Detection of straw default by artificial vision

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Abstract—The aim of our work is the development of a detection method of straw default on the surface of a rolled steel sheet, in order to integrate it into a vision system. Our study is based on a bidimensional classification by two classes. It is divided into three parts: The classification, the detection of the presence of a defect and the recognition of this type of defect.

We simulate the straw default with Matlab. First, we proceeded to a preliminary study to obtain the density functions and the priori probabilities of the sheet and the straw defect, and then we integrated them in the Bayes formula. Such as the histograms of sheet flawless and straw defect have an allure close to the Gaussian distribution, we made a statistical inference from a significant number of samples of these histograms and we estimate the parameters (expectation μ and standard deviation σ) of Normal distribution representatives of these density functions with method of the maximum-likelihood.

Seen that these histograms overlap on a common interval, detecting the presence of a defect based only on the attribute of the intensity of grayscale will be always with a probability of error. It was then necessary to add a second attribute, that of the spatial variability to minimize this error and ensure the reliability of the detection of presence of the defect.

Finally, to optimize the operation of straw defect detection, we introduced geometrical attributes of this defect (elongation criteria, dimensional criteria, criteria specific to the shape and area ratios).

This method will subsequently be implemented in a program using image processing software adapted to a matrix camera.

In conclusion, this work will contribute to early detection of straw defect which will increase the quantity and the quality of the product, prevent the evolution of defects (and therefore the stops of the chain and rejection of the product) and simplify working conditions of the operator.

Keywords: Classification, histogram, attribute, probability, sheet.

I. INTRODUCTION

The aim of our work is the development of a detection method of straw default on the surface of a rolled steel sheet, in order to integrate it into a vision system. [1]

These sheets are obtained from hot-rolled sheet and pass into the cold rolling mill by four main steps: The pickling, rolling, annealing and skin-passing [2]. After the pickling step
the sheet may have defects such as folds, rips and marks of cylinders, or metallurgical defects such as creeks and straws. Appearance defects can also be formed such as claws, cut away, spots of residual calamine, spots of rinsing… etc. These surface defects have different levels of severity, according to their influence on the rolling mill, the production and the functions to which they are intended. If these defects are not detected in time, they will evolve during rolling and the other process steps. The combination of thermal, metallurgical and mechanical factors will amplify the defect by its lengthening, increasing its depth, its transformation into a more harmful default, its propagation… etc. The evolution of these defects can cause the deterioration of mill rolls, the break of the steel strip and many other problems [3]. These incidents involve stopping production for a period ranging from several hours to several days. The engendered damage and decreased productivity directly drive to financial losses.

We opted for a detection method based on a bidimensional classification by two classes.

To optimize the operation of straw defect detection, we introduced geometrical attributes of this defect (elongation criteria, dimensional criteria, criteria specific to the shape and area ratios).

The paper is organized as follows. The next section presents the mathematical tools used in our work and details our detection method of surface defects [4]. Histograms of images of sheet with and without straw defect the calculation of grayscale field of three classes and the approximation to the normal distribution are considered in Section 3. We will specify the essential points of our study in Section 4. Finally, we will give the conclusion in section 5.

II. METHODOLOGIE

II.1 CHOICE OF CLASSIFICATION ATTRIBUTES
Classification is an image segmentation operation obtained by comparing the gray levels to a threshold. In our case, we have segmented the image into two classes: Class of straw default and of perfect plate. Our classification is two-dimensional because we used a second attribute, that of spatial variability. It consists in measuring the dispersion of the gray levels in the immediate vicinity of each point image. This attribute will classify the pixels of the intersection of two classes.

II.2 MATHEMATICS TOOLS
Our detection method implements mathematical tools that we will present firstly.

II.2.a STATISTICAL INFEREN CE
Statistical inference is a set of methods that allow making reliable conclusions from data of statistical samples. It consists in inducing the unknown characteristics of a population from a sample taken from this population. The characteristics of the sample, once known reflect with a certain margin of possible error those of the population. Indeed, statistical inference is used to estimate population parameters using sample's observed data. The values of the parameters will be close to the real values if the sample is great.

