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DEFECT DETECTION OF FABRICS MADE FROM NON-NEWTONIAN FLUID BASED ON DCT AND DWT SUB-BLOCK METHOD

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ABSTRACT

Non-Newtonian Fabrics are produced from Polymerization of Terephthalic Acid and Etylene Glycol. In view of manufacturing defects, the finished products are sold at a massive discount of 45%-65%. Presently manual inspection is being done, where an expert inspector detects only 70% of defects. Here, we are simulating automatic defect detection of fabrics by means of using computers. We proposed two algorithms; those are Discrete Cosine Transform and Discrete Fourier Transform.

KEYWORDS: Fabric defects, Non-Newtonian fluid, Discrete Cosine Transform (DCT), Discrete Fourier Transform (DFT), Nearest Neighbour Classifier (NNC).

The Non-Newtonian fluid fabrics are made from polymerization of Terephthalic Acid and Etylene Glycol. It has several types of defects such as Torn fabrics, Oil stains, variation of density of fibers, variation of dye uptake and variation of tensile strength. The above types of defects can be mathematically characterized by variation of texture. Texture is nothing but regular or irregular pattern, smooth or rough surface present in the flat type of surface. Texture as a Primitive visual cue has been studied for a long time. Various techniques have been developed for texture segmentation, classification and synthesis. Although texture analysis has a long history, its application to real image data has been limited to-date.

Most of the existing approaches for texture feature extraction make use of Statistical techniques. Processing the texture image data requires large storage space and computational load to calculate the future matrix such as GLCM (Grey Level Co-occurrence Matrix, Geetanjali et. al. The above GLCM has given 94% result with nearest neighbour classifier and had given 100% with recurrent neural network. State of the art technology using spectral analysis (DCT, DFT) have been tried. Geetanjali, worked on the following features proposed by Harallick.

1. Energy $$E = \sum_x \sum_y P(x,y)^2$$
2. Contrast $$I = \sum_x \sum_y (x-y)^2 \; P(x,y)$$
3. Entropy $$S = \sum_x \sum_y P(x,y) \log P(x,y)$$
4. Inverse difference $$H = \sum_x \sum_y \frac{1}{1+(x-y)^2} P(x,y)$$
5. Maximum Probability $M = Max$ $$\frac{x,y\,P(x,y)}{\sum_x \sum_y P(x,y)}$$
6. Polynominal Entropy $$P = \sum_x \sum_y P(x,y) * e^{-(a*P^3(x,y)+b*P^2(x,y)+c*P(x,y)+d)}$$
7. Correlation $$R = \frac{\sum_x \sum_y (x-1)(y-1)P(x,y) - \mu_x \mu_y}{\sigma_x \sigma_y}$$

Where are $\mu_x, \mu_y, \sigma_x, \sigma_y$ the means and standard deviation of P_x and P_y respectively.

P_y is the transpose of P_x.

Bodnarova, used optimal Gabor filter for Fabric flaw detection. When it was applied non-defective texture, the filter response maximizes a Fisher Cost Function. A Pixel of Potentially flawed texture is classified as defective or non-defective based on the Gabor filter response at that pixel. Henry, proposed a statistical texture measured computed from Gray level run-length matrices. In statistical texture analysis, texture features are computed from statistical distribution of observed combinations of intensities at specified positions relative to each other in the image.

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According to the number of intensity points (pixels) in each combination, statistics are classified into first-order, second-order and higher-order.

The Gray Level Run Length (GLRM) method is a way of extracting higher order statistical features. The technique has been described and applied by Galloway et. al.

A small (4 x 4) sub-image with 4 gray levels and its corresponding gray level run length matrices $P(i,j\,|\,\theta=0^0)$ is illustrated below.

$$\begin{pmatrix} 1 & 2 & 3 & 4 \\ 1 & 3 & 4 & 4 \\ 3 & 2 & 2 & 2 \\ 4 & 1 & 4 & 1 \\ \multicolumn{4}{c}{\text{Image Matrix}} \end{pmatrix}$$

Grey level i	Run length (j)			
	1	2	3	4
1	4	0	0	0
2	1	0	1	0
3	3	0	0	0
4	3	1	0	0

Figure1: A small image and its Gray level Run Length Matrix $P(i,j\,|\,\theta=0^0)$**.**

Galloway, introduced five statistical texture features to be extracted from the Gray Level Run Length Matrix.

