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ABSTRACT
This paper presents a Texture based approach for detecting and characterizing defects on steel surfaces, through which the quality inspection of steel products is performed. Our objective is to detect the defects in the surface of steel products. Major defects like corrosion, crack, scratch and fracture are considered for testing and training process. The Discrete Wavelet Transform (DWT) based Local Configuration Pattern (LCP) features are given as input to the KNN classifier. In order to explore multichannel discriminative information of both the microscopic configuration and local structures, DWT based LCP which is a combination of Local Binary Pattern (LBP) and Microscopic Configuration modeling (MiC) method is proposed. LCP and Defect Severity Index values are calculated for the sub-images obtained after applying DWT. The overall accuracy of DWT based LCP method is 96.7%. The results show that the proposed method produces better classification accuracy when compared to the classical methods.

INTRODUCTION
In the modern era, steel is one of the basic building blocks. Automobiles, appliances, bridges, oil pipelines, and buildings are all made with steel. Also steel is necessary in micro level manufacturing of chips in electronic devices. Hence quality inspection of steel is significant. During the manufacturing process of steel, several kinds of surface defects such as corrosion, scratch, crack, hole, pit & fracture may occur. These flaws not only affect the appearance of the product, even more fatally reduces the corrosion resistance, wear resistance and fatigue properties (Sathyabama, B., 2012). Surface inspection system is important in steel strip manufacturing industry, as the customer require high quality product and to compete with their competitors. Vision based analysis has been a fundamental open problem, with industrial applications, such as automation and production of quality products. Accurate and micro level detection and recognition of various defects in composite materials needs the SEM image analysis (Jeffery Price, R., 2008). Mike Muehlemann has analyzed steel quality problems using surface inspections [3]. Lee et al (2008) investigated surface defects in hot rolling process. Shigeru and Kenzo (2005) analyzed stress corrosion cracking in welded parts of the stainless steel using a magnetic non-destructive method. Kuldeep et al (2010) inferred the process knowledge based multi class support vector classification approach for surface defects in hot rolling process. Young jo lee et al (2014) detected defect in SEM images using quadtree decomposition. From the survey of all these inspection systems, defect detection process was undertaken only for specific type of defect and defects arising from specific processes. Further these defects are...
formed on the material surface. Surface texture can be defined as typical surface of a material, including geometric irregularities in or the composite of certain deviations. It includes roughness, waviness, lay (grain), etc.

This paper aims at developing texture based recognition of steel surface defects using SEM images. Texture based methods will give a clear representation to analyse this surface defects (Yimo Guo, 2011). The paper is organized as follows. Section 1 explains the proposed methodology; Section 2 discusses the experimental results and Section 3 conclusion and future research.

1. Methodology:

Figure 1.1 shows the proposed defect classification methodology. Initially DWT is applied to the input image to analyze the defects at multi scale level and the resultant sub-images are calculated for Local Configuration Pattern value. LCP combines the local structural information and Microscopic configuration information. The LCP feature vector is given as input for KNN classifier to categorize the defect. It is used to measure the Defect Severity Index (DSI). The aim of calculating this parameter is to provide a direct measurement of the quality of the product specifically reliability, fault tolerance and stability.

![Proposed methodology.](image)

A. GLCM features:

In statistical texture analysis, texture features are computed from the statistical distribution of observed combinations of intensities at specified positions relative to each other in the image. The Gray Level Co-occurrence Matrix (GLCM) technique is a method of extracting second order statistical texture features. Some of these measures related to the specific texture characteristics of the image such as homogeneity, contrast, energy and the presence of organized structure within the image.

B. Tamura features:

The Tamura features, including coarseness, contrast, directionality, line likeness, regularity, and roughness, are designed in accordance with psychological studies on the human perception of texture. Coarseness, contrast and directionality are essential factors in texture and have high potential to distinguish different textures. All of them were measured by human subjects.

C. Laws mask:

Laws identified the following properties as playing an major role in describing texture uniformity, density, coarseness, directionality, roughness, regularity, linearity, direction, frequency, and phase. Laws texture energy measures determine texture properties by assessing Edges, Spots, Average Gray Level, Ripples and Waves in texture. The measures are derived from three simple vectors. \( E_3 = (-1, 0, 1) \) calculating first difference (edges), \( L_3 = (1, 2, 3) \) which represents averaging, and \( S_3 = (-1, 2, -1) \) corresponding to the second difference (spots).

