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Analysis of Automatic Crack Detection in Metal

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Abstract- **The streak image caused by metal implants degrades the image quality and limits the applications of metal, that results in loss of image quality. The proposed method uses LDA with fractional wavelet transformation to extract the texture features. Diffusion method used in this work is efficient for detecting the pitting and laminating defects. By using Gradient Magnitude and structure coherance the exact level of defect is found.**

Keywords-- **LDA, Lamination, Automatic metal crack detection.**

I. Introduction

Iron machines and materials are used in most of industries for manufacturing products. In industries these iron materials come into contact with humidity and pollution, therefore increases the rusting of iron. Corrosion takes place when the mechanical materials come into contact with humidity and pollution in industries. Due to the attack of the corrosion, these mechanical materials undergo the fatigue that affects the integrity of the metallic surfaces. This rusting caused by corrosion causes wastage of iron materials, reduction in efficiency and costly maintenance. Different departments make use of materials that are made up of iron. In Civil department, for maintaining the good quality of steel bridges, it is important to detect rust defects in advance. By detecting rust defects in advWith these ance, bridge managers can make important decisions whether to paint bridges immediately or later [1].Metallic objects like dental implants, surgical clips, or steel-hip prostheses lead to severe shadow and streak artifacts in CT images that superimpose the structures of interest and deteriorate image quality. The reason is that metallic objects have a very high density in the human body, which creates a barrier to the transmitted x-ray beam during CT examination. It results a lack of data in the projection data that lead to the production of streak in CT images. This photo deficiency caused by metallic object would become more severe under low dose scanning. During the last decade, many approaches have been proposed to reduce these artifacts. These methods can be roughly classified into iterative and interpolation-based methods.[2].If material is heated with infrared radiators, the temperature of the surface will rise suddenly.

The speed at which the heat front is subsequently dissipated depends on different thermal properties of the material such as density, heat capacity, thermal conductivity and the bonding quality between top surface layer and the base material. A defect in the sub-surface creates a barrier for the heat diffusion process and, therefore, the surface temperature above the defect will decrease more slowly than the temperature in other regions. The region above such a defect will show a hot area much longer than the surrounding containing good quality bonding. This causes a problem in quality assurance.[3]. Component-based representation with LDA. Is carried out based on a full metal image analysis [5]. The image is partitioned into several metal components to simplify the modeling of image statistics. The components are encoded by LDA to compensate for the effect of illumination and expression variation. LDA is then applied to the collection of the component-based LDA representations yielding a compact description referred to as 'cascaded LDA'. The decomposition of the face image and its re-combination in the LDA space effectively solves the problem of face retrieval and person identification.[4]. The proposed system Analysis Automatic Crack Detection in Metal Using Lamination and Pitching Process is explained in this paper. The paper is categorized as six sections. The first section is introduction, followed by proposed system. The third is the existing system and next section explains about the results and discution. The remaining sections states the conclusion followed by the list of references.[5].

Metallic rod is an important joining process in modern industries, which is widely used in metallic rod, etc. Metallic rod with cracks is regarded as in the worst condition based on many standards in the world, which may lead to fatal accidents and cause great losses. [6]. The classification is a processing step, which is decoupled from the feature definition and extraction. Any classifier in the related literature could be used for the classification of defects and the field would obviously benefit from more advanced classification methods.[7]. To minimize the chance of removing or breaking cracks at this step, the threshold level was slightly overestimated initially, which also caused the cracks thicknesses to be overestimated.

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A simple erosion with a cross structuring element could be used to correct the thicknesses, but again could cause crack breaking [8]. Hierarchical approach to detecting weld defects is proposed. Comparing with existing techniques, different thresholds are selected to control the scales of defects that make it more flexible to meet various requirements. By using proper parameters we are able to locate most of defects from the radiographic image at a desired scale, however, in practice it still is a difficult problem to tell "false" defects from "true" [9]. To ensure low deformation of profile region, corroded surfaces were covered with an epoxy resin before cutting and mounting with phenolic resin for mechanical polishing. A representative number of 1260-960-8 bit digital images[10].

