Detection and classification of steel defects using machine vision and SVM classifier

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Abstract— **the importance of quality control of steel products is increasing day by day in the manufacturing industrial systems because it offers the possibility of knowing the state of the products without stopping the production line which allows the control of a defect before it becomes a complex problem and avoiding production losses. Human quality control of steel products remains tedious, fatiguing, bit fast, bit robust, dangerous or impossible, therefore the use of automated vision system can significantly improve the quality inspection process, because the machine vision technology can overcomes the majority of manual inspection problems cited above and provide an interesting solution especially, with the impressive increasing of computing power of today's computers and the good quality of images that offer the current cameras.**

The main objective of this research is to propose an efficient control system based on machine vision technology and SVM classifier to classify different types of steel defects.

Keywords—Defects steel; machine vision; pattern recognition; HOG; GLCM; SVM classifier.

I. INTRODUCTION

Human steel inspection systems are really incapable to ensure good quality of steel products with a reasonable consuming of time and costs. Therefore, many automatic steel products inspection techniques were generated to meet the growing customer demands and minimize the economic losses: for instance, infrared ray, X-ray image processing, strobe light, ultrasonic inspection technology, eddy currents, magnetic leakage flux, conoscopic holography and industrial vision technology. This study focuses on the automated inspection of steel products by using artificial vision and machine learning techniques. Fig. 1 shows a general structure of control system of steel strip based on machine vision technology.

In the literature, many systems have been proposed with varying degrees of success. Surveys on several techniques for steel products inspection can be found in [1].

A novel intelligent non-contact inspection technique based on machine learning using deep auto-encoder Networks is presented in [2].

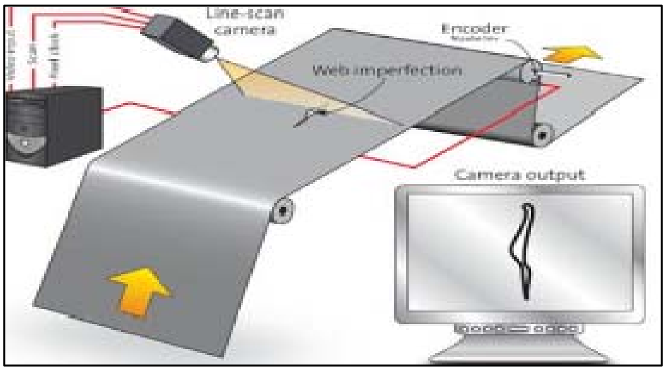

Fig.1. Detection system of steel strip defects based on machine vision.

Where it processes directly on the raw data and automatically provides accurate results without any feature extraction phase. Furthermore, a system based on supervised artificial neural networks and two statistical features as histogram and edge detection was introduced.

Luiz A. O. Martins proposed an automated inspection system to detect and classify rolled steel defects based on artificial neural network and using a Hough Transform as features extractor [3]. T. Ramesh presents a simple and efficient method for metal defects detection and classification using artificial neural network classifier and based on three distinct features extraction methods, such as, Gray scale features, Gray scale co-occurrence, and Geometric features [4]. A metal inspection system based on industrial vision technology has been introduced in [5]. The proposed approach is based on morphology and genetic algorithms, which is employed to find the optimal morphology processing parameters such as structuring elements and defect segmentation threshold. Another approach based on morphology and neural network is proposed by M.R. Yazdchi[6], to detect and classify five famous defects of cold rolling mill steel. A special substractive method is used to enhance the acquired image and the position of defects was determined using Local entropy and morphology.

Then, a neural network classifies these defects based on statistical features extracted from the region of defect.

Based on machine vision technology, this paper presents a reliable and efficient control system to classify six famous different types of defects in steel products such as: crazing (Cr), patches (Pa), pitted surface (PS), inclusion (In), rolled-in scale (RS), and scratches (Sc).

The main steps involved in the proposed steel products inspection system are summarized in Fig. 2 while each of these steps is discussed in detail in the following sections.

