 13 shows that if the percentage of its intersection over the target region is less than 0.2, the region can be calssified as *Positive*. Any region that meets any of these conditions will be classified as *Positive*, that is, an incorrectly placed cathode.

The correctly placed cathodes detected in this step are added to those detected in the previous steps. Any target region in which a not well positioned cathode is detected is declared as an error, meaning that in said target region a cathode is missing or not in its proper place. Regions without an associated cathode define slots in the rack in which there is a risk of a cathode falling when the crane lifts the set of cathodes to take it to the electrolytic cell.

IV. Experimental Results

The evaluation of this type of system is a complex process. Environmental conditions can greatly influence data collection since light impacts differently depending on the time the images are taken. The same occurs with the period of year in which the data is obtained.

In order to obtain data that best represents the variability of environmental conditions, it was decided to conduct three data collection campaigns in a real facility. These three datasets, together with the data from the set used for the development and adjustment of the system, are shown in the Table I.

Table I describes the sets in two different ways, by cathode and by rack. The description was initially made by rack because the aim of the system is to detect if a rack full of cathodes presents any risk of a cathode falling, in which the system will alert an operator to fix the problem. This approach has an important deficiency in terms of evaluation as when a rack is identified as problematic, even if it is truly problematic, the detection may not be accurate. The problem may have been detected in the wrong cathode, while a cathode that could potentially cause a problem may not have been detected. Therefore, the results will be given also by cathode, which gives a better evaluation of how well the placements are identified by the system.

Evaluation by cathode makes the difference between classes even greater. The problem of unbalanced classes is often carried out by over-sampling or under-sampling the instances [14] but these techniques are not suitable in this context. In this context, a single image (of a rack) contains a set of cathodes which are

TABLE II
DEFINITION OF THE VALUES USED FOR EVALUATION

Value	Definition
TP	Incorrectly placed cathode classified as incorrectly placed
FP	Well placed cathode classified as incorrectly placed
FN	Incorrectly placed cathode classified as well placed
TN	Well placed cathode classified as well placed
TPR	$\frac{TP}{TP+FN}$
FPR	$\frac{FP}{FP+TN}$

TABLE III
RESULS OF THE SYSTEM

	Instances	TP	FP	FN	TN	TPR	FPR
	By cathode						
Dev Set	4575	114	72	7	4382	0.9421	0.0162
Test Set 1	2127	13	14	1	2099	0.9286	0.0066
Test Set 2	1706	72	14	3	1617	0.9600	0.0086
Test Set 3	1758	20	18	7	1713	0.7407	0.0104
Total Test	5591	105	46	11	5429	0.9052	0.0084
	By rack						
Dev Set	85	35	17	3	30	0.9211	0.3617
Test Set 1	41	9	10	0	22	1.0000	0.3125
Test Set 2	33	12	6	1	14	0.9231	0.3000
Test Set 3	34	12	7	2	13	0.8571	0.3500
Total Test	108	33	23	3	49	0.9167	0.3194

individually classified as well placed or not well placed individually. Over-sampling or under-sampling the cathodes could be done by processing the cathodes individually. However, the main step of the process is a segmentation that takes into account the light conditions of the whole image, making over-sampling well positioned cathodes difficult in this context.

The evaluation metrics used are standard, for two class classification problems. The metrics used are *TPR* and *FPR* based on the values of *TP*, *FP*, *FN* and *TN* which are defined in Table II.

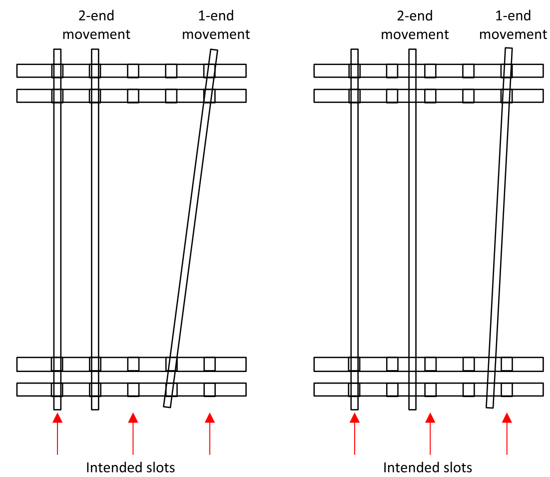
The results of the evaluation, seen in Table III, show that of 116 cases, only in 11 was a incorrectly placed cathode misclasified as as well-placed, while only 46 cathodes of more than 5400 were misclassified as incorrectly placed.