II. PROPOSED SYSTEM

In the proposed system these images are mainly subjected to two different operations in the proposed analysis system. The first step is to preprocess and the second step is to identity the edges. The image of the metal surface has many features that need to be treated as such and all the information present in the image are analyzed.

In order to automatically detect the crack using LDA algorithm and diffusion method and also using the texture classification and segmentation are analyzed.

In the LDA Focusing on Linear Discriminant Analysis (LDA), the method proposed in this paper finds the most discriminative set of image processing operations to increase training samples. We represent an image processing applied to an image x by a matrix G (called generating matrix) to generate a new training sample x′ represented by x′ = Gx. This equation is similar to those in which they have formulated transformation between two images.

In the proposed system implement the concept as Fractional Wavelet Transform. The proposed transform not only inherits the advantages of multi resolution analysis of the WT-Wavelet Transform, but also has the capability of signal representations in the fractional domain which is similar to the FRWT. Compared with the existing FRWT, the novel FRWT can offer signal representations in the time-fractional-frequency plane. Besides, it has explicit physical interpretation, low computational complexity and usefulness for practical applications.

Diffusion Method

In the diffusion they are various types of filter can be implemented, but in this paper implement the three filter,

- Linear Isotropic Diffusion Filters
- Non-linear Isotropic Diffusion Filters
- Anisotropic Non-linear Diffusion Filters

Linear Isotropic Diffusion Filter

- If diffusion tensor is a constant it gives $j = -\nabla u$ so we have Linear Isotropic Diffusion equation which is of the form

$$\frac{\partial u}{\partial t} = \frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial x^2}$$

- For e.g. given ∂t u = Δu ,u(x,0) =f(x) where f is a image brightness function then the solution of this linear diffusion possesses the unique solution

$$u(x,t) = \begin{cases} f(x) & (t=0) \\ (K_{\sqrt{2t}} * f)(x) & (t>0) \end{cases}$$

- Solution is convolution with a Gaussian filter of increasing variance which would lead to diffusion i.e. low noise reduction
- But along with removing noise, Linear diffusion filtering (Gaussian filters) blurs edges, dislocate the edge as we move form fine to coarse scale.

Non-Linear Isotropic Diffusion Filters

- To avoid the blurring & the localization problems of LDF we reduces the diffusivity at those location which have larger likelihood to be edges
- Since this likelihood can be measured by $|\nabla u|^2$.
- Non linear isotropic edge detection is much better than linear edge detector because the Diffusion and edge detection interact in one single process
- In the interior of the segment the nonlinear isotropic diffusion behave almost like linear diffusion but at edges diffusion is inhibited hence noise is not eliminated there
- So it would be desirable to rotate the flux towards the orientation of features of interest and this requirement can be satisfied by a diffusion tensor leading to anisotropic diffusion filter.

Anisotropic Non-Linear Diffusion Filters

- These not only take account the modulus of the edge detector but also its direction.
- So mostly finite difference methods are preferred, since they are easy to handle and the pixel structure of a real digital image already provide a natural discretization on a fixed rectangular grid.

Texture Classfication

In the texture analysis can be divided into components, in the texture analysis can be applied into various stages of the process. At the preprocessing stage, images could be segmented into contiguous regions based on texture properties. Texture features could provide cues for classifying patterns or identifying objects.

