Early Defect Detection in Conveyor Belts using Machine Vision

Guilherme G. Netto[1,3][a], Bruno N. Coelho[1,3][b], Saul E. Delabrida[2][c], Amilton Sinatora[3][d], Héctor Azpúrua[3][e], Gustavo Pessin[3][f], Ricardo A. R. Oliveira[2][g] and Andrea G. C. Bianchi[2][h]

[1]*Department of Engineering of Control and Automation, School of Mines, Federal University of Ouro Preto (UFOP), 122 Diogo de Vasconcelos, Ouro Preto, MG, 35400-000, Brazil*

[2]*Computing Department, Federal University of Ouro Preto (UFOP), 122 Diogo de Vasconcelos, Ouro Preto, MG, 35400-000, Brazil*

[3]*Vale Institute of Technology (ITV), 31 Juscelino Kubitschek, Ouro Preto, MG, 35400-000, Brazil*

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Abstract: Continuous belt monitoring is of utmost importance since wears on its surface can develop into tears and even rupture. It can causes the interruption of the conveyor, and consequently, loss of capital, or even worse, serious or fatal accidents. This paper proposes a laser-based machine vision method for detecting defects in conveyor belts to solve the monitoring problem. The approach transforms an image of a laser line into a one-dimensional signal, then analyzes it to detect defects, considering that variations in this signal are caused by defects/imperfections on the belt surface. Differently from previous works, the proposed method can identify a defect through a 2D reconstruction of it. The results reveal that the proposed method was capable to detect superficial imperfections in simulated conveyor belt experiments, achieving high values in metrics such as precision and recall.

1 INTRODUCTION

Conveyor belt has been developed and used for decades as an essential part of transportation processes (Pang and Lodewijks, 2005), it can be cited as the most cost-effective equipment for the continuous transport of large amounts of material due to their high efficiency, large capacity, relatively simple construction, and less maintenance required (Fedorko et al., 2014; fu Hou and rui Meng, 2008). A problem found in traditional monitoring systems for conveyor belt is operator dependence. At the same time, rollers and pulleys can only be monitored while they are running. On the other hand, conveyor belts can only be observed when they are not in operation. Also, it is often difficult to define whether a malfunction was caused by the conveyor's operation or by the act of taking the sample when there is a need for a destructive test on the belt (Fedorko et al., 2018).

Conveyor belts are prone to failures, such as: wear on the surface, degradation due to weathering, damage to the ends and longitudinal and perpendicular tears in sections of the belt, misalignment of the belt during operation, overheating of the rollers, among others, causing production risk (Yang et al., 2014). Failures in such equipment systems generally result in a production stoppage for repair, or in more serious cases, as accidents with workers, resulting in serious consequences to the company.

Traditional defect techniques and instruments usually require physical contact with parts of the conveyor to identify faults, or worst, just identify faults only when they occur, like a tear that crosses the thickness of the belt, causing material leaking. An example is a mechanical sensor as a misalignment sensors, which are composed of position switches that trigger an alarm when in contact with the misaligned belt. Depending on the severity of the misalignment, stop the conveyor operation.

There are some sophisticated techniques for monitoring conveyor belt components such as systems based in RFID sensors (Pang and Lodewijks, 2006), magnetic sensors (Nicolay et al., 2004), X-rays sen-

[a] https://orcid.org/0000-0001-7255-5708
[b] https://orcid.org/0000-0002-2809-7778
[c] https://orcid.org/0000-0002-8961-5313
[d] https://orcid.org/0000-0002-5004-4947
[e] https://orcid.org/0000-0002-4182-2540
[f] https://orcid.org/0000-0002-7411-9229
[g] https://orcid.org/0000-0001-5167-1523
[h] https://orcid.org/0000-0001-7949-1188

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sors (Yang et al., 2016) among others. It is notable that these monitoring methods, even though some have a better monitoring capacity than standard methods, need a special construction, with sensors inside the belt, or unusual equipment used in industrial areas, such as an X-ray emitter. Thus, image analysis using computer vision has been a strong candidate for this kind of approach.

