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Auteur correspondant : urasm_mz@yahoo.com

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Identification approaches for steel strip surface defects in hot rolling Process

MENTOURI Zoheir [a,b,*], MOUSSAOUI Abdelkrim[c], BOUDJEHEM Djalil [a], BOUDIAF Adel[b], ZIANI Slimane[b]

[a]*Laboratory of Advanced Control (LABCAV), University of May 8th 1945, Guelma, Algeria*
[b]*Research Center in Industrial Technologies (CRTI), BP64, Chéraga 16014, Algiers, Algeria*
[c]*Laboratory of Electrical Engineering (LGEG), University of May 8th 1945, Guelma, Algeria*

Abstract

In steel manufacturing process, flat products are greatly concerned with the surface quality and the possibilities of its on-line inspection. The visual control is obviously unable to continuously check the surface of the moving product, and the control at the ending stage remains not suitable although, it may provide information about process trends and parameters history. So, strip surface defects that are not detected yield to product downgrading or to costly rework operations for producer and/or end users. With such needed quality level, steel surface inspection systems are more and more implemented for detecting defects and allowing correction at appropriate time. Based on Computer vision, these applications make a use of detection and classification algorithms to identify these arising defects. The present work is related to a Project of a scientific and economic impact: The Development of an on-line inspection system for strip surface defects identification during the thermo-mechanical treatment in hot rolling process. We asses, in this work, some approaches in labeling each of the defects belonging to a database created for this aim. This Dataset is compound of five, among the most frequent, surface defect types and with 108 variants of each one. Obtained results shown the importance of the choice of a relevant image features extractor.

Keywords: Computer vision, Detection & Classification, Rolling process, Quality & Surface defects

1. General issue

In steel industry, the ongoing objective is the control of parameters at all stages of the process, for providing a product with the required material grade, homogeneity, geometry and even the surface characteristics. In fact, any non-compliance of the product with requirements may lead to needless additional expenses caused by the product downgrading or its rejection and in the worst case, by the disturbance of the production. As in steel strips manufacturing, the surface condition is an important quality indicator and producing strips with a free-defect surface is, still, a major challenge owing to the random occurrence, the complexity and the variety of such defects.

2. Introduction

The ever-increasing need of surface quality of flat products and particularly steel strip pushed producers and developers to implement computer vision based automatic inspection systems; to identify, on-line, the occurring defects and to apply, in time, the appropriate corrections of the rolling process. These systems should meet all requirements in terms of speed, accuracy and reliability and are, generally, based on detection and classification algorithms, where the extracted image properties should be, enough, class-discriminant to ease the defects categorization.

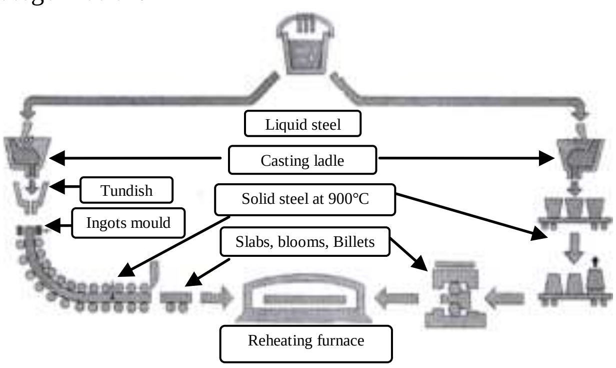

Figure 1: General scheme of steel making process

Published research works showed that for many categories of steel surfaces, different features extractors dealing with spatial or frequency domains and statistical analysis combined with some classifiers were successfully applied, as mentioned in the survey studies on defects detection and classification [1, 2]. As cited in the first reference, in some works a background difference with a region growing techniques or the co-occurrence matrix [3, 4] were used in detection of four to five hot or cold rolled strip defects and obtained interesting identification results. Whereas those based on the frequency domain as the FFT or the spatial-frequency analysis as Gabor, wavelet and Haar used with different adaptive learning methods SVM, NN-BP, SOM or LVQ allowed reaching classification rates exceeding 90% in strips, thick plates and slabs defect categorization.