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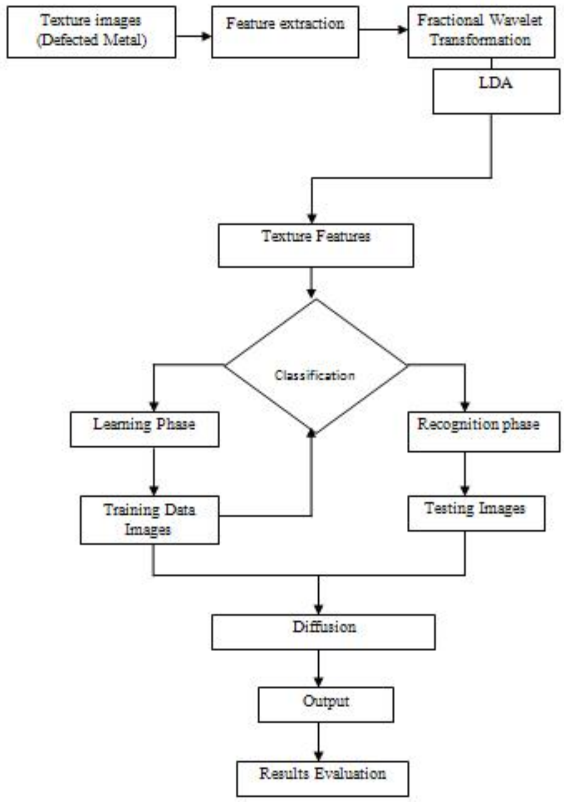
In the texture analysis, the image acquisition is the first process and preprocesses the image and feature extraction process can be done for the image and finally classify the images.

In the Texture classification process involves two phases: the learning phase and the recognition phase. In the learning phase, the target is to build a model for the texture content of each texture class present in the training data, which generally comprises of images with known class labels. The texture content of the training images is captured with the chosen texture analysis method, which yields a set of textural features for each image. These features, which can be scalar numbers or discrete histograms or empirical distributions, characterize given textural properties of the images, such as spatial structure, contrast, roughness, orientation, etc. In the recognition phase the texture content of the unknown sample is first described with the same texture analysis method. Then the textural features of the sample are compared to those of the training images with a classification algorithm, and the sample is assigned to the category with the best match.

In training phase, the classifier will be trained by labeling the input image to a specific texture class. On the other hand, the classifier will test and classify the input image into the correct texture class in testing phase, based on the available trained data. In this project, a set of collected dataset will be divided into two portions for each training and testing phase. Lastly, the output results produced by the classifier will be evaluated.



III. EXISTING CONCEPT

Lamination And Pitting Defects

A lamination defect is also called a de-lamination defect, lamination flaw, lamination fault, laminar, or simply lamination. As , it happens as a result of a flaw in the planchet, whether an incomplete mixing the metal in the alloy or a foreign substance such as dirt or gas trapped in the alloy, causing a layer of the coin's surface to peel or flake away before, during, or after striking, leaving a smaller or larger depression in the coin.

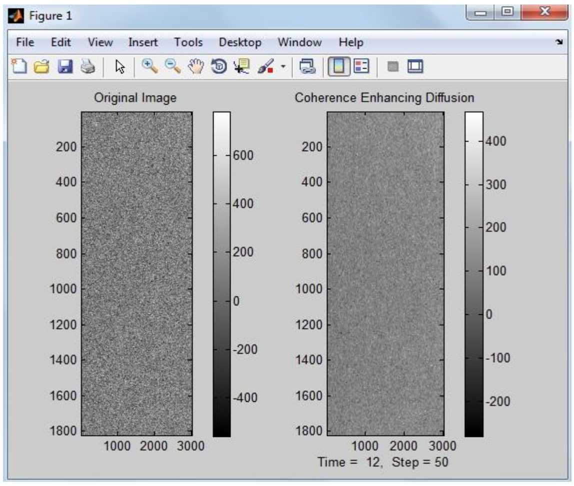


Figure 1

In laminated materials, repeated cyclic stresses, impact, and so on can cause layers to separate, forming mica -like structure of separate layers, with significant loss of mechanical toughness. De-lamination also occurs in reinforced concrete structures subject to reinforcement corrosion, in which case the oxidized metal of the reinforcement is greater in volume than the original metal. The oxidized metal therefore requires greater space than the original reinforcing bars, which causes a wedge-like stress on the concrete. This force eventually overcomes the relatively weak tensile strength of concrete, resulting in a separation (or de-lamination) of the concrete above and below the reinforcing bars.