D. Local Configuration Pattern (LCP):

LCP feature decomposes the information architecture of images into two levels, as (1) local structural information; (2) microscopic configuration information that involves image configuration and pixel-wise interaction relationships. For local structural information, LBP is used in feature extraction framework, whereas a microscopic configuration model is developed to explore microscopic configuration information.

(i) Local Binary Pattern (LBP):

LBP is defined as an ordered set of binary comparisons of pixel intensities between the center pixel and its eight surrounding pixels (Yimo Guo, 2011). The decimal form of the resultant 8-bit word (LBP code) can be expressed as follows.

\[
LBP \ (x_c, \ y_c) = \sum_{n=0}^{7} s(i_n - i_c) 2^n
\]  

Where \( i_c \) corresponds to the gray value of the center pixel \((x_c, y_c)\), in to the gray values of the 8 surrounding pixels, and function \( s(x) \) is defined as:

\[
s(x) = \begin{cases} 
  1 & \text{if } x \geq 0 \\
  0 & \text{if } x < 0 
\end{cases}
\]
The LBP_\text{s} operator produces 256 (2^8) different output values, corresponding to the 256 different binary patterns. To remove the effect of rotation, i.e., to assign a unique identifier to each rotation invariant LBP, a circular bit-wise right shift operator is performed on the pattern to obtain minimal number of transitions.

$$LBP_\text{s}^i = \min(ROR(LBP_\text{s}, i)) \quad i = 0, 1, \ldots, 7$$  \hspace{1cm} (3)

(ii) **Modeling of Microscopic Configuration (MiC):**

To model the image configuration with respect to each pattern, optimal weights associating with intensities of neighboring pixels are estimated, to linearly reconstruct the central pixel intensity [6]. This can be expressed by:

$$E(a_0, \ldots, a_{p-1}) = \left| g - \sum_{i=0}^{p-1} a_i g_i \right|$$  \hspace{1cm} (4)

where, \(a_i\) are intensity values

\[ a_i(i = 0, \ldots, p-1) \]

are weighting parameters

$$C = \begin{bmatrix} C_{0,0} & C_{0,1} & \ldots & C_{0,N-1} \\ C_{1,0} & C_{1,1} & \ldots & C_{1,N-1} \\ \vdots & \vdots & \ddots & \vdots \\ C_{N-1,0} & C_{N-1,1} & \ldots & C_{N-1,N-1} \end{bmatrix}$$  \hspace{1cm} (5)

The intensities of their neighboring pixels \(V_{i,0}, \ldots, V_{i,p-1}\) (i=0,\ldots,N-1) can thus be organized as

\[ V_i = \begin{bmatrix} V_{i,0} \; V_{i,1} \; \ldots \; V_{i,p-1} \\ V_{i,0} \; V_{i,1} \; \ldots \; V_{i,p-1} \\ \vdots \; \vdots \; \ddots \; \vdots \\ V_{i,0} \; V_{i,1} \; \ldots \; V_{i,p-1} \end{bmatrix} \]

In order to minimize the reconstruction error in eqn (6), the unknown parameters \(a_i\) (i=0,\ldots, P-1) are constructed as a column vector:

$$A_L = \begin{bmatrix} a_0 \\ a_1 \\ \vdots \\ a_{p-1} \end{bmatrix}$$  \hspace{1cm} (6)

In this way, the problem to be solved becomes a least-squares problem \(C_L = A_L V_L\). When the system is over-determined, optimal parameter vector \(A_L\) is determined by:

$$A_L = (C_L^T V_L V_L^T C_L)^{-1} V_L^T C_L$$  \hspace{1cm} (7)

In texture analysis, rotation invariant analysis is a widely studied problem, aims at providing texture features that are invariant to rotation angle of the input image. To produce rotation invariant features, 1D Fourier transform is applied to the estimated parameter vector \(A_L\). The transformed vector can be expressed by:

$$\mathbf{h}_L(K) = \sum_{i=0}^{p-1} A_L(i) \cdot e^{-j2\pi K i/p}$$  \hspace{1cm} (8)

Where \(h_L(K)\) is the \(K\)th element of \(h_L\) and \(A_L(i)\) is the \(i\)th element of \(A_L\). Although image rotation would lead to cyclic translations of \(A_L\), Fourier transform is invariant to this kind of translations so that \(h_L\) could achieve rotation invariant property. The magnitude part of vector \(h_L\) is taken as the MiC feature, which is defined by:

$$\mathbf{LCP} = \left[ \left| h_L(0) \right| \left| h_L(1) \right| \ldots \left| h_L(p-1) \right| \right]$$  \hspace{1cm} (9)