It is worth of mentioning, that surface defects in hot rolling process are of a random occurrence and characteristics. Thus, there is not a standard method that could be used for the detection and classification of all defects, whatever may be their size, position or orientation and that is, what may explain the wide range of implemented techniques which depend of needs and application specificities. For instance, to classify seven steel sheet defects, a Convolutional Neurol Network approach, where the classifier and a feature vector were learnt simultaneously, was applied and considered as efficient [5]. Or the study, that used an improved SVM variant and combined it with a binary tree to classify defects, from a large-scale and sparse dataset [6].

In fact, the classification efficiency is increased with a prior suitable features extraction operation. Many studies dealt more with this aspect. As in [7], a simple approach based on human inspectors to characterize defects used some heuristics; such as viewing scratch as sharp edges with almost white pixels or Dents as areas with extreme gray values. Extracted features enabled a binary-defective or free-defect- classification with the means of SVM. Furthermore, images features are more highlighted with the use of filtering operations. As with Gabor filtering, numerous studies used this pixels-neighborhood based transformation technique for defect detection of different steel products. In [8] Gabor filtering was employed with an adaptive double threshold method to detect seem cracks defects in plates, and for other various defect types as scabs, scratches, and roller marks on the surface of thick plates a dual switching lighting method was used to help in increasing the efficiency of a Gabor filters application [9]. The method allowed a good detection of the three lumpy defects. Further, in more recent work enhanced Gabor filters application resulted in some accuracy and speed improvements in detecting spots and scratch of metal surfaces [10].

The work we are presenting is related to the development of an on-line inspection system for strip surface defects identification during the hot rolling process. The paper starts with presenting the general issue and introduces research works in this field. In the next section an overview is given about steel surface defects followed by a description of some applied techniques. In the section five, the experimental study introduces the used surface defects database, as well as the scheme adopted in extracting image features and classification. Results are presented in section six followed by a conclusion to end the paper.

3. Strip surface defects overview

In hot rolling process, the strip being shaped, may exhibit some surface defects of which the origin may be some internal discontinuities of the input product or the transformation of the material in the process itself. Among the most frequent surface defects, there are : Patches : A surface with oxide not completely removed by a faulty pickling process; Rolled-in-scale : a scale partially rolled into the surface of the sheet; Inclusions : non-metallic particles that shows through at the surface of the steel, Scratches: sharp indentation in the surface caused by a machine; Cracks : slight material damage with lines appearing on the surface resulting from a temperature difference between material regions; Holes : Inner skin-hole formed during casting process and after being elongated during the subsequent rolling operation. These types of defects represent an example of the numerous and complex defects that may seriously affect the product quality.

4. Features extraction methods and data reduction

4.1. Principal Component Analysis

The purpose of PCA is to reduce the large dimensionality of the data space (observed variables) to the smaller features space (independent variables), which are needed to describe the data economically. The process is as follows:

For the 2D defect images, represented by M image matrices (m, n), each one is transformed to a 1-D long thin vector by concatenation (m×n, 1), and centered by subtracting the mean of the M images ψ from each image vector,

$$\Psi = \frac{1}{M}\sum_{i=1}^{M} \Gamma_i \quad (1)$$

$$\Phi = \Gamma_i - \Psi \quad (2)$$

The covariance matrix C is computed by:

$$C = \sum_{i=1}^{M} \Phi_i . \Phi^T = A.A^T \text{ , } A = [\Phi_1 , \Phi_2, \ldots \Phi_M] \quad (3)$$

The resulting covariance matrix is of high dimension and not practical to compute directly, with it, the eigenvectors. The solution applied is to compute e_i and λ_i respectively the eigenvectors and eigenvalues by:

$$\begin{cases} e_i = A.v_i \\ \lambda_i = \mu_i \end{cases} \quad (4)$$

where ν_i and μ_i are respectively the eigenvectors and eigenvalues of $L = A^T.A$;

