

# Scale Invariant Texture Classification using Fuzzy Logic

Shailendrakumar M. Mukane, Sachin R. Gengaje, Dattatraya S. Bormane

**Abstract-** In this paper, scale invariant texture classification method based on Fuzzy logic is developed. It is applied for the classification of texture images. Two types of texture features are extracted one using Discrete Wavelet Transform (DWT) and other using Gray Level Co-occurrence matrix (GLCM). Two features are obtained from each sub-band of DWT coefficients up to fifth level of decomposition and eight features are extracted from GLCM of whole image and each sub-band of first level DWT decomposition. The fuzzy classifier is developed with Gaussian membership function. The performance is measured in terms of Success Rate. This study showed that the proposed method offers excellent Success Rate with WSF1, WSF3, and HWSCF6, proposed HWSCF3, HWSCF7, and HWSCF9. The results of our method outperform earlier methods available.

**Index Terms-** Discrete Wavelet Transform, Feature Extraction, Fuzzy Logic Classifier, Gaussian Function, Gray Level Co-occurrence Matrix, Scale Invariant, Texture Classification,



## 1. INTRODUCTION

Content Based Image Retrieval (CBIR) method where in images are expressed by their visual content of images. The key component of any CBIR system is classification of images. Texture, Shape, and Colour are the general visual content features of image.

Texture features are very important because it is an intrinsic property of virtually all surfaces such as skin, bricks, tree, fabric, grass, hair, clouds, etc. It contains information about the structural arrangement of surfaces and their relationship to the surrounding environment [1]. Texture analysis is basic step to many applications such as industrial monitoring of product quality, remote sensing of earth resources, medical diagnosis, image retrieval systems, etc.

Weszka *et al.* [2] compared the classification performance of Fourier power spectrum, second order Gray Level Co-occurrence Matrix (GLCM), and first order statistics of gray level differences for terrain samples and commented that Fourier methods performed poorly. Haralick [1] suggested GLCM texture features and used these features to analyze remotely sensed images. Wan *et al.* [3] presented comparative study of four texture analysis methods such as gray level Run-length method[RLM], Co-occurrence matrix method, Histogram method, and Auto-correlation method and shown that Co-occurrence method is superior. Wavelet Transform [4, 5] provides a multi-resolution approach for the problem at hand. Smith and Chang [6] used mean and variance extracted from wavelet sub-band coefficients, as the texture representation.

Classification methods can be divided into categories such as parametric, non-parametric, stochastic methods, non-metric methods [7]. Classification task involves classifying images based on the feature vectors provided by the feature extraction methods. If no prior parameterized knowledge about the probability structure then classification is based on non-parametric techniques. That classification will be based on information provided by training samples alone. These techniques include fuzzy classification, neural network approach, etc. Avci [8] used multilayer perceptron neural network classifier to classify scale invariant texture images. Avci [9] presented Wavelet packet entropy adaptive network based fuzzy inference system (WPEANFIS) for scale invariant texture image classification of the 20 texture images. Mukane *et al.* carried out the features for scale invariance [10], size invariance [11], with wavelet and co-occurrence matrix based features using fuzzy logic classifier. Cui *et al.* [12] perform experiment for scale invariant texture classification based on Radon transform and multi-scale analysis with Mahalanobis classifier.

---

S.M.Mukane is pursuing Ph.D program in Electronics Engineering at Department of Electronics and Telecommunication Engineering, SVETI's College of Engineering, Pandharpur, Maharashtra State, India. 413209. Tel.: +91-2186 225083; fax: +91-2186 225082 Email: [smmukane@gmail.com](mailto:smmukane@gmail.com)

S.R.Gengaje is working as Professor in Electronics Engineering at Walchand Institute of Technology, Solapur, Maharashtra State, India. Email: [srgegaje@rediffmail.com](mailto:srgegaje@rediffmail.com)

D.S.Bormane is working as Principal at, JSPM's R.S. College of Engineering, Tathawade, Pune, Maharashtra State, India. Email: [bdattatraya@yahoo.com](mailto:bdattatraya@yahoo.com)

In this study, scale invariant texture classification method is proposed using fuzzy logic. 25 texture images are taken from the Brodatz texture Album. Fifteen feature sets are formed from the extracted features of DWT based features, and DWT-GLCM based feature set. The average success rate of fuzzy classifier to classify texture images with training to testing ratio 1:1 is obtained. These results are compared with some of the best results available in the literature.