The metrics obtained makes the system suitable for operating in a real factory as it is capable of detecting the cathodes that could produce a fall in 90% of cases, reducing the risks associated to a human operator detecting these problems by hand.

The system was also measured in terms of response time, which depends on the number of target regions to be evaluated in the local segmentation step defined in Section III-F. The best way to establish if the system is suitable for working in real-time in a industrial process is by the maximum response time, which in this case is 5 seconds. The time spent by the crane in lifting and moving the cathodes from the rack to the electrolytic cell is close to 2 minutes in the industrial context studied, so in this case, 5 seconds would not slow down the production pace.

A. New Deployment and System Validation

A second evaluation is performed in order to validate the results in a different facility. The new deployment is in the same industrial context, with the same restrictions and physical definition, but the facility itself is different, so the illumination conditions vary. However, the illumination conditions should not influence the system because, as explained in Section III-A, the exposure times are changed dynamically so all the images have similar conditions. The system now is evaluated with three sets of images.



(a) Validation set 2 (b) Validation set 3

Fig. 14. Validation set examples of incorrectly placed cathodes.

The first set of images, *Val Set 1*, corresponds to images of a typical operation in the industrial facility. In this set, there are 88 racks containing 5 395 cathodes, which is a standard production for the installation. Of these, only 4 cathodes in two racks could have produced a problem. This number of positive-class instances is not sufficient to evaluate the *TPR*. To guarantee the validity of the test, the next two sets contained cathodes that were incorrectly placed deliberately.

The second set of images, *Val Set 2*, corresponds to images of 9 racks in which 81 cathodes of 549 were incorrectly placed by moving one or both of the ends of the cathodes to an adjacent slot. This is a worst possible case, in which the cathode is completely outside its intended slot at one or both ends. Examples of these movements can be seen in Fig. 14(a).

The third set of images, *Val Set 3*, corresponds to images of 5 racks in which 44 cathodes of 305 were incorrectly placed by moving one or both of the ends of the cathodes half way to the adjacent slot. This is more difficult to detect because the cathode is not as far from its slot as in the previous set of images. The separation between adjacent slots is 90 mm, so in this case, one or both of the ends of the cathode is moved only 45 mm from its intended slot. Examples of these movements can be seen in Fig. 14(b).

The results of the evaluation of these new sets of images are shown in Table IV, showing that the system gives even better results than those obtained with the test sets. Thus, the system is validated.

As the instances from the Validation Sets are acquired in a different facility from that in which the Test Sets were acquired, the environmental conditions are different. The illumination conditions in the second facility are completely different due

TABLE IV
RESULTS OF THE VALIDATION OF THE SYSTEM

	Instances	TP	FP	FN	TN	TPR	FPR
	By cathode						
Val Set 1	5429	4	30	0	5395	1.0000	0.0055
Val Set 2	549	81	0	0	468	1.0000	0.0000
Val Set 3	305	44	0	2	258	0.9565	0.0000
Total Test	6283	129	30	2	6121	0.9847	0.0049
	By rack						
Val Set 1	88	2	14	0	72	1.0000	0.1628
Val Set 2	9	9	0	0	0	1.0000	0.0000
Val Set 3	5	5	0	0	0	1.0000	0.0000
Total Test	102	16	14	0	72	1.0000	0.1628