This paper aims to present an automatic method based on computer vision, clustering and statistical basic techniques capable of detecting and describe defects in the conveyor belt, as well as rebuild a 2D shape of those identified defects. The proposed method can identify tears, bubbles, and wear on the belt surface. Instead of using regular laser belt surface scanning, this approach uses curvature outlier values of a one-dimensional signal extracted from a laser line's image to represent defects through the belt surface. The major contributions of this work are as follows: a new machine vision approach to detect a defect in conveyor belts using a camera and a laser, interpretability with a 2D shape of those identified defects and recognition of various types of defects, such as bubble, wear and rips.

This paper is organized as follows: Section 2 discusses the techniques used in the literature to deal with the same problem. Section 3 introduces the proposed materials and method. Section 4 presents a short explanation of the database and method evaluation. Section 5 presents the experiments and obtained results. Then, the conclusions and future works are exposed in Section 6.

2 RELATED WORKS

Sophisticated and intelligent techniques that monitor the belt conveyor's status have already been developed. (Nicolay et al., 2004) proposed a system that made use of RFID using *tags* spread over the entire length of the belt, making it or a very long time large between readings or the lack of a *tag* would trigger the tearing alarm on the belt. (Pang and Lodewijks, 2006) proposed using magnets inside the belt and using an external sensor, making it determine the belt conditions such as: operating speed, wear, among others. (Guan et al., 2008) proposed the use of X-rays in conjunction with a receiver so that by observing the attenuation of the signal received by the receiver, the system was able to identify ruptures in the steel webs of the belts. Considering the overheating, (Nascimento et al., 2017) proposed using computer vision in an unmanned aerial vehicle (UAV) for the inspection of rollers through the image of a thermal camera.

(Fromme et al., 2006) proposed a system capable of detecting defects in sections of the belt using data from at least one camera, using a *encoder* to adjust the camera *frames*. (Kurihara et al., 2006) developed an apparatus using a camera and laser to detect tears in conveyor belts by spacing the laser beam in the case of a tear in the belt.

(Li et al., 2011) proposed an intelligent method using characteristics of the binary image of the belt (such as shape, position and size of the identified objects) together with *ANDs* and *ORs* to determine whether or not the belt has tears. (Peng, 2013) proposed using the MDNMS algorithm to identify tears in grayscale images of conveyor belts and developing a method of automatic false positive detection using the classifier AdaBoost.

(Yang et al., 2014) developed an apparatus using a camera focused on a brightly lit area, providing a system capable of identifying tears and misalignment in conveyor belts. (Li and Miao, 2016) proposed using the SSR algorithm to identify slots present in conveyor belts through characteristics of the resulting binary image, such as boundary areas of rectangles of the identified objects, among others

(Yang et al., 2016) proposed to transform the two-dimensional signal obtained by the camera into a one-dimensional vector, and from there, detect the tears in conveyor belts through the difference between the intensities obtained by the one-dimensional vector. (Qiao et al., 2016) proposed using two cameras (infrared and CCD) and a laser beam emitted on the belt, detecting tears through the discontinuity of the laser by the CCD, and the histogram obtained by an infrared camera. (Qiao et al., 2017) used a camera in conjunction with a laser beam emitted on the belt surface to detect tears in conveyor belts, using edge detection and Hough transform.

Although the aforementioned works can identify defects such as longitudinal tears in conveyor belts, there are still few, if any, that can inform any other information or details about other types of defects, such as surface erosion, for example. To inform more about different types of defects detected, such as bubbles and surface erosion, the present work proposes to use a camera focused on a section of the belt where a laser beam is used perpendicular to the direction of movement of the belt, assuming that defects present in the belt profile cause deformations in the shape of the laser captured by the camera, and, capturing these deformations, identify and reconstruct the shape of these defects.