The eigenvectors are sorted in a decreasing order corresponding to their eigenvalues. The eigenvector associated with the largest eigenvalue is the one that reflects the greatest variance in the image. With the selected eigenvectors a new smaller sub-space is created and images are projected onto the new computed space of dimension M'<< M, $\Omega^T=[\omega_1 , \omega_2 , . , \omega_{M'}]$, as follows:

$$\omega_k = e_k^T(\Gamma_i - \Psi) \text{ , with } k=1, M' \quad (5)$$

A distance is computed to find to which class belongs an image. The following, expresses the Euclidian distance.

$$\varepsilon_k^2 = \|\Omega - \Omega_k\|^2 \quad (6)$$

Where Ω_k represents the k^{th} class,

4.2. Linear Discriminant Analysis

This method is known for its maximization of a ratio of the between-class variance to the within-class variance in any particular data, guaranteeing maximal class-separability. It uses the two representative matrices: the between-class scattering matrix and the within-class scattering matrix. For a multi-class set, data are organized to compute the following:

Compute the within-class scatter matrix Sw with:

$$S_w = \sum_{i=1}^{c}\sum_{\Gamma_{k\in c_i}}^{q_i}(\Gamma_k - \Psi_{c_i}).(\Gamma_k - \Psi_{c_i})^T \quad (7)$$

Compute between-class scatter matrix S_b with:

$$S_b = \sum_{i=1}^{c}(\Psi_{c_i} - \Psi).(\Psi_{c_i} - \Psi)^T \quad (8)$$

where ψ: overall mean of the data classes, q_i: image number in class c_i , Γ_k : k^{th} sample in the class c_i , Ψc_i : mean image in class c_i , c : number of classes.

Find the W that optimizes the Fisher criterion argmax(J(T)), [10] , by resolving the equation :

$$S_b W= \lambda_w S_w W \quad (9)$$

Project all processed images with:

$$P(\Phi_k) = W^T.\Phi_k \quad (10)$$

where Φ_k is a learning or test image,

Finally, compute the matching distance as with the previous method

4.3. Gabor filters

Gabor filters have been widely used in image processing. These linear filters, of which the operation is close to human visual treatments, have the advantage of being customizable in frequency and orientation and are obtained from the modulation of a sinusoidal function by a Gaussian envelope. A Gabor filter represents the best compromise between frequency and spatial localizations.

Used for image application, the 2D general function is the complex response, defined by the Equation11 [11].

$$\Psi_{\mu,\nu}(x,y) = e^{\left(\frac{x'^2+\gamma^2 y'^2}{2\sigma^2}\right)}.e^{j\left(\frac{2\pi}{\lambda}x'+\varphi\right)} \quad (11)$$

where the coefficients μ and ν determine respectively the number of filter orientations and scales of the filters bank, λ is the wavelength of the sinusoidal factor, θ is the orientation of the normal to the parallel stripes of Gabor function, φ is the phase offset , σ. is the standard deviation of the Gaussian envelope and γ is the spatial ratio.

The real part is defined by:

$$R_{\mu,\nu}(x,y) = e^{\left(\frac{x'^2+\gamma^2 y'^2}{2\sigma^2}\right)} cos\left(\frac{2\pi}{\lambda}x' + \varphi\right) \quad (12)$$

The imaginary part by:

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$$I_{\mu,\nu}(x,y) = e^{\left(\frac{x'^2+\gamma^2 y'^2}{2\sigma^2}\right)} sin\left(\frac{2\pi}{\lambda}x' + \varphi\right) \quad (13)$$

with :

$$\begin{cases} x' = x.\cos(\theta) + y.\sin(\theta) \\ y' = -x.\sin(\theta) + y.\cos(\theta) \end{cases} \quad (14)$$