Considering that \(h_L\) encodes the image configuration and pixel-wise interaction relationship of each specific pattern, it together along with the pattern occurrences of local binary patterns would construct a complementary feature for both the discrimination of microscopic configuration and local structures. The final feature is

$$\mathbf{LCP} = \left[ \left| h_L(0) \right| \left| h_L(1) \right| \ldots \left| h_L(p-1) \right| \right]$$  \hspace{1cm} (10)

Where \(h_L\) is calculated by Equation (10) with respect to the \(i\)th pattern of interest, \(O_i\) is the occurrence of the \(i\)th local pattern of interest (i.e., the LBP), and \(q\) is the total number of patterns of interest. Moreover, multi-scale analysis can be achieved by constructing LCPs for different decomposed level of input image by wavelet transforms.

This is very much useful to analyze the severity level of defects. Further, texture defects are multi directional thus the rotation invariance property of LCP allows recognizing such defects correctly. The six magnitudes of MiC and corresponding local binary pattern forms the LCP feature vector:
E. **KNN classifier:**

K-Nearest Neighbor (KNN) is one of the most popular algorithms for pattern recognition. The classification rules are generated by the training samples themselves without any additional data. The KNN classification algorithm forecasts the test sample’s category according to the K training samples which are the nearest neighbors to the test sample, and judge it to that category which has the largest category probability [9]. The process of KNN algorithm to classify example X is:

- Suppose there are j training categories $C_1, C_2, \ldots, C_j$ and the sum of the training samples is N after feature reduction, they become m-dimensional feature vector.
- Make sample X to be the same feature vector of the form $(X_1, X_2, \ldots, X_m)$, as all training samples.
- Calculate the similarities between all the training samples and X. Taking the $i^{th}$ sample $(d_{i1}, d_{i2}, \ldots, d_{im})$ as an example, the similarity $SIM(X, di)$ is as follows,

$$SIM(X, d_i) = \frac{\sum_{j=1}^{m} X_j d_{ij}}{\left(\sum_{j=1}^{m} X_j^2\right)^{1/2} \left(\sum_{j=1}^{m} d_{ij}^2\right)^{1/2}}$$

(12)

- Choose k samples which are larger from N similarities of $SIM(X, di)$, $(i=1, 2, \ldots, N)$, and treat them as a KNN collection of X. Then, at last calculate the probability of X belong to each category respectively with the following formula.

$$P(X, C_j) = \sum_{d_i} SIM(X, d_i) \cdot y(d_i, C_j)$$

(13)

$$y(d_i, C_j) = \begin{cases} 1, & d_i \in C_j \\ 0, & d_i \notin C_j \end{cases}$$

(14)

Where $y (d_i, C_j)$ is a category attribute function.

Judge sample X to be the category which has the largest $P (X, C_j)$.

**RESULTS AND DISCUSSIONS**

Experiments have been conducted to calculate the performance of the proposed method using the 156 SEM images of steel collected from various web resources. It includes various steel defects like scratch (29), corrosion (40), fracture (23), hole (25) and crack (39). (.) shows the number of images in each type. In that 5 images from each type with a single rotation i.e. a total of 50 images are considered for training and 350 images (which include 156 original images and its distorted versions) are used for testing. Some of the samples (Corrosion, Crack, Fracture and Scratch) from the formed dataset are shown in Fig.2.1

**A. Data Set:**

![Sample SEM images of Steel defects.](image)

**B. Wavelet Decomposition:**

The texture energy is stored in different frequencies for different types of defects. An example is shown in Fig 2.2. Thus, instead of extracting the features on the original image, it is extracted in different frequency components (LL, LH, HL, HH) of the image. The maximum value of features in LL, LH, HL and HH is considered as the representative feature value.

