MACHINE VISUALIZATION FOR REAL TIME INDUSTRIAL APPLICATION

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ABSTRACT

Machine vision has many applications like medical imaging, defect detection, biometrics. The research in the above fields has been primarily started in the last decade. The primary aim is to reduce the cost by means of computer application so that the common man can access it .We have studied with fabric texture and nice result has been obtained.

KEYWORDS: Newral Network, GLCM.

The class of Textiles produced from terephthalic acid and ethylene glycol by condensation polymerization has many end-uses for example these are used as filter fabric in railway track to prevent soil erosion, in cement industry these are used in boiler department as filter fabric to prevent the fly-ash from mixing in the atmosphere. Presently ,the quality checking is done by the human in naked eye The automation of quality check of the non-newtonian fabric can be termed as Image Analysis or texture analysis problem .WE have done a Simulation study by the process of Image Analysis which consists of two steps the former is feature extraction and the second part is recognition. Various techniques or tools that are presently in research for texture feature extraction are GLCM, Markov Random Field, Gabor filter. We have used here GLCM with 20 haralick features.

The authors had done a simulation Study for defect detection and estimation by taking 25 nice sample and 25 defective still image samples and then extracted 28 Haralick features .Also,20 polynomial entropy features were taken .When combined it has given 48 features. The pattern recognition problem for fault detection problem of Non-newtonian fluid is done by Back propagation neural network, Recurrent newral network, Radial basis function newral network and Learning Vector Quantization newralnetwok.

METHODOLOGY

The co-occurrence matrix method of texture description is based on the repeated occurrence of some gray-level configuration in the texture. We are taking a window of size256 x 256 go on sliding until the completion of the total image.

The texture is measured according to the following formulas.

$$P_{0^0},d(a,b) = |\{[(k,l),(m,n)]\} \in D: k-m=0,|l-n|\ (k,l)=a, f(m,n)=b\}|$$

Here angle between two pixels $\alpha=0^0$

Distance d=1 ,means all the gray patters at a pixel distances 1 are counted for calculating the frequency count of a particular pattern.

Similarly angles at different orientations are being considered. The Angle positive 135^0 means all the pattern which are lying in the principal Diagonals are being considered

$$P_{45^0},d(a,b) = |\{[(k,l),(m,n)]\} \in D: (k-m=d, l-n=-d) \text{ OR } (k-m=-d, l-n=d)\ f(k,l)=af(m,n)=b\}|$$

$$P_{90^0},d(a,b) = |\{[(k,l),(m,n)]\} \in D: |k-m|=d, l-n=0, f(k,l)=a, f(m,n)=b\}|$$

$$P_{135^0},d(a,b) = |\{[(k,l),(m,n)]\} \in D: (k-m=d, l-n=d) \text{ OR } (k-m=-d, l-n=-d), f(k,l)=a, f(m,n)=b\}|$$

The input image size for the theoretical purpose, the author has chosen the window size as 5 x 5.

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0	0	0	1	2
1	1	0	1	1
2	2	0	1	1
1	1	0	2	0
0	0	1	0	1

P $_{135,\ 1}$

8	2	1
2	6	2
0	2	0

It is to be noted that P(0,0)=8,P(0,1)=2,P(0,2)=1

P(1,0)=2,P(1,1)6,P(1,2)=2

P(2,1)=2

All other P values of the 256x256 size array are zero for 135 degree and distance Equal to 1.Similar the case for all other Orientation and distances.

Different parameters to measure texture

- Energy
- Contrast.
- Hanmandlu Entropy Function
- maximum Probability.
- Inverse Difference Moment

Energy

It is defined as the angular second moment, the more the energy, the image is more homogeneous in the direction Θ.

$$\sum_{a,b} P^2{}_{\theta,d}(a,b)$$

a, b = gray values.

Θ = direction of scanning.

d = distance between two pixels.

Contrast

$\sum_{a,b} |a-b|^K P^{\lambda}{}_{\theta,d}(a,b)$ **(a measure of local image variation.)**

K = order of moment.