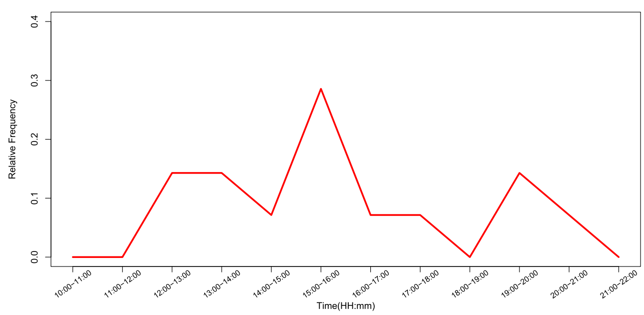


Fig. 15. Errors in racks against time of the day.

to the structure of the building. However, the results of the validation and test sets are similar, proving that the influence of the illumination conditions is low or at least the same in both facilities. In order to study this influence, the errors in detection are shown in Fig. 15 against the time of the day. The distribution shows that the environmental light does affect the algorithm during the hours of light, when the sunlight can enter through the windows in the ceiling of the facility. However, the influence of changing illumination is negligible given the small number of errors generated, proving that image acquisition with an automatically changed exposure time is reliable.

The system has been proved robust and efficient in two different facilities with different light conditions. However, the influence of the environment could be an issue in another facility in which the artificial lights are not turned on at all times, providing semi-constant illumination conditions in the image acquisition area despite changing light conditions due to sunlight.

V. Conclusion

This paper proposes a novel cathode location monitoring system that can be used in a industrial electrolytic process. This system provides an efficient way to prevent cathodes from falling during the process, avoiding significant economic losses. The system uses a single camera that is located perpendicularly over the rack where the cathodes are left for the crane to lift them. Before the crane is located over the rack to lift the cathodes and take them to the electrolytic cells, an image is taken to ensure that the cathodes are placed properly for the crane to lift them safely.

The camera used in this system is designed for video-surveillance purposes, so its cost is significantly less than the cost of a computer vision camera. This low-cost image acquisition system further increases the benefit provided by the system by reducing the costs caused by the incorrectly placed cathodes. The system can be easily deployed in any facility as it automatically detects the position in which the cathodes should be placed: odd or even slots. It can be easily integrated in the control system of the facility as the results can be given as a tuple of 0/1 indicating whether a cathode is detected in a slot or not.

The algorithm that detects whether the cathodes are well placed is based on a sequence of steps that follows the classic pipeline of computer vision algorithms. First a segmentation based on the gray level histogram of the image is performed in order to extract the cathodes from the background. Resulting regions go through a set of morphological operations that eliminate the noise and undesired regions and generate a single region per cathode. The regions are then assigned to the slots in which the cathodes are supposed to be located, detecting if there is a cathode in each region or not. After this step, if any target region does not have any cathode assigned, a second detection process is performed using now the information of the target region locally, so that any illumination changes there might have been in the image have less influence on the segmentation. After these two steps of detection, any target region without a cathode associated is reported.

The system was tested with more than 5 500 cathodes in real conditions providing 90% detection rate of the cathodes that were incorrectly placed and failing in only 0.8% of the cathodes that were well-placed, classifying them as incorrectly placed. These results prove the reliability of the system in detecting situations likely to lead to a cathode falling in the industrial facility.

After the evaluation of the system the results were also validated in a second evaluation to prove that the first results were not favoured by the environmental conditions of the facility. In this case, more than 6200 cathodes were used, some of them intentionally moved from their intended slots in the rack to validate the detection rate. The results of the validation gave a 98% detection rate and 0.5% of the well-placed cathodes being classified as incorrectly placed. The validation proves that the evaluation sets were not biased and the system is reliable and robust in terms of detection.

It is important to reduce the risk of a cathode falling from the crane while it is being taken to the electrolytic cell. If one of this cathodes falls, it can produce severe damage to other cathodes or to the electrolytic cells, leading to significant economic losses. Worse, the fall of a cathode could endanger human operator involved. The proposed system reduces the risk of cathode falling by giving the operators a diagnosis of the stability of the cathodes in the rack before the crane tries to lift them. In this cases the rack can be manually inspected and the potentially dangerous situation rectified.

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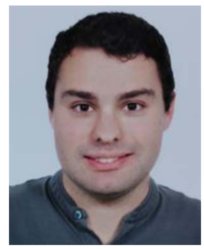

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