II. ACQUISITION

In order to evaluated the performance of the proposed system to classify hot-rolled steel defects. A series of experiments are conducted on the NEU surface defect database [7]. This database comprise 1800 gray scale images, with the original resolution of each image is 200 × 200, 300 samples each of six different classes of typical surface defects such as: crazing (Cr), patches (Pa), pitted surface (PS), inclusion (In), rolled-in scale (RS), and scratches (Sc).Sample images of six classes of typical surface defects are illustrated in Fig. 3.

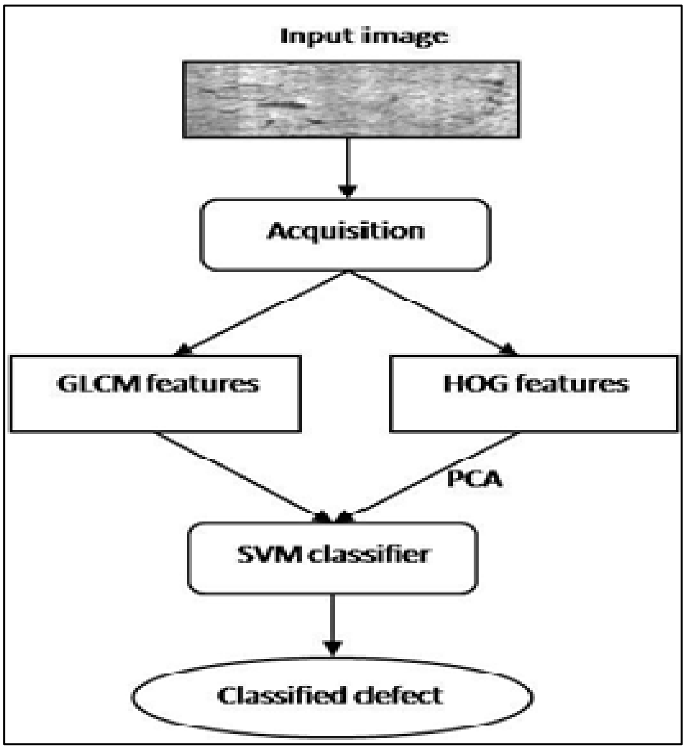

Fig. 2. Block diagram of the proposed system.

III. FEATURE EXTRACTION

Feature extraction is one of the most important components of any pattern recognition system, while its major task is to find an appropriate representation of the pattern under study [8]. There is several feature extraction techniques, and the most suitable ones of them are generally found experimentally. In this study, two feature extraction methods were used Histogram of oriented gradients and Gray Level Co-occurrence Matrix.

A. Histogram of oriented gradients (HOG)

Histogram of Oriented Gradients (HOG) is a gradient based feature descriptor that was first proposed by Dalal&Triggs in the human detection framework [9]. HOG has been widely used in pedestrian detection and has shown great success in other various computer vision applications. The basic idea of this descriptor is to represent the appearance and shape of an object in an image by the way in which the intensity of the gradient or the direction edges is distributed. This is by dividing the image into cells and calculating for each cell a histogram of the directions of the gradient for the pixels within this cell. The concatenation of these histograms forms the Hog descriptor. In addition, a step of normalization is necessary to avoid the changes of illuminations and the shadows effects. The following steps outline the computational procedure of the HOG descriptor [10].

Step1: Calculates the horizontal and vertical gradient of the image by convolving the image with the respective gradient masks ($[-1, 0, 1]$ and $[-1, 0, 1]^T$).

Step2: Uses (1) and (2) to compute the strength and orientation of the gradient.