3 MATERIALS AND METHODS

To identify defects covering belt surfaces, the experimental set up used a camera and a laser line out of phase and positioned below the lower belt. A schematic representation is shown in Figure 1. The hypothesis assumes that with this configuration, a laser line on the belt surface can emphasize irregularities present on it, even if not visible to the naked eye. When combined with automatic computer vision techniques, it can automatically detect defects.

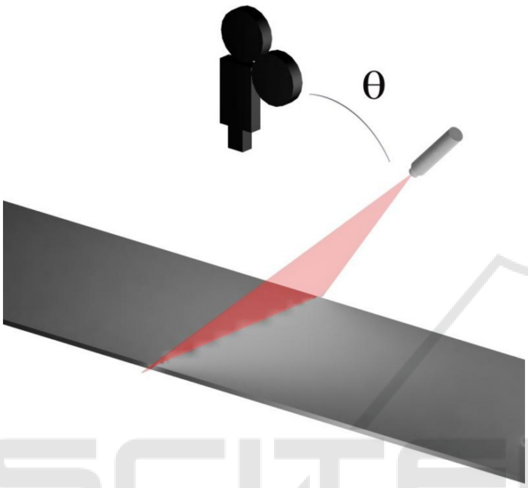


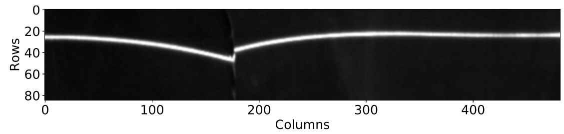
Figure 1: Schematic representation of the experimental setup for image acquisition.

The first step is image acquisition and laser segmentation as an object of interest. Then, the object is transformed into a one-dimensional signal, and its 1D curvature is calculated. The statistical analysis identifies outlier points of curvature, assuming that such points are caused by irregularities on the belt surface, and consequently in the one-dimensional signal. The discrepant points are grouped using an unsupervised algorithm, and a bounding box is drawn around them, a 2D defect representation, the identification itself. The following sections present the description of the proposed method in detail.

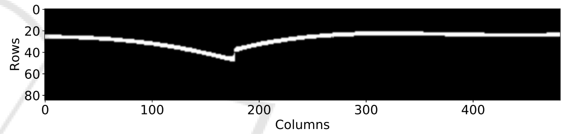
3.1 Laser Segmentation

In this work, the more we save time processing, the better. So, we proposed to simulate a system that could use a monochromatic digital camera with a specter filter. Since we proposed to use a laser, the filter must be at the same specter frequency of the chosen laser. This way, we could achieve the same result of an RGB-Gray color transformation without any computational cost. The result is shown in Figure 2a, a grayscale image with high intensity was the laser is present and low intensity in the remainder of the image.

Bilateral Filter (Elad, 2002), a non-linear filter capable of reducing noises without loss of image information was used. The filtering result is a smooth image without most of the acquired noises, keeping the format of the laser. The bilateral filter has two parameters: spatial (σ) and range (r). The spatial parameter is proportional to the size of the image, and the range parameter is proportional to the amplitude of the edges. After the non-linear smoothing, Otsu's Method (Otsu, 1979) was used to binarize the image, since it has an excellent performance in bimodal images. The result is an image with $0s$ representing foreground and $1s$ for laser line, as shown in Figure 2b.



(a) R-channel of the RGB image



(b) Resulting binary image after preprocessing

Figure 2: Gray and preprocessed image, respectively.

3.2 One-dimensional Signal Transformation

Due to the laser's width, the segmented line has a width as well. Furthermore, as an image is usually toughest to process than a one-dimensional signal, we propose to transform it in a one-dimensional signal named y.