**C. LCP & defect severity index:**

The six magnitudes of MiC and corresponding local binary pattern forms the LCP feature vector. This LCP features are given as input to KNN classifier LCP also used to measure the severity of defects using Defect
Severity Index (DSI). This parameter determines the quality of the product, based on which one can take decision for releasing the product i.e. it indicates the product quality. The DSI is defined as

\[
DSI = \frac{\sum_{\text{defect} \text{, severity level}} \text{defect}}{\text{total no. of defects}}
\]  

(15)

![Wavelet Decomposition of Defects](image)

**Fig. 2.2:** Wavelet Decomposition of Defects.

### D. Classification Results:

![Classification of various defects](image)

**Fig 2.3:** Classification of various defects from left to right corrosion, crack and fracture.

To calculate the Defect Severity Index (DSI) the LCP magnitude is grouped into minor, medium, major and critical. Weights are assigned to each severity level. This varies for different types of defects. To achieve this minimum and maximum values of LCPs each training set are spitted into four bins and each bin is assigned with a weight after defect detection the DSI value is calculated using eqn (13). Table 2.1 shows the DSI and LCP values taken for the sub-images of input SEM corrosion image.

<table>
<thead>
<tr>
<th>IMAGE</th>
<th>HH</th>
<th>DSI</th>
<th>HL</th>
<th>DSI</th>
<th>LH</th>
<th>DSI</th>
<th>LL</th>
<th>DSI</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.987</td>
<td>8.41e^0</td>
<td>0.139</td>
<td>0.029</td>
<td>2.08</td>
<td>0.005</td>
<td>0.008</td>
<td>430.7</td>
</tr>
<tr>
<td></td>
<td>32.211</td>
<td>647.16</td>
<td>1.301</td>
<td>0.1606</td>
<td>15.856</td>
<td>16.14</td>
<td>1.071</td>
<td>0.329</td>
</tr>
<tr>
<td></td>
<td>43.904</td>
<td>177.31</td>
<td>23.74</td>
<td>4.855</td>
<td>0.245</td>
<td>0.035</td>
<td>0.389</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>0.65</td>
<td>1.5e^03</td>
<td>0.053</td>
<td>2.834</td>
<td>0.007</td>
<td>4.3e^{-6}</td>
<td>0.292</td>
<td>0.52</td>
</tr>
</tbody>
</table>

**Table 2.1:** LCP and DSI Computation of corrosion image.

E. Performance Analysis:

Performance of the proposed system can be evaluated using precision and Error rate. The data base consists of different defects in SEM images. Many groups of relevant images are stored in the data base. Precision, Retrieval efficiency and error rate can be calculated as follows:
Table 2.2: LCP and DSI Computation of crack image.

<table>
<thead>
<tr>
<th>IMAGE</th>
<th>HH</th>
<th>DSI</th>
<th>HL</th>
<th>DSI</th>
<th>LH</th>
<th>DSI</th>
<th>LL</th>
<th>DSI</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>17.89</td>
<td>0.0081</td>
<td>0.350</td>
<td>1.5e^-5</td>
<td>3.711</td>
<td>0.0252</td>
<td>0.099</td>
<td>3.244</td>
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<tr>
<td></td>
<td>75.88</td>
<td>0.0047</td>
<td>7.653</td>
<td>422.98</td>
<td>2.333</td>
<td>0.0095</td>
<td>0.016</td>
<td>85.509</td>
</tr>
<tr>
<td></td>
<td>53.03</td>
<td>0.0022</td>
<td>0.068</td>
<td>0.628</td>
<td>0.018</td>
<td>0.0054</td>
<td>0.003</td>
<td>5.3e^-5</td>
</tr>
<tr>
<td></td>
<td>293.4</td>
<td>0.0187</td>
<td>28.99</td>
<td>1.184e^-5</td>
<td>28.16</td>
<td>0.0033</td>
<td>0.089</td>
<td>6.018</td>
</tr>
</tbody>
</table>

Table 2.3: LCP and DSI Computation of scratch image.

<table>
<thead>
<tr>
<th>IMAGE</th>
<th>HH</th>
<th>DSI</th>
<th>HL</th>
<th>DSI</th>
<th>LH</th>
<th>DSI</th>
<th>LL</th>
<th>DSI</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>952.76</td>
<td>1.5e^-6</td>
<td>250.24</td>
<td>1.8e29</td>
<td>35.84</td>
<td>5.9e^-5</td>
<td>0.0643</td>
<td>2.8e^-3</td>
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<tr>
<td></td>
<td>44.282</td>
<td>5.4e^-5</td>
<td>0.9653</td>
<td>265.15</td>
<td>2.2528</td>
<td>0.0075</td>
<td>0.0059</td>
<td>0.0187</td>
</tr>
<tr>
<td></td>
<td>42.928</td>
<td>4.7e^-4</td>
<td>0.0787</td>
<td>1.07e3</td>
<td>7.2006</td>
<td>0.0014</td>
<td>0.0056</td>
<td>0.0066</td>
</tr>
<tr>
<td></td>
<td>252.53</td>
<td>0.0022</td>
<td>21.841</td>
<td>1.57e4</td>
<td>26.089</td>
<td>0.0609</td>
<td>0.127</td>
<td>997.77</td>
</tr>
</tbody>
</table>

Table 2.4: LCP and DSI Computation of fracture image.