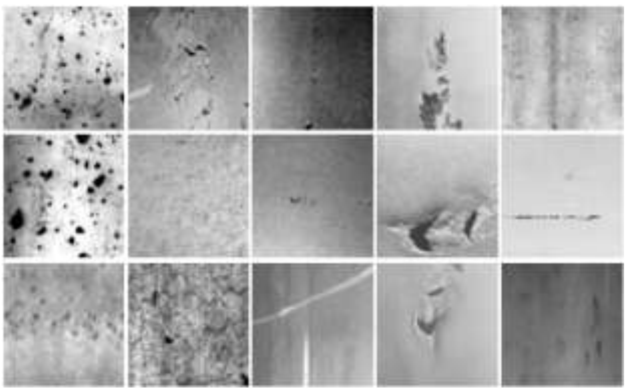
The Scale and orientation are the two most important parameters. For a given tuned values of these parameters, a bank of μxν Gabor filters is obtained by the above equations. Filtered responses are obtained by the convolution of Gabor filters with each defect image input Γ_i (x, y) by:

$$R_i(x, y, \mu, \nu) = \Gamma_i(x, y) * \Psi_{\mu,\nu}(x, y) \quad (15)$$

5. Experimental study

5.1. Surface defects database

Typically, the surface defects are countless, of a random occurrence and of different size, position and orientation. Moreover, on the product surface, the arising defects may be, as showed in figure 2, localized with a compact appearance and relatively clear edges as holes and scratches or scattered while affecting the whole surface such as rolled-in-scale or cracks



Scales Cracks Scratches Holes Inclusions

Figure 2: Samples of surface defects of hot rolled steel

For applying our approaches, a defect database is created with defect images collected from a steel hot rolling production line, of which samples are presented in the figure above.

Compound of some, of the most frequent, defects in this process; this set has been extended to introduce more property variabilites of the defect types. Thus, with [200×200] sized images, the dataset counts five defect-types; with 108 variants of each one.

5.2. General scheme and features extraction methods

As mentioned above, numerous classification methods are used in defect categorization. In this work two approach types are assessed. The holistic matching algorithm with which the variance based features are extracted from the whole image and the second approach that extract local features from image regions to match them or their statistical properties in the classification stage. The general scheme is presented in figure 3

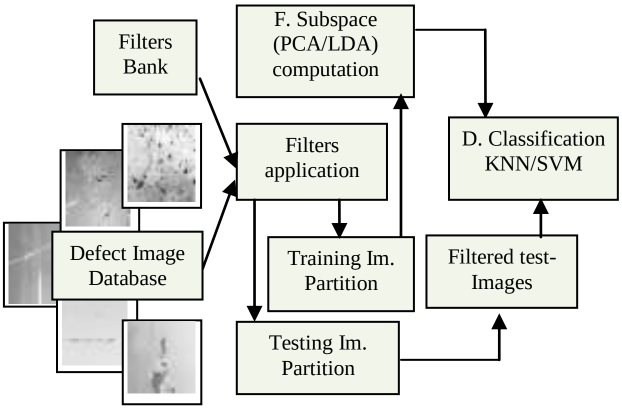


Figure 3: General Scheme of Defects identification

The main tasks in the general implementation scheme are filtering operation, data reduction and the matching of features distance for defects labeling.

With the use of the PCA method, which is known for its class variations description, even though, without, being efficient in class distinction and the LDA method which is, rather, oriented class discrimination, the scheme followed is the one that addresses the shortcomings of the two methods, as applied in [12].

Thus, with the use of these holistic based approaches, a training set is composed by randomly chosen vectors from all defect classes to which, the PCA method is pre-applied, as well as, a whitening operation of the resulting data. What yields to a PCA sub-space with an adopted reduction level around 80% of the computed eigenvectors. The LDA procedure application comes in the second step. It uses the projections into the PCA subspace of the scatter matrices computed in (7, 8) to compute the final model. The obtained new LDA subspace is used to project the testing partition images, providing, thus, features of the original images defects.