Consider the image denoted by $I(i, j)$, of size $M \times N$, where i and j represents the rows and columns of the image, respectively, being $i = 1$ to M, and $j = 1$ to N. The one-dimensional transformation occurs assigning to each column j of the image I the mean value of all the indices i of each row when $I(i, j) = 1$. Algorithm 3.1 presents the pseudo-code for one-dimensional transformation $y(j)$ with j varying from 1 to N, *i.e.*, image width now representing the length of transformed signal. Figure 3 shows the result of the one-dimensional transformation of the binary image of Figure 2b in a signal y with size N.

3.3 Curvature Calculation

It is well accepted that curvature provides an essential representation of salient shape points, as well as

Algorithm 3.1: One-dimensional transformation.

```
for j = 1 → N do
    m ← 0; cont ← 0;
    for i = 1 → M do
        if I(i, j) ≠ 0 then
            m ← m + i;
            cont ← cont + 1;
        end
    end
    if cont = 0 then
        cont ← 1;
    end
    y(j) = m / cont;
end
```

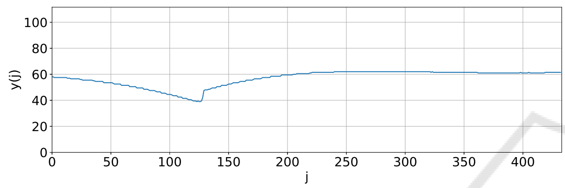


Figure 3: One-dimensional signal.

invariant to rigid-body transformations (Estrozi et al., 2003). Once the one-dimensional signal y was obtained, a numerical curvature κ of it was calculated through Equation 1

$$\kappa = \frac{|y''|}{\sqrt{(1+y'^2)^3}} \tag{1}$$

where y' is the first and y'' the second derivatives of one-dimensional signal. The complete description of numeric curvature calculation is explained in (Xianguo et al., 2018) and (Junior and Costa, 1996).

Figure 4 presents the curvatures κ as function of length of one-dimensional signal y for two different image frames (belt position), where the blue curve represents the calculated curvature in a region with defect and red without one.

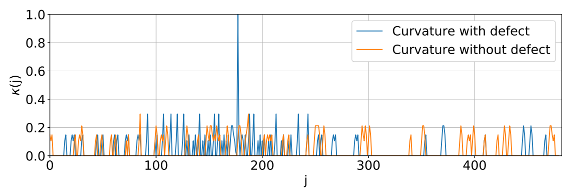


Figure 4: Curvature of the section with (blue) and without (orange) defect.

As shown in Figure 4, both curvatures are very similar, except in the location of the defect, region of the curvature peak in the blue curve. Consequently, the main hypothesis is that outlier curvature values may represent defects at the belt surface.

A closer look at Figure 4 shows that in the regions close to the defect, the curvature values are higher, or an outlier in that exact frame, whereas in the remaining part of the signal, the curvature is relatively similar. We did not use a static threshold value because it is difficult to choose a curvature value for a belt surface representing a defect on it since the same belt may have different surfaces: straight in a location and noisier in another one. Therefore, a curvature point representing a defect in the straight section of the belt may not represent in the noisily. Thus we propose to use outlier curvature points as a descriptor of the defects. In other words, the outlier will represent a curvature value that diverges from an overall pattern on a sample.

In data processing, there are many techniques for outlier detection. In this work, four known statistical techniques were used: Z-Score (Hodge and Austin, 2004), Chauvenet Criterion (Lin and Sherman, 2007), Median Absolute Deviation (MAD) (Leys et al., 2013) and Interquartile Range (IQR) (Jeong et al., 2017). The first two use concepts of mean and standard deviation, whereas the last two use quantile concepts. As every technique has particularities, to use all of them was proposed, and accept an outlier detection only if three of them detect the same point. The detection becomes more robust to noises, as at least one of the two concepts (mean+standard deviation or quantile) can detect the same outliers. Moreover, in data processing, usually, the outliers are removed or replaced in the data. However, in this work, we identify these outliers' index and assign these points as defects.