Bonded metal laminations to high accuracy and consistency. The use of a specialized resist provides both insulating properties within the stack as well as bonding capabilities. The etching process provides a burr free finish, ideal to eliminate problems during winding. The full process is available, including post stacking services such as grinding where required.

Metal Laminations:

- It can produce and bond stacks of laminations the stack height is completely customizable which incorporates top and bottom resist layers which also acts as an insulated coating and a good bonding agent.
- The liquid photosensitive resist that we use on most laminations is the ideal solution for the above.
- In the lamination standards for all applicable mechanical and physical characteristics meet or exceed the recognized industry standards.
- A layer of rust inhibiting paper (V.C.I. or equivalent) shall be packed between lamination layers.
- In the laminations are made from various grades of electrical steels, silicon steels, nickel-iron alloys, and cold rolled motor lamination steel. To find out more about the metals available.

Major disadvantages in lamination defects are

- Producing poor bonds between layers
- Poor surface finish
- Difficulty in producing hollow parts.

Pitting Defects

The inspection of fine pitch surface-mounted devices by comparision of defect-free and defective packages is a promising area of research. The types of defects considered include missing pins, bent pins, broken pins, and bad solder connections on mounted packages. The feature extraction steps include morphological filtering for thresholding, skeletonization. The diffusion method are used as input for detecting the defects.

In texture classification the goal is to assign an unknown sample image to one of a set of known texture classes. Texture classification is one of the four problem domains in the field of texture analysis. The other three are texture segmentation (partitioning of an image into regions which have homogeneous properties with respect to texture; supervised texture segmentation with a priori knowledge of textures to be separated simplifies to texture classification), texture synthesis (the goal is to build a model of image texture, which can then be used for generating the texture) and shape from texture (a 2D image is considered to be a projection of a 3D scene and apparent texture distortions in the 2D image are used to estimate surface orientations in the 3D scene). In the learning phase, the target is to build a model for the texture content of each texture class present in the training data, which generally comprises of images with known class labels. The texture content of the training images is captured with the chosen texture analysis method, which yields a set of textural features for each image. These features, which can be scalar numbers or discrete histograms or empirical distributions, characterize given textural properties of the images, such as spatial structure, contrast, roughness, orientation, etc. In the recognition phase the texture content of the unknown sample is first described with the same texture analysis method.

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Then the textural features of the sample are compared to those of the training images with a classification algorithm, and the sample is assigned to the category with the best match.

Using the diffusion techniques image enhanced scaling should be measured. In the texture analysis In the Texture classification process involves two phases: the learning phase and the recognition phase. This domain coincides with the one where the enhancement of the diffusion coefficient versus the tilting force is the most rapid. The necessary and sufficient conditions for the non-monotonic behaviour of the diffusion coefficient as a function of temperature are found. The effect of the acceleration of diffusion by bias and temperature is demonstrated to be very sensitive to the value of the asymmetry parameter of the potential. In the learning phase, the target is to build a model for the texture content of each texture class present in the training data, which generally comprises of images with known class labels in the texture classification images using the fractional wavelet transform image enhanced should be effectively,

IV. RESULT AND DISCUSSION

In this concept, mainly detect the lamination and pitting defects using LDA and Filtering and texture process. LDA is then applied to the collection of the component-based LDA representations yielding a compact description referred to as 'cascaded LDA'. The decomposition of the metal image and its re-combination in the LDA space effectively solves the problem of metal identification.

