A New Approach to Aircraft Surface Inspection Based on Directional Energies of Texture

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Abstract

Non Destructive Inspections (NDI) plays a vital role in aircraft industry as it determines the structural integrity of aircraft surface and material characterization. The existing NDI methods are time consuming, we propose a new NDI approach using Digital Image Processing that has the potential to substantially decrease the inspection time. The aircraft imagery is analyzed by two methods i.e Contourlet Transform (CT) and Discrete Cosine Transform (DCT). With the help of Contourlet Transform the two dimensional (2-D) spectrum is divided into fine slices, using iterated directional filterbanks. Next, directional energy components for each block of the decomposed subband outputs are computed. These energy values are used to distinguish between the crack and scratch images using the Dot Product classifier. In next approach, the aircraft imagery is decomposed into high and low frequency components using DCT and the first order moment is determined to form feature vectors. A correlation based approach is then used for distinction between crack and scratch surfaces. A comparative examination between the two techniques on a database of crack and scratch images revealed that texture analysis using the combined transform based approach gave the best results by giving an accuracy of 96.6% for the identification of crack surfaces and 98.3% for scratch surfaces.

1. Introduction

NDI techniques are used in aerospace industry for analyzing the aircraft surface and sub-surface defects.These techniques along with the visible cracks detect the microscopic cracks too. As stated in [1], the importance of aircraft surface inspections lies from the fact that a typical heavy inspection of a commercial aircraft is 90% visual and 10% NDI. Visual inspection helps in isolating the surface of the aircraft that may suffer from any failure. Commonly employed NDI techniques are Dye Penetrant Method, Fluorescent Penetrant Inspection, Magnetic Particle Inspection (MPI), Eddy Current Losses, Radiography, and Ultrasonic Inspection. These NDI techniques suffer from more down time and requires large and costly setups.

Robotics Institute of Carnegie Mellon University has carried out a research in development of a robot known as Crown Inspection Mobile Platform (CIMP) [1], [2]. This robot is capable of moving over the aircraft body and transmitting live stereoscopic imagery of the aircraft to the control center. The control center applies image enhancement and understanding algorithm to highlight areas of cracks and scratches.

Alberts et al made a similar research by acquiring aircraft images by a robot and subsequently processing them by Neural Networks [3]. Training was performed by giving different images of multiple fasteners used in a modern aircraft. The technique resulted in differentiating healthy and crack areas of the aircraft surface.

This paper summarizes our research on aircraft visual inspection by means of normalized directional energy distribution using Contourlet and Discrete Cosine Transforms. Although spatial domain techniques are simple to put into practice yet they are susceptible to non-linear transformation of sleek aircraft skin. On the other hand frequency domain methods yield promising results but these techniques, like the Fourier transform, are thin-skinned to the asymmetric illumination conditions. Hence we have opted for two frequency based methods. In our approach we have catered for lop-sided illumination conditions by calculating the normalized directional energy contents of the aircraft surface. A known set of defected and healthy images of the aircraft are analyzed for the training purpose. A comparative analysis is then performed to evaluate the effectiveness of the technique. This approach has the advantage of reduced maintenance time and cost effectiveness. Additionally this approach has the advantage of better record keeping of the previous inspection re-

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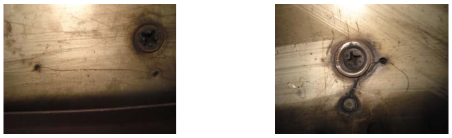

(a) (b)

Figure 1. (a) Crack on engine exhaust su face (b) Cracks around the screw

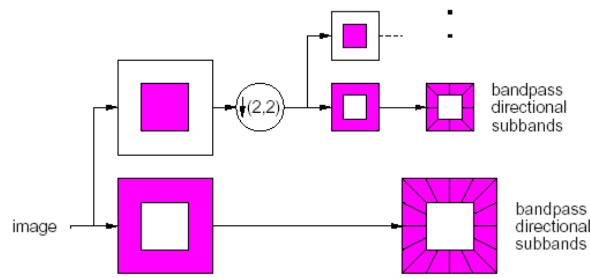

Figure 2. Contourlet Structure

sults, analyzing the trend of structural deformation of an aircraft and reducing inspector fatigue. Details related to image acquisition and pre-processing are described in Section 2. Section 3 gives a brief overview of the Contourlet Transform and its application to our problem with results, whereas introduction to Discrete Cosine Transform, application and results are presented in Section 4. The combination of transforms in explained in Section 5. The paper is concluded in Section 6.