3.4 Defect Detection

Many frames with defect information in the laser line will be captured depending on the velocity of the conveyor and the size and shape of the defect, so many outlier curvature points can be recognized. These points are allocated into a defect matrix, with the same dimensions *rows*×*columns* of the image, in the correspondent column j that they were found in the signal, but updating the row value in every frame according to the velocity of the conveyor. After the laser passes through a complete defect, the points identified has an approximate shape of the defect, which was defined as the 2D reconstruction of the defect.

The Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm (Ester et al., 1996), which has the capacity of clustering data according to the density of points in a spatial location, makes the defect detection itself. The algorithm analyzes the defect matrix, grouping the nearby points as a single defect. As DBSCAN is an unsupervised machine learning clustering algorithm, it does not need previous training. Also, as it groups points locally, it does not need to know the number of clusters inside the data. Therefore, it makes the defects detection possible, even not knowing the shapes or number of defects present in the belt surface.

4 DEFECTS DATABASE AND METHOD EVALUATION

The core of this work is to propose a method that even with low-cost techniques, should be possible to achieve a good result detecting defects in conveyor belts, so before the implementation of the solution on real conveyor belts, we tested our hypotheses on simulated images. The images samples were illuminated by laser, according to the scheme presented in Figure 1. The database were constructed to simulates the movement of a conveyor belt with defects illuminated by a laser and filmed by a camera, where videos simulating the laser, and the movement of the conveyor were recorded.

4.1 Synthetic Database

The synthetic database was developed using *3D* Studio Max® software. The environment was simulated using a virtual conveyor belt with 4500mm×900mm×20mm. A video simulating the movement of the conveyor was built with 30 seconds of duration and 30 frames per second. To investigate the configurations between camera and laser, many simulations with the same video characteristics were built, as duration and frame rate, but changing the positions of the laser and the camera. The laser was lagged in 30°, 45°, and 60° degrees of the camera, whereas the camera was positioned perpendicular to the belt. Also, the reverse of these configurations was used as well.

To simulate defects, some irregularities (visible and invisible with the naked eye) of many shapes and sizes were inserted randomly in the simulated belt image. The regions with the irregularities are shown in Figure 5. These irregularities intend to describe real defects such as rips, erosion, tears, wears, among others.

4.2 Performance Evaluation

Considering the proposed method for defect detection, its evaluation is based on three known pattern recognition metrics: Precision, Recall, and F1 Score. These metrics measure how good the method's detection was compared with the ground truth of the synthetic database. Precision and recall are metrics useful for measure relevance (Perruchet and Peereman, 2004), since they show the amount of data obtained that are relevant (precision), and the amount of relevant data obtained (recall). The Equations 2 and 3 describe precision and recall, respectively

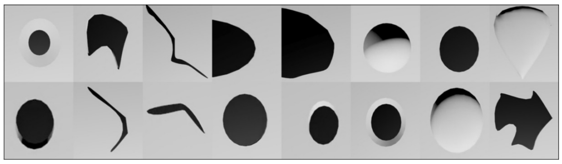


Figure 5: Examples of different irregularities proposed in the simulation.

$$\text{Precision} = \frac{TP}{TP+FP} \tag{2}$$

$$\text{Recall} = \frac{TP}{TP+FN} \tag{3}$$

where TP is the true positive, corresponding to defects that were correctly detected, FP, the false positive, a defect that was detected incorrectly, and FN, the false negative, indicating no detection when it does.

Using precision and recall, we can calculate the F1 Score (Sasaki et al., 2007), which represents the balance between the two metrics, and can be described by Equation 4.

$$F1 = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

5 EXPERIMENTS AND RESULTS

The proposed method was developed in *Python* programming language, running Ubuntu 16.04 64 bits as operational system. All experiments were performed on a DELL Inspiron 15 7559, Intel® Core™ i7 − 6700*HQ* processor with a 2.60*Hz* × 8, SSD 120*Gb*, 16*Gb* RAM.