## 2. FEATURE EXTRACTION

Features of texture images are extracted as a first step in the classification and retrieval application. Pyramid structured DWT is used to decompose the textures up to five levels. Wavelet Statistical Features (WSF) is obtained [10]. Gray Level Co-occurrence matrix (GLCM) is derived for distance vector  $d(i, j)$  i.e. offset is taken as  $d(0, 1)$ . This matrix is obtained for whole image and four sub-bands of first level DWT of the image. From the GLCM the co-occurrence parameters namely contrast, inverse difference moment, energy, norm entropy, local homogeneity, cluster shade, cluster prominence, & maximum probability are obtained [8]. These features are called as Wavelet Co-occurrence Features (WCF).

## 3. CLASSIFICATION

A fuzzy logic system is a nonlinear mapping of an input feature vector into a scalar output [13]. Fuzzy logic provides innovative tools to handle the complex and ill-defined systems where classical tools become unsuccessful. Fuzzy systems are universal approximators of non linear functions. Two aspects are important in fuzzy system one generating the best rule set and second the membership function. These should relate properly the independent and dependent variable.

Membership function maps elements of a given universal set which is always a crisp set in to real numbers in a specific range. The most commonly used membership functions  $\mu(x)$ , are triangular, trapezoidal, piecewise linear, or Gaussian. Whether a particular membership function is suitable or not can be determined only in the context of a particular application. The membership function required for the fuzzy classifier in the present research is Gaussian function. This is derived from the histogram plots of the features extracted. The Gaussian function is as shown in Fig.1

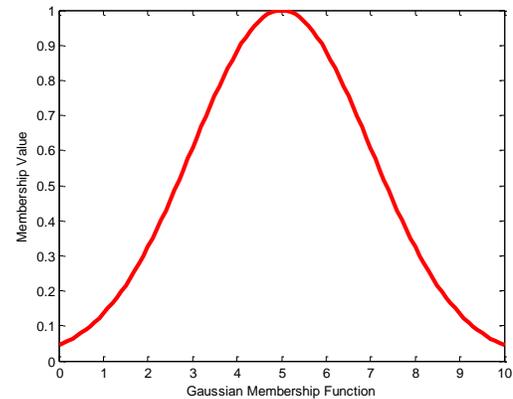


Fig.1. Gaussian Membership function of Eq. (4.4) for  $m = 5$  and  $\sigma = 2$

Inputs to the fuzzy system are WSF and WCF features. The outputs of the system are specific texture image. Fuzzy sets with Gaussian membership functions are used to define these input variables. These fuzzy sets can be defined using the following equation Eq.1 [14].

$$\mu(f) = e^{-0.5\left(\frac{f-m}{\sigma}\right)^2} \quad (1)$$

where  $m$  is the mean of the fuzzy set and  $\sigma$  is the standard deviation from the mean.

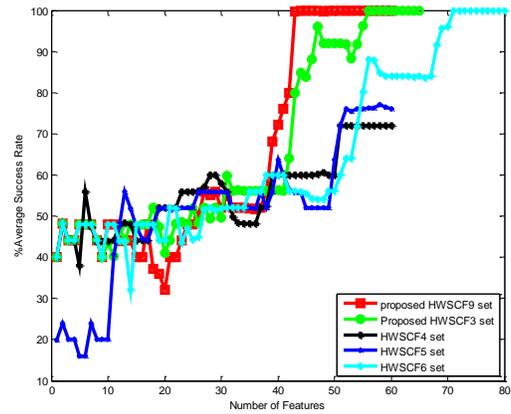
## 4. RESULTS AND DISCUSSIONS

In this experiment twenty five texture images [8] from the Brodatz texture [15] are used for classification. Texture images are then sampled to  $256 \times 256$  sizes [11]. To have different scales, 3000 texture samples each of  $64 \times 64$ ,  $128 \times 128$ ,  $256 \times 256$ , and  $384 \times 384$  are randomly generated and resized to  $256 \times 256$ , [16]. This leads to 12000 samples. This way 12000 samples used for training and testing of Fuzzy logic Classifier is carried for another 12000 samples generated in the very same way. Ratio of training to testing is maintained 1:1. In this experiment pyramid structured type of DWT is used with dB2 as a wavelet filter [12].