2 Image Acquisition and Pre-Processing

Different critical areas of the aircraft like elevator surface, flaps, wing corners, rudder, engine intake and exhaust surface were identified according to technical manuals. These critical areas are photographed weekly for a period of 6 months. A total of 10 Cessna T-37 Tweet aircrafts were monitored resulting in a database of 1200 images. Optimal locations and slant angles for image acquisition were empirically found for the different critical areas. Images were acquired using a digital camera of 7.2 Mega pixels resolution. The acquired images were subjected to enhancement techniques for illumination invariance and for the pre-processing stage for subsequent application of algorithm. Some of the vulnerable surfaces of the aircraft are shown in Fig. 1.

3 Contourlet Transform (CT)

3.1 Introduction

Contourlet, a new discrete transform, can efficiently handle the intrinsic geometrical structure containing contours. It is proposed by Minh Do and Martin Vetterli [4] and provides sparse representation at both spatial and directional resolutions. Contourlet transform uses a structure similar to that of curvelets [5]. Fig. 2 shows a double filter bank structure comprising the Laplacian pyramid capturing the point discontinuities followed by a directional filter bank to link point discontinuities into linear structure.

3.2 Proposed Algorithm

The images are decomposed into sub-bands at four different resolution levels. At each resolution level 'k' the images are decomposed in 2^n sub-bands where 'n' is the oder of the directional filter.

The highest resolution level (level 1) corresponds to the actual size of image i.e. 128 x 128. The next resolution level is determined by the expression $2^{(N-1)}$ where N in this case is 7. This gives us an image of size 64 x 64 at level 2. Similarly the image is further reduced by subsampling at levels 3 and 4 and generating images of sizes 32 x 32 and 16 x 16 respectively. We have empirically chosen to apply a 5th order filter at resolution level 1 thus giving a total of 32 subbands. By applying a 4th order filter at resolution level 2, 16 subband outputs are obtained. Similarly resolution levels 3 and 4 gave 8 and 4 subbands respectively. Resultantly, 60 valued feature vector is calculated by finding the directional energies in respective sub-bands.

$E_{k\theta}$, defined as the Energy value in directional subband $S_{k\theta}$ at k^{th} resolution level is given by:

$$E_{k\theta} = \sum_{S_{k,\theta}} |F_{k,\theta}(x,y) - \overline{F}_{k,\theta}| \qquad (1)$$

Where $\overline{F}_{k\theta}$ is the mean of pixel values of $F_{k\theta}(x,y)$ in the sub-band $S_{k\theta}$. $F_{k\theta}(x,y)$ is the contourlet coefficient value at position (x,y). Additionally, the directional sub-bands vary from 0 to $2^n - 1$. The normalized energy value $\hat{E}_{k\theta}$ is defined as

$$\hat{E}_{k\theta} = \frac{E_{k\theta}}{\sum_{\theta=0}^{2^n-1} E_{k\theta}} \qquad (2)$$

$\hat{E}_{k\theta}$ represents the normalized energy value of subband θ at k^{th} resolution level. Taking the constant F_{max}

value equal to maximum intensity level of 255, the feature value $F_{k\theta}$ is calculated as:

$$F_{k\theta} = F_{max} \times \hat{E}_{k\theta} \tag{3}$$

We have evaluated the performance of our proposed algorithm by using the Contourlet Toolbox available at [6]. We used PKVA (Ladder Filter) as the selected filter for our algorithm. Feature vectors are calculated for the images and are stored in a gallery.

3.3 Experimental Results of Contourlet Transform Based Approach

Proposed algorithm has been implemented in MATLAB on a 1.5 GB RAM, 1.67 GHz Intel Core Duo processor PC. The data set of 600 images of crack and 600 images of scratch were divided into two parts. Therefore, out of 600 images of crack and scratch each, 300 images were used for the purpose of training respectively. These training images were subjected to the Contourlet transform as described in the previous section and their feature vectors were stored separately. The rest 300 images of crack and 300 images of scratch were used for the purpose of validation. These test images were subjected to Contourlet Transform and their feature vectors were passed through the Dot Product Classifier with the feature vectors of training images. The dot product giving the highest result with the training images was finalized to give decision of the crack or scratch. It was observed that the directional energy components of the image of crack and scratch are highly overlapping resulting in classification errors as depicted in Fig. 3. This method was able to identify 200 images of scratch and 225 images of crack out of 300 images of crack and scratch respectively.