<table>
<thead>
<tr>
<th>IMAGE</th>
<th>HH</th>
<th>DSI</th>
<th>HL</th>
<th>DSI</th>
<th>LH</th>
<th>DSI</th>
<th>LL</th>
<th>DSI</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.875</td>
<td>0.056</td>
<td>0.203</td>
<td>0.2476</td>
<td>0.2021</td>
<td>2.966</td>
<td>0.0191</td>
<td>2.3e-03</td>
</tr>
<tr>
<td></td>
<td>18.196</td>
<td>0.0022</td>
<td>0.7481</td>
<td>0.2741</td>
<td>1.6963</td>
<td>1.9985</td>
<td>0.052</td>
<td>0.057</td>
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<tr>
<td></td>
<td>19.227</td>
<td>0.0071</td>
<td>0.0314</td>
<td>11.473</td>
<td>0.7386</td>
<td>20.152</td>
<td>0.002</td>
<td>18.516</td>
</tr>
<tr>
<td></td>
<td>84.14</td>
<td>1.8e-3</td>
<td>21.8</td>
<td>6.3e-31</td>
<td>41.908</td>
<td>0.0187</td>
<td>0.0117</td>
<td>2.4e-3</td>
</tr>
</tbody>
</table>

Precision = No.of relevant images retrieved / Total no.of images retrieved  
Error rate = No.of non relevant images retrieved / Total no.of relevant images retrieved  
Retrieval Efficiency = No.of relevant images retrieved / Total no.of images retrieved

Table 2.5: Comparison of Retrieval efficiency.

<table>
<thead>
<tr>
<th>Defects</th>
<th>GLCM</th>
<th>Tamura</th>
<th>Laws – mask</th>
<th>LCP</th>
<th>DWT-LCP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Retrievals</td>
<td>115</td>
<td>138</td>
<td>143</td>
<td>148</td>
<td>151</td>
</tr>
<tr>
<td>Precision</td>
<td>.733</td>
<td>.884</td>
<td>.916</td>
<td>.948</td>
<td>.967</td>
</tr>
<tr>
<td>Error Rate</td>
<td>.26</td>
<td>.115</td>
<td>.083</td>
<td>.05</td>
<td>.032</td>
</tr>
<tr>
<td>Retrieval Efficiency</td>
<td>73.3%</td>
<td>88.4%</td>
<td>91.6%</td>
<td>94.8%</td>
<td>96.7%</td>
</tr>
</tbody>
</table>

Table 2.5 shows the comparison of existing methods like Tamura [10], GLCM (Grey Level Co-occurrence Matrix) (Haralick, M., 1978) and Laws mask methods (Rachidi, M., 2008) with DWT-LCP. In GLCM method different GLCM feature values obtained for test and training images in the database and classified. The retrieval efficiency for this method is 73.3% and the discrimination power is very low. This is because of the overlapping characteristics of steel defects. Similarly the overall retrieval efficiency for Tamura feature method is 88.4% because sometimes cracks may be looked like fracture and scratch may viewed as cracks and so on. This needs a magnified structural information and micro level structural information. Since the Laws filters separates the
images into level, ridge, wave, edge and line it can well discriminate cracks, corrosion and so on. This provides an accuracy of 91.6% & 94.8% for LCP which is comparatively high than Tamura and GLCM.

The SEM images provide a magnification view of surface defects which can be clearly separated by wavelet decomposition. Further LCP provides both the structural and micro level configuration information which improves the retrieval efficiency to 96.7%. The proposed method gives better results for all types of defect category which is shown in Table 2.5.

3. Conclusion:

In this paper, a DWT enabled LCP texture features have been developed for the classification of steel. The magnification of defects in SEM images provides an opportunity to analyse the steel surfaces at micro level. This can be directly computed using MiC and LBP. Further DWT has made the possibility of analysing the defects in various sub bands. The results obtained, indicate that the proposed method have better classification accuracy when compared with other methods by obtaining an overall accuracy of 96.7%. Thus classification of defects is possible with image analysis and may be used for correlating service/failure conditions based on morphology of the products.

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REFERENCES