1. Short Runs Emphasis:

$$SRE=\sum_{i=1}^{G}\sum_{j=1}^{R}\frac{p(i,j\,|\,\theta)}{j^2}\Big/\sum_{i=1}^{G}\sum_{j=1}^{R}P(i,j\,|\,\theta)$$

By dividing each run length value by the square of its length, short run lengths are emphasized. The denominator is the total number of runs in the image.

2. Long Runs Emphasis:

$$LRE=\sum_{i=1}^{G}\sum_{j=1}^{R}j^2P(i,j\,|\,\theta)\Big/\sum_{i=1}^{G}\sum_{j=1}^{R}P(i,j\,|\,\theta)$$

Here we multiply each run length value by the square of its length, in order to give higher weight to the long runs.

3. Gray Level Non-uniformity:

$$GLN=\sum_{i=1}^{G}\left(\sum_{j=1}^{R}P(i,j\,|\,\theta)\right)^2\Big/\sum_{i=1}^{G}\sum_{j=1}^{R}P(i,j\,|\,\theta)$$

High run length values will contribute most to this feature. The GLN feature will have its lowest value if the runs are evenly distributed over all gray levels.

4. Run Length Non-uniformity:

$$RLN=\sum_{j=1}^{R}\left(\sum_{i=1}^{G}P(i,j\,|\,\theta)\right)^2\Big/\sum_{i=1}^{G}\sum_{j=1}^{R}P(i,j\,|\,\theta)$$

The RLN feature will have its lowest value if the runs are evenly distributed over all run lengths.

5. Run Percentage:

$$RP=\frac{1}{n}\sum_{i=1}^{G}\sum_{j=1}^{R}P(i,j\,|\,\theta)$$

This feature is the ratio between the total number of observed runs in the image and the total number of possible runs if all runs had a length of one.

Chu et al. (1990) introduced two additional features, namely Low Gray Level Emphasis (LGRE) and High Gray Gray Level Emphasis (HGRE). These features make use of the gray levels of the runs, and are introduced in order to distinguish textures that are similar according to their SRE and LRE features, but differ in gray level distribution of the runs.

6. Low Gray Level Runs Emphasis:

$$LGRE=\sum_{i=1}^{G}\sum_{j=1}^{R}\frac{P(i,j\,|\,\theta)}{i^2}\Big/\sum_{i=1}^{G}\sum_{j=1}^{R}P(i,j\,|\,\theta)$$

7. High Gray Level Runs Emphasis:

$$HGRE=\sum_{i=1}^{G}\sum_{j=1}^{R}i^2P(i,j\,|\,\theta)\Big/\sum_{i=1}^{G}\sum_{j=1}^{R}P(i,j\,|\,\theta)$$

Proposed Method: The defect in the Non-Newtonian fabrics are made up of high frequency components. Hence we will take only the high frequency components of the 2-D image signal as shown in figure 2.

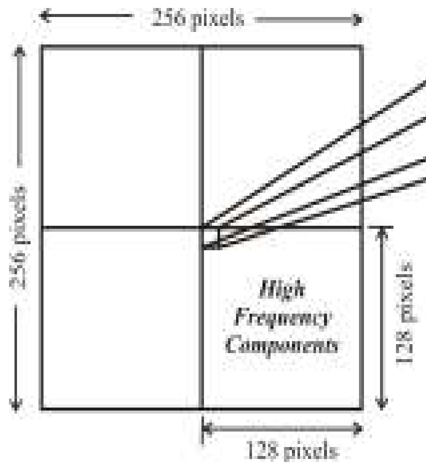

Figure - 2

In the above figure 2, the High Frequency Components of the image (256 x 256) is cropped by (128 x 128). The (128 x 128) sub-image is divided into further small blocks of size (16 x 16). So total number of sub-blocks will be 64 in the High Frequency Components i.e. 4th quadrant. The above result is obtained by DCT and DWT separately in the MATLAB 7.1 platform using the following equations.

$$F(k,l)=\alpha(K)\alpha(L)\sum_{m=1}^{N}\sum_{n=1}^{N} f(m,n)\; Cos\left(\frac{(2m+1)\pi k}{2N}\right) Cos\left(\frac{(2n+1)\pi l}{2N}\right)$$

$$\begin{aligned} where,\ \alpha(x) &= \sqrt{\frac{1}{N}}\ \ if\ \ x=0 \\ &= \sqrt{\frac{2}{N}}\ \ if\ \ x\neq 0 \end{aligned}$$

$F(k,l)$ is the frequency domain matrix of the transformed image $f(m,n)$ by the DCT. The two Cos terms are called as the Kernels or basis vector.