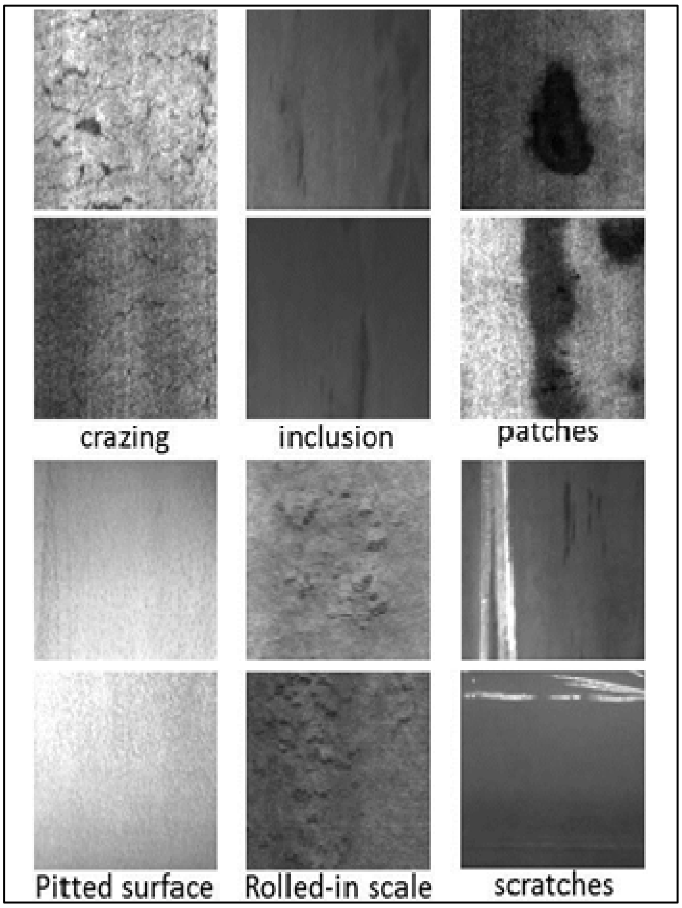

Fig. 3. Samples images of six classes of typical surface defects.

$$SG = \sqrt{G_h(x, y)^2 + G_v(x, y)^2} \quad (1)$$

$$OG = \arctan \frac{G_h(x, y)}{G_v(x, y)} \quad (2)$$

Where: G_h and G_v denote the horizontal and vertical gradient; SG and OG represent the strength and orientation respectively at point (x, y) in the image.

Step3: Divides the image into N*N cells and computes the histogram of orientations for each cell. If the histogram is divided into *k* bins based on the orientation, the value of the i^{th} bin V_i for cell *C* is computed using (3).

$$V_i = \sum_{(x, y) \in C} SG(x, y)/OG(x, y) \in bin_i \quad (3)$$

Step4: The L2 Norm is used to normalize the histogram of each cell.

Step5: Forms the HOG descriptor by concatenating the histograms of all cells.

In addition, to reduce the dimensionality of HOG descriptor, the principal component analysis (PCA) is applied.

B. Gray Level Co-occurrence Matrix (GLCM) method

Because of their richness in texture information, the co-occurrence matrices are become the most known and most commonly used to extract these textures features. GLCM is a statistical method of texture analysis, also called as Gray level dependency Matrix. It consists of constructing a matrix that able to quantify the spatial relationship of pixels over an image. This co-occurrence matrix analyzes image texture by measuring the probability of appearance of pairs of pixel values located at a certain distance in the image. Rather than using this matrix directly as feature descriptor, a number of second order statistical texture features can be extracted from this matrix such as: Autocorrelation, Correlation, Energy, Entropy, Contrast, .Etc. In this study, 19 GLCM features are used to describe the steel surface defect image.

IV. SVM CLASSIFIER

Support vector machine (SVM) is a well-known learning algorithm that has been successfully applied to various regression and classification problems. It is based on the structural risk minimization principle of the statistical learning theory [11]. The SVM algorithm proceeds by mapping the input data to a higher dimensional space by using kernel functions and aims to find the optimal hyper-plane in the space that maximizes the margin between classes. In addition the SVM classifier is able to simultaneously minimize the empirical classification error and maximize the geometric margin. SVM was originally designed for binary classification as presented in (4) and was later extended to solve multi-class applications as well. Two strategies are commonly applied to solve multi-class problems by combining several binary classifiers: one-against-one or one-against-all strategies.

For a given input x, the decision function of an SVM binary classifier is given by the following equation.

$$f(x) = \text{sign}\left(\sum_{i=1}^{n} y_i \alpha_i k(x, x_i) + b\right) \quad (4)$$

Where x_i represent the input training feature vector and $y_i \in [-1, 1]$ the respective output label; b represents the bias, α_i is the Lagrange multiplier while $k(x,x_i)$ corresponds to the kernel function.

