A NOVEL FEATURE EXTRACTION AND SELECTION METHOD FOR STEEL SHEET DEFECTS CLASSIFICATION

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Abstract: This paper presents a novel approach for detection and classification of steel sheet defects. A Defects database with enough samples and good imaging conditions introduced. A set of new features proposed to extract the appropriate textural characteristics from defects images. This is followed by the selection of important features using SFFS algorithm. Modifications to SFFS feature selection method were presented to achieve the real-time needs of research. The proposed scheme decrease computational complexity in cost of little decreasing of classification accuracy.

1 INTRODUCTION

In this paper we propose an algorithm utilizing novel feature extraction and selection method with an SVM classifier to detect, recognize and classify the surface defects of steel strip.

Most of researches in this field suffer from lack of acceptable steel images with good imaging conditions and improper consideration for high-speed production lines ((Guha, 2001), (Swaroop, 2000)) To respond these needs, a system with the aim of imaging and archiving cold rolled steel sheets was implanted in Isfahan's Mobarakeh Steel Company.

2 STRUCTURE OF IMPLEMENTED SYSTEM

Our scheme, which was implemented in Isfahan's Mobarakeh Steel Company, was based on these main subdivisions:

1. Imaging: imaging system with advanced line scan camera and illumination unit provides 400 micrometer resolution.
2. Pre-processing and image enhancement.
3. Defect Detection and classification: the pre-processed images have been segmented to non-overlapping cells with 100 pixels by 100 pixels dimension. A feature vector has been extracted from each cell, which passed to classifier block for labeling the cell with a specific defect.
4. Labels revision and extra information extraction: the probability of a specific defect occurrence depends on the position of cell within the sheet and also the occurrence of defects in neighbor cells. Regarding to these facts, in this stage, the labels of defected cells should be revised and extra information like distance between periodic defects, could be extracted.

The main issue in this paper is describing the third stage, which is the most significant procedure in the processing algorithm.

3 DEFECTS DATABASE

To acheive an acceptable database, implemented system in Isfahan's Mobarakeh Steel Company,

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archives thousands kilometers of steel sheet images. A collection of defects have been collected from archived images with supervision of quality control technicians. The database with 2958 samples from 6 defects gathered so far and it's still growing.

In table 1 the frequency of samples in different classes has been reported.

Table 1: The frequency of samples in different defects classes.

Defect Name	Train	Test	Total
Punture	114	110	224
Roll mark	124	127	251
Scratch	285	283	568
Pressure line	423	420	843
Luder bounds	25	26	51
No-Defection	511	510	1021
Total	1482	1476	2958

4 FEATURE EXTRACTION

Appropriate to visual look and the texture content of defects, multiple types of features have been developed. These features described, here:

- Histogram based Features:
  A number of defects can be discovered by means of image histogram. To extract some features from histogram, there are two approaches. In first approach, histogram can be modeled by its statistics, like central moments of different degrees. In second approach, the histogram can be quantized to fewer levels and there is no need to have uniform quantization level. Here, mean and variance, from former group and eight features from later one have been selected. The later features, represents number of pixels with grayscale value among ranges [0,50], [51,71], [72,92], [93,113], [114,134], [135,155], [156,176], [177,255]. These ranges have been selected wisely to have most discriminative features over different defects.
- Morphology based Features:
  To discover the vertical and horizontal edges, that made by defects, nonlinear gradients can be employed. In this paper, morphological operators have been utilized to extract features, measuring quantitatively presence of vertical and horizontal edges in image. To reach this purpose, morphological operator of $(im \oplus SE_1) - (im \ominus SE_1)$ derived with two horizontal and vertical structuring elements. In each case the number of pixels in gradient image greater than an adaptive threshold calculated to represent features.
- Linear Gradient based Features:
  To extract the edges, linear filters can be used instead of morphological operators. Here, vertical and horizontal Prewitt masks utilized to find the horizontal and vertical edges. Similar to morphological features, the number of pixels in gradient image greater than an adaptive threshold calculated to represent features.
- Adaptive Thresholding based Features:
  If grayscale values of image's pixels have the mean of M, thresholds αM, βM have been determined, where $\alpha < 1$, $\beta > 1$. The number of pixels with grayscale value greater than βM and the ones with grayscale value less than αM make two features. To determine the values of coefficients α and β, pattern search algorithm used to maximize the Mahalanobis distance between feature vectors of defects images. (A slight number of database images used in this stage, have been omitted from training and test sets). The optimal result is $\alpha = 0.92$ and $\beta = 1.11$.
- Quadratic Surface Modeling Features (Guha, 2001):
  To identify defects like indents, Quadratic Surface Modeling can be utilized. A grayscale image can be assumed as a three dimensional surface. This surface can be modeled with a quadratic one.
  Once the polynomial parameters are determined, we get a fairly well idea of the surface profile from them. The coefficients of the second order terms X^2 and Y^2, determine the surface curliness and can be used as features (Guha, 2001).
- Hu set of Invariant Moments:
  The Hu set consist of a group of nonlinear centralized moment expressions, which are invariant under scale, position and rotation.
- Radon Transform based Features:
  The radon transform computes projections of an image along specified directions (Gonzalez and Woods, 2008). Lines with specified direction in original image make maximums (or minimums) in radon transform space. By mean of calculating transform in various directions from 0 to 180 degrees, we are able to find line shaped defects in specified directions. The features selected as direction and location of maximum in transform space.
- Hough Transform based Features:

To discover line-shaped defects, the Hough transform also can be used (Gonzalez and Woods, 2008).