As for the use of local based method, a prior Gabor filtering operation is carried out before the data partitioning step. Each image is convolved to the filters of the created bank. Filters parameters are set to the optimal values 8, 5 and 64 respectively the orientation, scale and down-sampling coefficients. Then for each image, there are $\nu.\mu$ corresponding responses, and the magnitude of each response is computed with the use of its two real and imaginary parts. These pixels transformations provide a more relevant data, used as input for subsequent operations PCA/LDA.

5.3. Used classifiers

In the classification step, distance similarities are computed to label all defects of the transformed test dataset. This task is performed with the two commonly used techniques. The non-parametric K-nearest neighbor classifier (with K=3), based on the Euclidian matching distance and the supervised learning machine algorithm: multi-class SVM, with a radial basis kernel function (Rbf).

6. Results

With the introduction of some defect variabilities in size, position, orientation and even illumination effects, we created more constraints to identify the surface defects, and then better assess the applied combination of features extractor with different classifiers.

The table below, shows, for each method, the average of its 100 identification scores, obtained for each one with randomly chosen training and testing sets. The standard deviation corresponding to each average is presented to show the results spread and give an idea about the methods robustness.

Table 1:
Surface defects identification rates

F. Extractor	Classifier	Results (%)
PCA	KNN	50.13 ±0.02
PCA	SVM	43.11 ±0.02
Gabor_PCA	KNN	81.70 ± 0.03
Gabor_PCA	SVM	50.35 ± 0.02
PCA/LDA	KNN	70.76 ± 0.03
PCA/LDA	SVM	48.84 ± 0.03
Gabor_LDA	KNN	78.14 ± 0.03
Gabor_LDA	SVM	68.28 ±0.06

With an average around 80%, the methods based on the use of a prior filtering operation outperform the others. Moreover KNN is more relevant for this multi-class identification in terms of results improvement and computational cost comparing to SVM.

The performance curves in the figure 4 show that the method based on a prior Gabor filtering operation used with the LDA and KNN classifier, outperforms all the other methods whatever is the size of the selected training set, even though the curve shows at 50% of size of the training set, a higher Gabor_PCA score. As the training set is randomly chosen, this case may be explained by identification errors caused by training images that present too much binding conditions in illumination. Indeed, in such industrial application the Lighting intensity and quality should be maintained higher than a critical level.

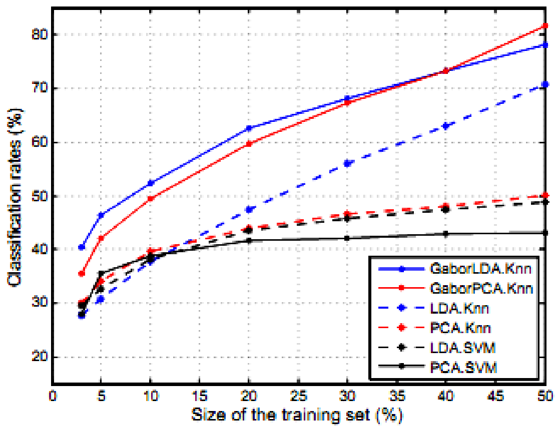


Figure 4: Averages of defect identification rates

7. Conclusion :

Defects identification is a complex task and an important challenge in steel industry. It still attracts researchers to develop novel approaches, or make innovation that may improve performance level in terms of features extraction, classification accuracy and computing coasts. The work in this paper is related to a development project of hot rolled steel strips inspection. We assessed some methods in labeling defects of a created database from a local industrial production line.

The study revealed that a prior filtering operation improves considerably the identification rates. The future work would be concerned with the application of more relevant features extractor and the optimization of the different parameters to reach the more suitable combination of techniques for defect types identification that occur in the concerned production line, as well as the extension of the application to other cold rolled products or slabs.

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