In this work, we use the SVM classifier with RBF kernel, which its efficiency depends widely on two principal parameters, kernel parameter (g) and soft margin or penalty (C). The optimal choice of C and g is based on the grid search for which classification produced the best validation accuracy. For implementation, we used the LIBSVM package that supports multi-class using one-against-one strategy [12].

V. EXPERIMENTAL RESULTS

In this section, we will evaluate the performance of steel products inspection system based on machine vision technology and SVM classifier. All the experiments in the framework of this work are carried out on images extracted from the NEU surface defect database. These defects are crazing, patches, pitted surface, inclusion, rolled-in scale, and scratches, which are previously shown in Fig. 3.

In our experiments, we use 5-cross validation to verify the performance of our SVM classifier. Each time 66.67% of the samples in the NEU surface defect database (200 images of each class) are used for training and the remaining 33.33% (100 images of each class) for testing.

A. The results related to (HOG) features

The computation of HOG features requires setting of two important parameters, the number of cell (N) and the number of orientation bins (K), which produces a descriptor of dimension N*N*K. For experiments, we consider a number of configurations for the parameters (N, K). In addition, the principal component analysis (PCA) is used to reduce the dimensionality of the HOG descriptor. The number of principal components is determined empirically after many tests.

Table I summarizes the recognition accuracy of the SVM classifier by computing the HOG features for different values of N, fixing the value of K to 4.

TABLE I. RECOGNITION RATES AS A FUNCTION OF NUMBER OF CELLS (N).

Hog features (N*N*K)	HOG-PCA	SVM (C=1000, g=0.08)
3*3*4	36	69.66%
4*4*4	64	76.83%
5*5*4	60	79.00%
6*6*4	**80**	**84.33%**
7*7*4	100	83.33%
8*8*4	130	81.50%
9*9*4	160	75.16%
10*10*4	220	72.83%
11*11*4	240	70.16%
12*12*4	280	68.66%

TABLE II . RECOGNITION RATES AS A FUNCTION OF NUMBER OF ORIENTATION BINS (K).

Hog features (N*N*K)	HOG-PCA	SVM (C=1000, g=0.06)
6*6*3	70	77.16%
6*6*4	80	84.25%
6*6*5	**100**	**86.22%**
6*6*6	120	81.50%
6*6*7	130	80.16%
6*6*8	140	81.33%
6*6*9	150	82.16%
6*6*10	170	82.66%
6*6*12	200	79.16%
6*6*14	250	77.66%
6*6*16	270	75.00%

The impact of the number of orientation bins in the HOG features on the overall recognition rates is studied by fixing the cell size N to 6 and varying the number of bins K. The results of these evaluations are presented in Table II.

Table I and Table II summarize the recognition rates realized by the SVM classifier for different configuration of HOG descriptor. The highest recognition rates achieved stand at 86.22% for a number of cell N=6 and a number of orientation Bins k=5. It is worth noting that the use of PCA reduces the number of features less than half without lowering the performance.

B. *The results related to (GLCM) features*

For each defect image, Gray Level Co-occurrence Matrix (GLCM) has been formed and 19 statistical texture features such as autocorrelation, contrast, correlation, homogeneity, energy, dissimilarity, information measure of correlation, maximum probability, sum of squares variance and entropy, were extracted. Table III shows an example of GLCM feature extraction method. The best accuracy recognition which is equal to 89.17% was achieved. For the SVM classifier, the optimum pair of values for the penalty (C) and the kernel parameter (g) is (10000, 0.0008).

TABLE III . EXAMPLE OF GLCM FEAUTURE EXTRACTION METHOD.