λ = a homogeneous constant

Polynomial Entropy Function

$$I_k = \sum_{10 \le a,b} \sum_{c,d \le 200} e^{-\left(a*P(i,j)^\wedge 3+b*P(i,j)^\wedge 2+c*P(I,j)+d\right)}$$

k	A	B	c	d
ent(1)	10	10	10	10
ent(2)	10	10	10	10
ent(3)	10	10	10	10
ent(4)	10	10	10	10
ent(5)	20	20	20	20
ent(6)	50	50	50	50
ent(7)	100	100	100	100
ent(8)	200	200	200	200
ent(9)	20	20	20	20
ent(10)	50	50	50	50
ent(11)	100	100	100	100
ent(12)	200	200	200	200
ent(13)	20	20	20	20
ent(14)	50	50	50	50
ent(15)	100	100	100	100
ent(16)	200	200	200	200
ent(17)	20	20	20	20
ent(18)	50	50	50	50
ent(19)	100	100	100	100
ent(20)	200	200	200	200

Maximum Probability

$$\frac{\max_{a,b} P_{\theta,d}(a,b)}{\sum_{a,b} P_{\theta,d}(a,b)}$$

0<= a,b<=255

Pattern (a,b) occurs frequently

2.5. Homogenity

$$f_5 = \sum_{i=0}^{255}\sum_{j=0}^{255} \frac{1}{1+(i-j)^2} P(i,j)$$

2.6. Inertia

$$f_6 = \sum_{i=0}^{255}\sum_{j=0}^{255} (i-j)^2 \, P(i,j)$$

2.7.Correlation

$$f_7 = \frac{\sum_{i=0}^{255}\sum_{j=0}^{255} (i-1)(j-1)P(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y}$$

Where μ_x, μ_y, σ_x *and* σ_y are the means and standard deviation of p_x and p_y. p_y is the transpose of p_x.

Defect Detection by Artificial Neural Network

We have got 7 x 4 Haralik features in 4 orientation totals into 28 features. We have got 20 Hanmandulu features, total into (20+28) 48 features. The database for the 48 features is shown in figure-1. There are 50 patterns.

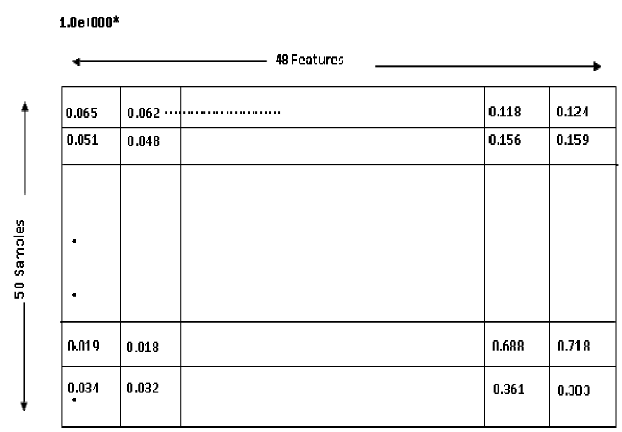

Figure 1: Feature Data Base

Supervised Machine Learning By Artificial Neural Network.

The above features selection was done by Choudhury D.K., Hanmandlu.Met al [10,11] had done the feature Selection by GLCM and Classified by Minimum distance Classifier.

We are doing classification by four ANN Techniques i.e Back propagation, Recurrent Neural Network, earning Vector Quantization and Radial Basis function. In this experiment we have got total 50 tuples having (48 +1) fields.

Defective samples are lying between recno(1) to recno(25).Nice samples are lying between recno(26) to recno(50) .Each of the above record contains 48 features.The 49th column contains the class level. The classlevel -1 (recno(1-25) is for defective samples and +1(26-50) is for nice samples. In the present machine learning expt. Supervised Learning is followed. Recno(1-18 & 26-43) are kept for training the machine. Recno(19-25) & (44-50) are kept for testing the samples.

Four types of Artificial Neural Networks are utilized for testing the samples.They are

a. Backpropagation Algorithm(BPN)
b. Recurrent Neural Algorithm(RNN)
c. Radial basis function Algorithm(RBF)
d. Learning Vector Quantization Algorithm(LVQ)

RESULT AND DISCUSSION

TYPE OF ANN	BNN	RNN	LVQ	RBF
CO-OCCURRENCE MATRIX	**90%**	**96%**	**85%**	**60%**

Form the Above experiment. It was concluded that RNN gives the best Result. Presently an Prototype ROBOT is being tried.

CONCLUSION

The above experiments can be extended to multi-class defect detection of fabrics having different types of defects. It will be convenient for detecting a particular defect which occurs frequently.

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