4 Discrete Cosine Transform (DCT)

4.1 Introduction

Discrete Cosine Transform packs image into its low frequency components [7]. DCT has many applications in the field of Image processing. It bears the property of decorrelation, energy compaction, seperability which means that 1-D DCT can be applied to rows and then columns of an image. DCT has vast applications in the field of feature extraction and pattern recognition. Two dimensional DCT is defined as:

$$C(u,v) = \alpha(u)\alpha(v) \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} f(x,y) \cos \frac{\pi(2x+1)u}{2N} \times \cos \frac{\pi(2y+1)v}{2N} \tag{4}$$

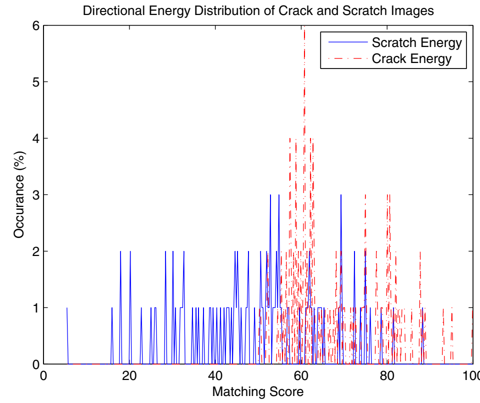

Figure 3. Directional Energy Distribution of Sub-bands

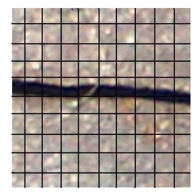

Figure 4. Division of image into 100 pieces

for u, v = 0, 1, 2,, N - 1 and $\alpha(u)$ and $\alpha(v)$ are defined as:

$$\alpha(u) = \left\{ \begin{array}{ll} \sqrt{\frac{1}{N}} & \text{for } u = 0 \\ \sqrt{\frac{2}{N}} & \text{for } u \neq 0 \end{array} \right\} \tag{5}$$

4.2 Application

The images that were previously used for training the CT were utilized for feature extraction by the DCT. Each image of crack and scratch was decomposed into 100 segments each of size 10×10 pixels as shown in Fig. 4.

The DCT of individual segment is calculated and values near or equal to zero are discarded. Standard deviation for the rest of the coefficient values were calculated. This procedure is applied to 100 segments of an image to generate a feature vector of 100 length.

4.3 Experimental Results of Discrete Cosine Transform Based Approach

The size of the database of the crack and scratch images for the purpose of training and validation remains

Table 1. Comparison of Three approaches on a database of 300 crack and 300 scratch aircraft surfaces

Test	CT	DCT	Combination of Transforms
Crack Images Identified	225	285	290
Scratch Images Identified	200	292	295
Recognition Rate of Crack Images(%)	75	95	96.6
Recognition Rate of Scratch Images(%)	66.66	97.3	98.3

same as that of Contourlet Transform. Each of the image of crack and scratch used for the purpose of training was passed through DCT as described in the previous section and its feature vector was stored separately. Similarly the images used for evaluation were subjected to DCT and their feature vectors were passed through the Dot Product Classifier with the feature vectors of training images. The dot product with the highest result was finalized to give decision of the crack or scratch. The DCT was able to identify 285 images of crack and 292 images of scratch out of 300 images of crack and scratch respectively leading to an accuracy of 95% and 97.3% respectively.

5 Combination of Transforms

To further enhance our approach, the feature vectors obtained from both the transforms of the training images were concatenated and stored in a separate gallery. The images used for validation were first passed through the Contourlet Transform and Discrete Cosine Transform as described in previous sections and their concatenated feature vectors were subjected to the Dot product classifier with rest of the feature vectors of the training images. The dot product with the highest result was observed with the training images to finalize the decision of crack or scratch. This technique resulted in better identification result, giving a higher recognition rate i.e. 96.6% for the crack surfaces and 98.3% for the scratch surfaces. This method identifies 290 images of crack and 295 images of scratch out of 300 images of crack and scratch surfaces respectively. Table 1 summaries the results for the three approaches.

6 Conclusion

We propose a new vision based approach to aircraft surface inspection based on directional energies of texture. The directional energies are extracted using Contourlet, Discrete Cosine Transforms and their combination. A correlation based approach is devised to differentiate between crack and scratch. The combination of transforms demonstrated the best classification results.

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