II.2.b THE ESTIMATOR
In mathematics, an estimator is a statistic for evaluating an unknown parameter relating to a probability distribution. From the parameters obtained on the sample we want to estimate the parameters of the population from which the sample is extracted. The techniques of descriptive statistics, such as histogram allow making hypotheses about the nature of the probability distribution that follow these xi sample data. So it comes to giving, in view of observations xi, an approximation or an evaluation of the different parameters of a mathematical law that we hope as close as possible to real parameters.

II.2.c ESTIMATION METHODS
The more usual methods of estimation are the method of moments, and the method of the maximum likelihood. To estimate a parameter θ we have only the data x1…. xn of a sample and therefore the estimation of θ will be realized based on these observations.
II.2.d PROBABILITY DISTRIBUTION

Probability distributions are used to represent the observed phenomenon. A probability distribution, known a priori is supposed to model the retrieved data. Statistical tests are then carried to confirm or refute the concordance of the probability distribution to the data. In many areas, the methods have evolved and best probability distributions were created to better match to the posed problem. The probability distributions have long been and are used for modeling systems in different domains. Probability distributions the most used in the approximation of the parameters are normal distribution, the Poisson distribution, the Student distribution, the binomial distribution, the gamma distribution and the F-distribution.

II.2.e BAYES‘THEOREM

Classification is a process that associates an observation to a class by an appurtenance test. In image processing, the Bayes‘ theorem is widely used for classification problems. Indeed, it allows calculating appurtenance probability of pixel of an image to a defined class. We recall the Bayes rule [5]:

\[ P(C_q/x) = \frac{P(x/C_q) * P(C_q)}{P(x)} \]

With \[ P(x) = \sum_{q=1}^{n} P(x/C_q) * P(C_q) \] and

C_q: Defined class in image.

x : Chosen attribute for the classification (pixels in our case).
n : Number of classes.
P(C_q/x): Appurtenance probability of pixel to the C_q class.
P(C_q) : Priori Probability of the C_q class.

II.3.a CLASSIFICATION

We opted for the two-dimensional classification in two classes. We chose two attributes of the gray level and spatial variability. We used the first attribute in a statistical approach based on the Bayesian philosophy. For this, we first evaluated the priori probabilities \( P(C_{stw}) \) and \( P(C_{sh}) \) of the two classes (straw and sheet). Then we realized the histograms of simulated images of the sheet without surface defects and with straw defect. We noticed that these histograms have a shape close to normal distribution which allowed us to approximate it to this distribution by performing a statistical inference. We obtained two normal distributions \( P(C_{stw}/x) \) and \( P(C_{sh}/x) \) which correspond to the occurrence probabilities of pixels to classes 'straw' and 'sheet'. We can thus calculate the probability that a pixel characterized by the value of its gray level belongs to the class of 'sheet' or one of defects. We can thus calculate the probability that a pixel characterized by the value of its gray level belongs to the class of 'sheet' or straw defect and this by calculating its appurtenance probability to each class. In the case of straw defect, upon the acquisition of the sheet image we are reading the gray level of each pixel, we calculate its appurtenance probability to class 'sheet' \( P(C_{sh}/x) \) and class 'straw' \( P(C_{stw}/x) \) and we apply following decision rule:

The pixel belongs to the class 'sheet'

If \( P(C_{sh}/x) > P(C_{stw}/x) \)

And the pixel belongs to the class 'crack'

If \( P(C_{stw}/x) > P(C_{sh}/x) \)

Also, since histograms of the sheet and straw default overlap we introduced the attribute of the spatial variability which consists in verifying the 24 nearest pixels to the pixel considered as belonging to the class 'straw'. If 80% of these pixels belong to the class 'straw' then the pixel will be confirmed as belonging to the default 'straw' and not to the
sheet. At this step we realized the classification of the acquired image pixels.

II.3.b DETECTION THE PRESENCE OF A DEFAULT

For detecting the presence of a defect, we calculated the ratio \( r = N_{stw} / N_{sh} \) that determines the presence of a defect for the condition: \( r > 0.01 \).

With \( N_{sh} \): Number of pixels representing the sheet.