	19 GLCM feature values of each type of defect					
GLCM feature	***Cr***	***Pa***	***PS***	***In***	***RS***	***Sc***
Autocorrelation	28.19	9.62	26.20	28.06	20.6	17.35
Cluster prominence	37.61	5.09	487.86	68.57	4.40	91.77
Cluster Shade	1.48	0.10	18.47	0.022	0.28	11.02
Contrast	0.46	0.07	0.37	0.11	0.16	0.16
Correlation	0.79	0.89	0.96	0.96	0.77	0.90
Difference entropy	0.75	0.26	0.69	0.34	0.45	0.41
Difference variance	0.28	0.06	0.25	0.09	0.14	0.15
Dissimilarity	0.43	0.07	0.34	0.10	0.16	0.13
Energy	0.12	0.45	0.08	0.18	0.33	0.35
Entropy	2.40	1.14	2.77	1.92	1.41	1.51
Homogeneity	0.79	0.96	0.83	0.94	0.92	0.93
Information measure of correlation1	-0.33	-0.68	-0.57	-0.75	-0.4	-0.63
Information measure of correlation2	0.79	0.83	0.94	0.95	0.74	0.87
Inverse difference	0.79	0.96	0.84	0.94	0.91	0.93
Maximum probability	0.21	0.64	0.17	0.27	0.42	0.54
Sum average	10.46	6.11	9.39	10.30	9.01	8.14
Sum entropy	2.05	1.09	2.49	1.85	1.29	1.42
Sum of squares variance	1.07	0.33	4.33	1.56	0.36	0.85
Sum variance	3.83	1.24	16.90	6.13	1.28	3.25

TABLE IV. CLASSIFICATION ACCURACY USING (HOG+GLCM) FEATURES.

	Feature extraction method		
Type of defect	***HOG*** ***($C=10^2$,g=0.06)***	***GLCM*** ***($C=10^4$, $g=8*10^{-4}$)***	***HOG+GLCM*** ***($C=10^3$, $g=2*10^{-3}$)***
Crazing	87.16%	89.33%	90.00%
Patches	88.00%	90.17%	90.33%
Pitted surface	85.16%	88.33%	89.83%
Inclusion	84.00%	89,66%	89.66%
Rolled-in scale	86.33%	88.50%	90.66%
Scratches	86.67%	89.00%	90.50%
Average	86.22%	89.17%	90.16%

Table IV lists the classification accuracy for for six popular classes of steel defects with the proposed inspection system.

It can be observed clearly from this Table, that in general, the GLCM features provide classification accuracy better then HOG features for steel defects classification and the concatenation of both of them provide the best recognition accuracy, which is equal to 90.16%. Fig.4 summarizes the highest recognition accuracy achieved as function of feature extraction method using SVM classifier.

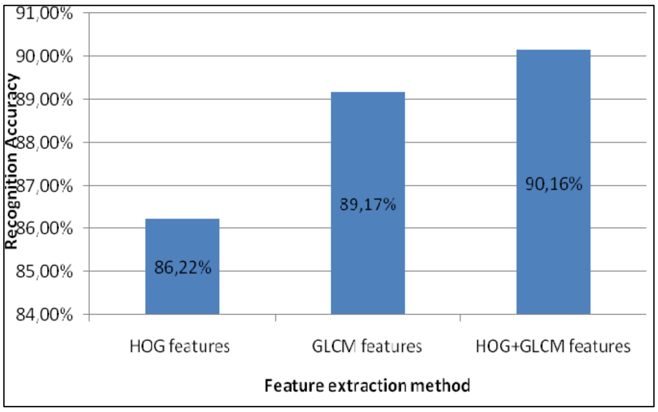

Fig. 4. Recognition accuracy as function of feature extraction method .

VI. CONCLUSION

In this study, we have presented new classification of steel defects system based on machine vision technology and SVM classifier. The system is composed mainly of two basic steps: feature extraction using two sets features were extracted by HOG and GLCM from training database and classification step based on SVM classifier. The effectiveness of the proposed approach is evaluated using 1800-grayscale images for six popular classes of steel defects that are collected at Northeastern University (NEU) as crazing (Cr), patches (Pa), pitted surface (PS), inclusion (In), rolled-in scale (RS) and scratches (Sc). Therefore proposed steel inspection system which is based on SVM classifier provide a better results and recognition accuracy of 90.16%.

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