Tests to obtain the best configuration between laser and camera were performed comparing the results obtained by the method with the ground truth. Table 1 presents the mean values of precision, recall, and F1 achieved by every configuration between camera and laser. The best configuration was obtained with the camera and laser lagged by an angle of 30° (camera perpendicular to the belt).

Using the best configuration, the experiment used the synthetic database presented in Section 4 to obtain

Table 1: Mean results of precision, recall and F1 for defects detection in every configuration.

	Laser 90°			Camera 90°		
Angle	Precision	Recall	F1	Precision	Recall	F1
30°	0.88	0.91	0.89	**0.92**	**0.94**	**0.93**
45°	0.87	0.89	0.88	0.90	0.93	0.91
60°	0.86	0.90	0.88	0.89	0.92	0.90

detection results of defects. The shape, size, and angle of the defects influence how the camera will capture the laser. Figure 6 shows an instant of time t with the laser on two imperfections that exceed the depth of the belt in the simulation, with a lagged entry angle (oblique and acute, depending on the position of the observer/camera) to the belt plane. The laser has a discontinuous shape due to the hole, and its visualization is only possible while it is reflected on the belt.

Figure 6: Simulation in time t.

Figure 7 presents the result of detecting the points of high curvature using the statistical analysis to detect *outliers*. The yellow dots in the image represent the algorithm's identification.

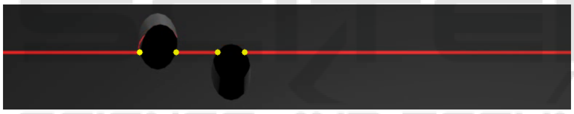


Figure 7: Outlier detection in simulation database.

As previously stated, detecting defects that cross the entire belt profile would be the best case for the proposed method. However, this would clearly be the worst case in a real environment, as it would be a serious defect in the belt. However, even in superficial defects, the algorithm could also detect the defect points, as shown in Figure 8.

The yellow dots describe imperfections on the belt surface due to their high curvature value. These points are allocated in a defect matrix after each *frame*. After the laser's complete passage over any defect, this matrix will have several points capable of describing the $2D$ format of that defect presented in the belt. To identify these points as a grouping of points (*cluster*) describing only one defect at a time, the DBSCAN algorithm was used. Figure 9 shows the defect matrix after the laser has passed through several defects of the simulated database.

Figure 10 shows the clustering result using DBSCAN algorithm in the defect matrix. It can be seen that it could group the defects separately, different bounding boxes, even though the number of defects

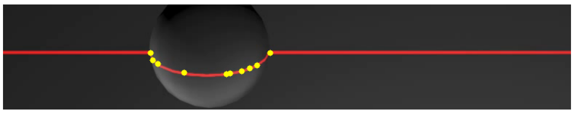


Figure 8: Outlier detection on a superficial defect.

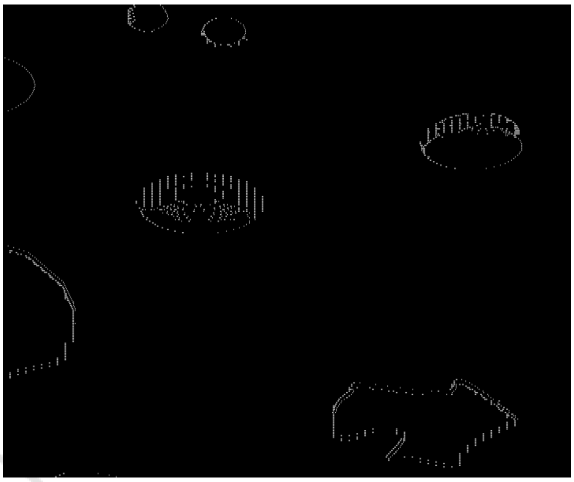


Figure 9: Defect matrix.

present in the matrix has not been entered. Also, we can check the interpretable shape inside the identified bounding box. The algorithm input was a vector composed of the indices (row $\times$ column) of the defect matrix points. However, such input data comprises large and integer values, since they represented pixel indices in an image. Therefore, they have been normalized for better tuning of the algorithm parameters. However, as the DBSCAN *default* parameters have already managed to identify each defect separately, these parameters were then used, which are $r = 0.1$ and $n = 10$.