\( N_{stw} \): Number of pixels representing the straw defect

**II.3.c RECOGNITION OF TYPE OF DEFECT**

Recognition of type of defect was based on geometric characteristics of straw defect. The straw has longitudinal and narrow shape substantially parallel to the ingot surface and composed of oxides and scoria. If we detect a part of a line of pixels corresponding to the class of the straw, we proceed to verification the neighboring parts of lines to this line. If the predefined number of these lines belongs to the class 'straw' then we can say that the defect is a straw.

**III. EXPERIMENTAL STUDY**

With Matlab we simulated images of the sheet without defects, and with straw defect(Figures 1, 2).

We evaluated a priori probabilities \( P(C_{stw}) \) and \( P(C_{sh}) \) which represent respectively proportions of classes of straw defect and sheet metal in the image, then we obtained

\[
P(C_{stw}) = 0.01 \quad \text{and} \quad P(C_{sh}) = 0.99.
\]

We delimited two zones corresponding to these classes(Figure 3) and realized their histograms (Figure 4,5).
We calculated fields grayscale of each class with a program developed with Matlab. The results are in Table 1.

By using the method of maximum likelihood[6], we made a statistical inference on these histograms to approximate them to normal distributions. We recall the function of the normal distribution:

$$f(x) = \frac{1}{\sigma \sqrt{2\pi}} e^{-\frac{1}{2} \left( \frac{x - m}{\sigma} \right)^2}$$

We used the values of grayscale fields of each class to estimate the parameters (mean $m$ and standard deviation $\sigma$) of each normal distribution. We noted the results in Table 2.

$$m = \frac{1}{n} \sum_{i=gray_1}^{gray_n} x_i$$

$$\sigma = \sqrt{\frac{1}{n-1} \sum_{i=gray_1}^{gray_n} (x_i - m)^2}$$

With

- $x_i$: Grayscale.
- $gray_1$: lower limit of the field of Grayscale.
- $gray_n$: Upper limit of the field of Grayscale.

### Table 1. Grayscale field of each class.

<table>
<thead>
<tr>
<th>Class</th>
<th>Grayscale field</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sheet without defects</td>
<td>[70,184]</td>
</tr>
<tr>
<td>Straw defect</td>
<td>[166,217]</td>
</tr>
</tbody>
</table>

### Table 2. Values of mean $m$ and standard deviation $\sigma$

<table>
<thead>
<tr>
<th>Class</th>
<th>$m$</th>
<th>$\sigma$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sheet without defects</td>
<td>127</td>
<td>33.3417</td>
</tr>
<tr>
<td>Straw defect</td>
<td>191.5</td>
<td>15.1548</td>
</tr>
</tbody>
</table>
IV. RESULTS AND DISCUSSIONS

We have developed a method for detecting straw defect on cold rolled sheets. We opted for a detection method based on a statistical approach using essentially the Bayesian philosophy seconded by specific criteria of detection and carefully selected attributes. Such as our work is based on reading grayscale of the studied images, it is imperative to strictly realize histograms of the three classes [7]. The calculation of the fields of grayscale of each class must be made meticulously because the step of classification of images depends on it directly. Also, prior probabilities must be fixed after a detailed inspection of the real state of each surface defect. The geometric attributes are key factors in the detection of the straw defect and the preliminary study of the shape of defect is crucial because it allows having etalons of comparison for the deduction of the type of defect.

V. CONCLUSION

In this work we presented a method for detecting surface defects on cold-rolled sheet in order to integrate it into a machine vision system. Indeed, the surface defects on cold rolled sheets have different levels of severity, according to their influence on the rolling mill, the production and the functions to which they are intended. If these faults are not detected in time, they will evolve during rolling and the other process steps. The combination of thermal, metallurgical and mechanical factors will amplify the default by its lengthening, increasing its depth, its transformation into a more harmful default, its propagation… etc. The evolution of these defects can cause the deterioration of mill rolls, the break of the steel strip and many other problems. These incidents involve stopping production for a period ranging from several hours to several days. The engendered damage and decreased productivity directly drive to financial losses. In conclusion, this work will increase the quantity and the quality of the product, prevent the evolution of straw defect (and therefore the stops of the chain), simplify working conditions of the operator and it allow the optimization of the sheet rolling process thanks to early detection of surface defects. We plan to extend this study to all major surfaces defects that occur on a rolling line and implement it in an artificial vision system.

REFERENCES