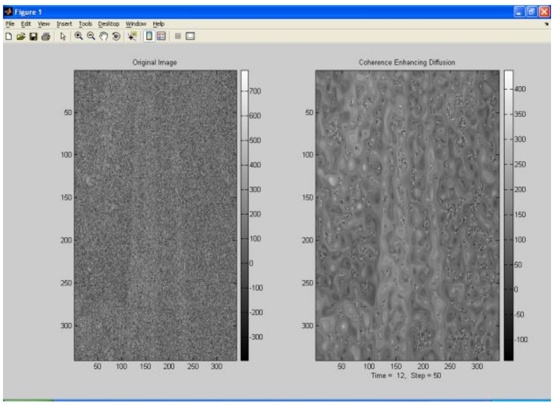

Figure 2(a)

The raw image (Figure 2(a)) is loaded, preprocessing is done . The noise on the borders is quickly eliminated. Diffusion is not inhibited on borders, a rounding effect occurs. The (Figure 2(b)) gradient magnitude is applied to detect the texture classification.

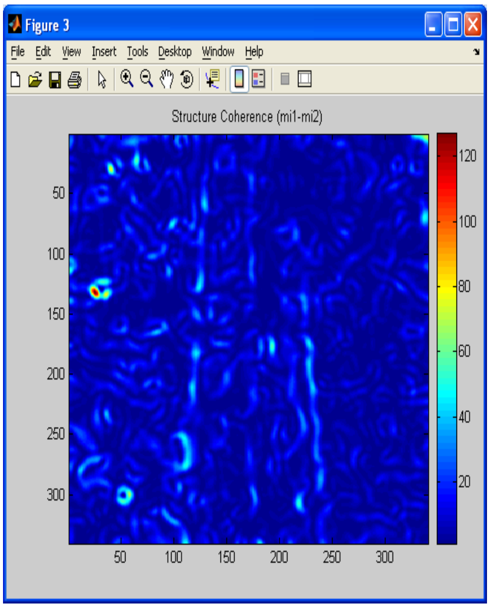

Figure 2(c)

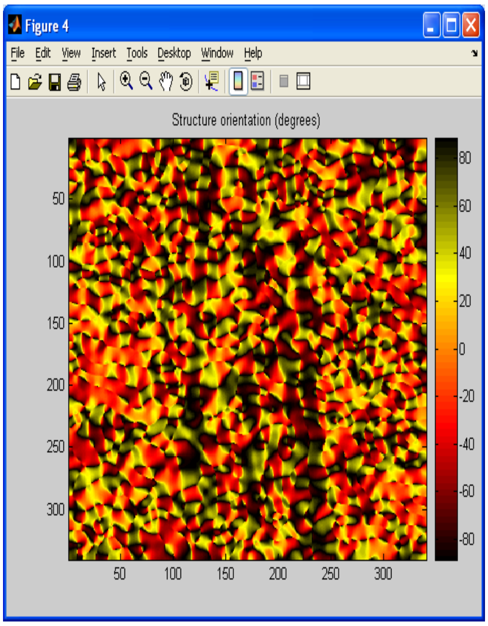

Figure 2(d)

In the images Figure (2c) Figure (2d) the texture orientation is seen visibly and the metal structure orientation is analysed. If there is a difference in texture elements, it indicates the defect. This defect on the metal surface is pitting defect which is detected fastly.

LDA explicitly attempts to model the difference between the classes of data. PCA on the other hand does not take into account any difference in class, and factor analysis builds the feature combinations based on differences rather than similarities.

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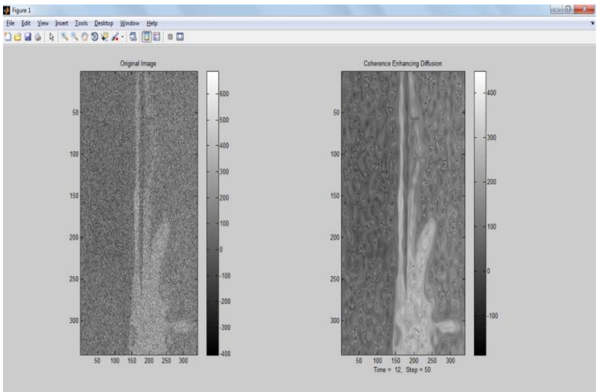
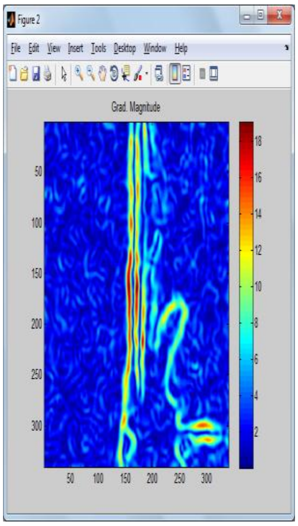