Let us write the equation for DFT

$$F(k,l)=\sum_{m=1}^{M}\sum_{n=1}^{M} f(m,n)\; e^{-j\frac{2\pi}{M}mk}\, e^{-j\frac{2\pi}{N}nl}$$

Here $F(k,l)$ is the frequency domain matrix of the two dimensional image $f(m,n)$ and the two exponential terms are called as the basis vector of the Discrete Fourier Transform.

Experimental Set-up:

Let $\overline{x_i}$ is the average value of the i^{th} block intensities of the sub-block in the 4th quadrant, here i varies from 1 to 64.

Let σ_i^2 is the variance of the i^{th} block intensities of the sub-block in the 4th quadrant, here i varies from 1 to 64.

$$M=\frac{\sum_{i=1}^{64}\overline{x_i}}{\sum_{i=1}^{64}\sigma_i^2}$$

Where M is called the statistical moment of the image. This is also called as the characterization of the texture or the feature of the image.

Here we have taken 25 defective fabrics of size 256 x 256 and 25 defect-free fabrics of size 256 x 256 and for each image one moment feature is obtained. So the database size is equal to 50 x 1.

This database is tested by Nearest Neighbour Classifier. Nearest Neightbour Classifier is a type of classifier comes under supervised learning. Here the pattern recognition is done by two phases viz. first phase is Training and second phase is Testing. Images from 1 to 12 record number in the database and 26 to 37 in the database are taken for training. The rest are taken for testing. The program code for the nearest neighbour classifier is given as follows. We got 98% using DCT and 89% result using DFT.

```
for i=3:3  %MAX 4 columns are present
   y(i)=0;
end
j=3;%
while j <=3
for i=1:12  % MAX two 12 tuples are taken for training of DEFECTIVE sample
y(j)=  y(j)  +  b(i,j);
end
j=j+1;
end
%y
for i=3:3
y(i)=y(i)/12.0;
end
%y
%centroed of defecttive training sample by minimum
```

```
% distance classifier is completed for 50*2 array
%**************************************************************************
%find the centroed of defectless sample now processing will start
%*********************
%*********************************************
for i = 3:3
z(i)=0;
end
j=3;
while j <=3
for i= 26:38
z(j)=z(j) + b(i,j);
end
j=j+1;
end
for i =3 :3
z(i)=z(i)/12.0;
end
%**************************************************************************
%TESTING STARTS FOR NICE SAMPLE
%*********
%*********************************************************
fprintf('\ncent def=....%d %d %d ',y(1),y(2),y(3));
fprintf('\ncent non-def...%d %d %d ',z(1),z(2),z(3));
d1=0;
d2=0;
m=1;
for i=1 :13
nice(i)=0;
end
k=38;
while(k <=50)
for i =3:3
d1=d1 + (y(i)- b(k,i))^2;
d2=d2 + (z(i)- b(k,i))^2;
end
if(d2 <=d1)
nice(m)=k;
m=m+1;
end
k=k+1;
end
for i=1:13
fprintf('\nnice***********%d',nice(i));
end
d1=0;
d2=0;
m=1;
for i=1:13
def(i)=0;
end
k=13;
while(k<=25)
for i=3:3
d1=d1+(y(i)-b(k,i))^2;
d2=d2+(z(i)-b(k,i))^2;
end;%end of for
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%d1
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%5d2
if(k==13)
fprintf('\nnice d2=%d,def d1=%d',d2,d1);
end
if(d2>=d1)
def(m)=k;
end
m=m+1;
```

```
k=k+1;
end;%end of while
for i=1:13
fprintf('\ndefective=......%d',def(i));
end
%after this the below is a single statement
%fprintf('\n p=%d...w=%d...tmeen2=%d',p,w,tmeen2);
```

Non-Defective fabric image

Defective fabric image

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