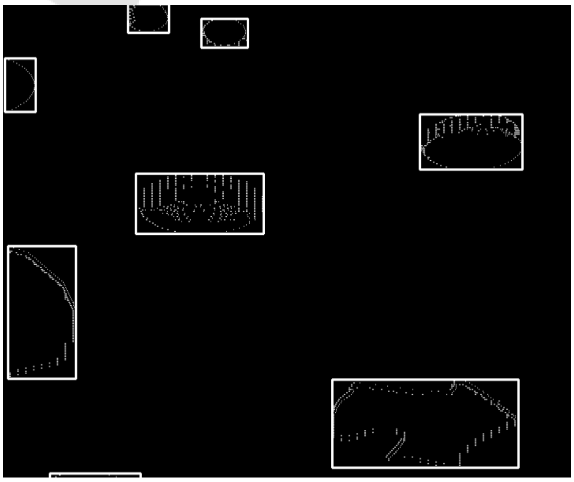


Figure 10: DBSCAN cluster in defect matrix.

Table 2 presents the results of all defect detection in the simulation. The mean precision was 92%, which indicates that the proposed method could capture a high ratio of relevant information for each defect (ratio between TP and FP). The mean recall was 94%, and the mean F1 Score was 91%, indicating that the method has a high rate of discrimination. Furthermore, literature shows that good values or a true detection for F1 are values above 70% (Radau et al., 2009), and for precision and recall, above 60% (GençTav et al., 2012). Thus, we can observe that the method obtained 100% of detection in the simulated environment with these values.

Table 2: Results of defect detection using the proposed technique.

Defect	Precision	Recall	F1
1	0.97	0.91	0.94
2	0.97	0.94	0.96
3	0.86	0.98	0.92
4	0.92	1.00	0.96
5	0.80	0.80	0.80
6	0.93	0.89	0.91
7	0.93	0.97	0.95
8	0.76	0.93	0.84
9	0.92	0.93	0.92
10	0.99	0.89	0.94
11	0.93	0.99	0.96
12	0.90	0.92	0.94
13	0.99	0.98	0.95
14	0.86	0.98	0.92
15	0.98	0.98	0.98
16	0.97	0.95	0.96
mean	0.92	0.94	0.93

6 CONCLUSIONS

The present work proposed a machine vision method for detecting defects in conveyor belts. A synthetic database investigated the best configuration between camera, laser, and belt, as well as the method's detection capacity.

The proposed method achieved a good result in the synthetic environment with a mean precision of 92%, mean recall 94%, and mean F1 score of 93%, indicating that the method has a good performance for the identification of target defects.

The performance shows that it has, in fact, the potential for identifying defects in the real environment of the industry. Moreover, the contribution of the method to the industry is great since the proposal is a remote interpretable monitoring system capable of presenting defects to the maintenance team without the necessity of an operator present at the location of the conveyor, an environment extremely dangerous and conducive to accidents, providing a safe and non-invasive way of monitoring. Also, with the camera calibration, it would be possible to perform a classification only looking at the size of defects, easy defining a threshold to it.

Future work is intended to assemble the equipment in a real operating situation of a conveyor belt to construct a database with a more significant number and variability of real defects. This new database will allow an exhaustive investigation in real situations and critical parameters for detection. All these improvements would be valuable, and once the defect is detected, we can develop models capable of recognizing the type of defect, and even learn how defect evolves. Machine learning techniques may be included in the investigation of the evolution of the defects in such a way as to allow the construction of predictive models that aid in maintenance.

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