To extract features from Hough transform, first, edges detected from the image, then each point of edges maps to a curve in Hough space, all the curves in Hough space sum together then maximum point determined, and r,θ of maximum point makes the features.

We can summarize all the features previously described:

1, 2. mean and variance

3, 4. number of pixels with greater than 25% in grayscale value after employing horizontal and vertical Perwiet masks.

5, 6. mean and variance for pixels with grayscale value less than threshold calculated with Otsu's method, if threshold effectiveness is more than 65%, else we use mean and variance of all pixels

7, 8. number of pixels greater than 1.11 times of pixel's mean and less than 0.92 times of pixel's mean.

9, 10, 11, 12. mean and number of pixels with grayscale value greater than 1.8 times of pixel's mean after performing described morphological operation.

13, 14. the r, θ of maximum point in Hough transform space.

15, 16. number of edge pixels after employing edge detection method based on zero-crossing

17, 23. Hu set of invariant moments

24, 25. The coefficients of the second order terms (X^2 and Y^2), after utilizing quadratic surface modeling.

26, 33. Requantized nonlinear histogram

34, 35. Direction and location of maximum point in radon transform space.

5 FEATURE SELECTION

The main goal of feature selection is to select a subset of d features from given set of D measurements, $d < D$ without significantly degrading (or possibly even improving due to the "peaking phenomena" (Pudil et al., 1994)) the performance of recognition system. We have been used Sequential Forward Floating Search (SFFS), which provides close to optimal solution at an affordable computational cost ((Pudil et al., 1994), (Jain and Zongker, 1997)).

5.1 Sequential Forward Floating Search Algorithm

SFFS algorithm, start with an empty subset and iteratively add or remove features, trying to maximize a criterion function, until some termination condition is met (Jain and Zongker, 1997).

The main issue remains is selecting criterion function. In most applications, the feature's interclass distance (i.e. Mahalanobis distance) being used as criterion function. It can also be selected as accuracy of a trained classifier with inspecting subset of features.

5.2 Criterion Function based on Computational Cost and Accuracy

In real time application, like automatic surface inspection, the computational cost is as important as accuracy. So it's more realistic to have a criterion function, which depends on both computational cost and accuracy. The computational cost consists the normalized time needed to calculate the inspecting subset of features.

If total time needed to compute the features of subset X_k is $T(X_k)$ and the accuracy of classifier trained with features of subset X_k is $A(X_k)$, the criterion, J, can be assumed as:

$$J(X_k) = \alpha A'(X_k) + \beta \frac{1}{T'(X_k)} \quad (1)$$

where A', T' are normalized values of A, T and coefficients α, $\beta = 1 - \alpha$ are selected upon to the relative importance of accuracy and time. It's obvious that accuracy criterion is a special case of accuracy-computational complexity with $\alpha = 1$.

6 EXPERIMENTAL RESULTS

In this section, we demonstrate the effectiveness of the proposed methodology compared with traditional methods. To test the described algorithms, the defects database divided into training and testing sets. All the purposed features calculated for whole images in database. In other hand, the mean time for calculating each feature measured to use in feature selection procedure as computational complexity.

In feature selection stage, three types of criterion function were compared:

Table 2: Comparing classification results for various feature selection methods.

Criterion function used by SFFS Algorithm	No. of Features in optimal subset	Optimal subset	Computational complexity	Classification Accuracy
Without feature selection	35	1 .. 35	10432.7	89.92%
Mahalanobis distance	22	13,34,30,31,14,32,29,24,10,33 16,4,11,8,2,3,27,1,21,23,22,18	9468.2	90.12%
SVM classifier Accuracy	10	13,9,10,35,1,8,34,16,28,5	8607	93.10%
Accuracy-Computational complexity with $\alpha = 0.5$	5	12,11,33,18,24	1021	85.36%
Accuracy-Computational complexity with $\alpha = 0.4$	4	12,11,33,18	922	83.98%
Accuracy-Computational complexity with $\alpha = 0.6$	8	12,11,33,18,24,25,32,3	1116	87.84%

a) Mahalanobis distance: in each SFFS iteration, Mahalanobis distance can be calculated simply from database samples for selected subset.

b) Classifier accuracy: In each iteration, a feature subset is selected by SFFS algorithm, then classifier have been trained upon to selected subset and training database. The classification accuracy have been calculated using trained classifier over testing database and it has been used as criterion value of SFFS for next iteration.

c) Classifier accuracy-computational complexity: Similar to former routine, we can obtain accuracy-computational complexity criterion, using eq. (1)

Several experiments were accomplished for each suggested criterion functions. SVM used as classifier with Gaussian kernel and $\sigma^2 = 1$. In each experiment, the optimal subset has been determined by SFFS procedure. The optimal subsets, accuracy and computational complexity were shown in table 2, where it can be seen that feature selection using accuracy-computational complexity criterion outperforms convectional criterions like, Mahalanobis distance. Also it's clear that by regulating α, we can attain desired classification accuracy in cost of computational complexity increasing and vice versa.

7 CONCLUSIONS

We have presented a scheme for detection and classification of steel sheet defects. A set of new features proposed to extract the appropriate textural characteristics from defects images. Feature selection methods utilized to select outperformed features, modifications to SFFS feature selection method were presented to achieve the real-time needs of research. We can decrease computational complexity in cost of little decreasing of classification accuracy

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