Figure (3a) Figure (3b)

The figure (3a) indicates an original image.The figure(3b) shows diffusion is done.The noise is removed and the defect is identified visually.



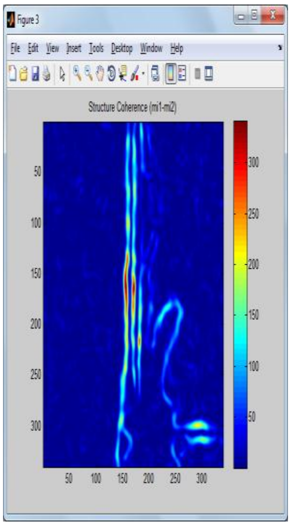


Figure (3c) Figure (3d)

The Figure (3c) and (3d) indicate the gradient magnitude level and structrure coherrance level which reveal the laminating defect occurred in depth.

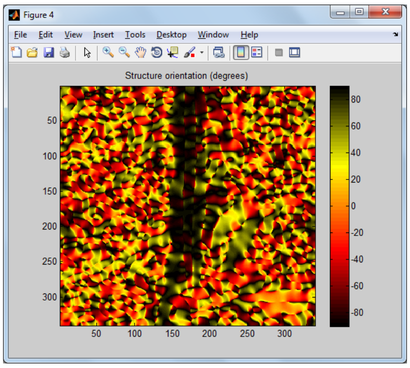


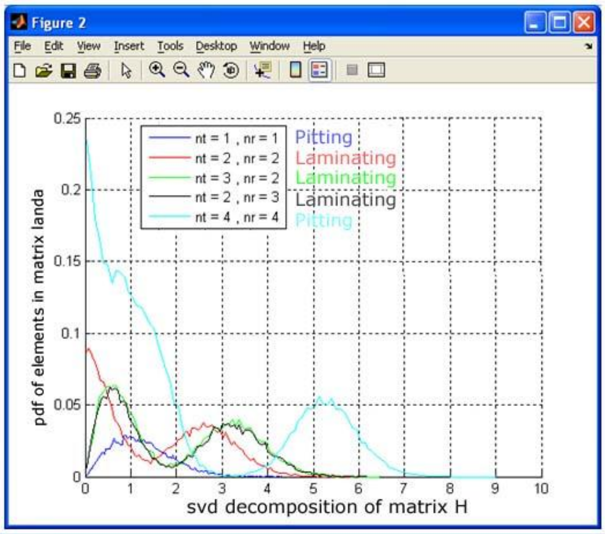
Figure (3e)

This Figure(3e) depicts the structure orientation of texture elements. Due to the differences in the structure orientation , laminating defect in depth is found. This raw material is rejected.Pixel weight is compared with the strength of the metal image decomposition is done.

The results of pitting is shown graphically

Table 1

S N	Size of the Image	Laminating Value (dia/mm)	Pitting Value (dia/mm)
1	256*256	0.05	0.25
2	256*256	0.04	0.15
3	256*256	0.03	0.10



Graph 1

The laminating and the pitting defects are shown graphically. The graph reveals that results obtained for the pitting defect is more efficient than the laminating defect. The noise is removed more efficiently using diffusion technique in pitting and laminating defects.

V. CONCLUSION

To replace the human inspection, we propose a visual automatic analysis approach in identifying the defects in metal surfaces. We analysed the lamination and pitting defects using Diffusion methods. The result is accurate for pitting than laminating defects. In future we can estimate the depth and width of the metal defect.

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