Feature database is created using wavelet decomposed sub-bands up to fifth level of decomposition. Total number of sub-bands up to fifth level will be 20. Energy and standard deviations of each sub-band coefficients are calculated. These features are stored as WSF. Another feature database is obtained using eight co-occurrence features by finding the co-occurrence matrix of original sample image and 4- sub-bands of the 1-level DWT coefficients' co-occurrence matrix. These are stored as WCF. This way, maximum WSF will be  $20 \times 2 = 40$  for five level decomposition and maximum WCF will be  $5 \times 8 = 40$  for a sample. Feature sets Classification is carried out for following feature sets.

- 1) WSF1- Energy only.
- 2) WSF2- Standard Deviation
- 3) WSF3- Energy + Standard Deviation

- 4) WCF1- proposed Five Co-occurrence features viz. contrast, energy, local homogeneity, cluster shade, and cluster prominence.
- 5) WCF2- Eight Co-occurrence features viz. contrast, inverse difference moment, energy, norm entropy, local homogeneity, cluster shade, cluster prominence, & maximum probability.
- 6) WCF3- proposed Four Co-occurrence features viz. contrast, inverse difference moment, norm entropy, energy.
- 7)HWSCF1- proposed WSF1+WCF1
- 8) HWSCF2- proposed WSF2+WCF1
- 9)HWSCF3- proposed WSF3+WCF1
- 10) HWSCF4- WSF1+WCF2
- 11) HWSCF5- WSF2+WCF2
- 12) HWSCF6- WSF3+WCF2
- 13) HWSCF7- proposed WSF1+WCF3
- 14) HWSCF8- proposed WSF2+WCF3
- 15) HWSCF9- proposed WSF3+WCF3



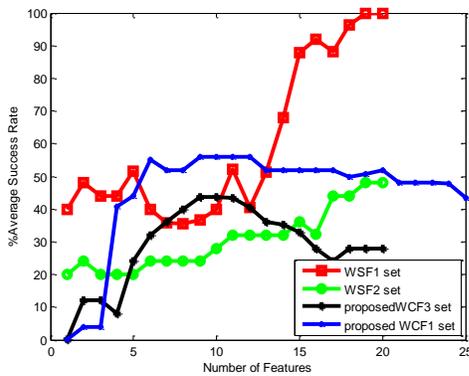
(c)

Fig. 2. Average Success Rate with various feature sets for 12000 samples of 256x256 sizes

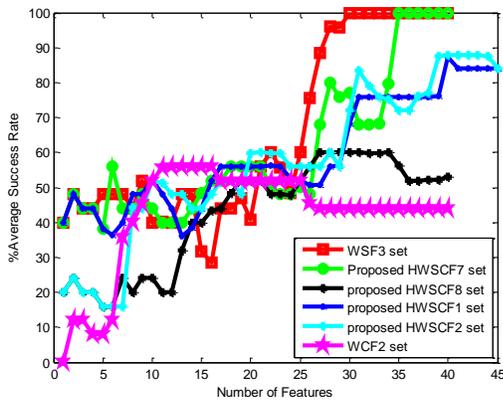
Performance of the above feature sets is tested with the help of a fuzzy classifier in terms of Success rate. Let  $N_T$  be the no. of samples to be tested and out of that if the system correctly classifies  $N_C$  times then success rate of the system for the fuzzy rule as a percentage is given by Eq.2.

$$S_R = \frac{N_C}{N_T} \times 100 \quad (2)$$

Fig. 2 shows graph of average success rate versus number of features for various feature sets. By observation of Fig. 2 (a), (b), and (c) it is noticed that WSF1, WSF3, HWSCF6, proposed feature sets like HWSCF7, HWSCF3, HWSCF9 offers 100% success rate for Scale Invariance. The results of this research work are compared with some of the earlier work published in the literature as presented in the Table 1.



(a)



(b)

## 5. CONCLUSION

In this study, traditional feature sets as well as proposed feature sets are tested with fuzzy classifier to classify scale invariant texture images. The some proposed feature sets as well as traditional feature sets outperform other feature sets. Fuzzy logic classifier tested for large sample size of 12000 providing excellent results. The proposed hybrid feature set HWSCF3, HWSCF7, HWSCF9, offers 100% success rate along with WSF1, WSF3, and HWSCF6 for scale invariant texture classification. Fuzzy logic classifier performs excellently with training to testing ratio of 1:1 and consistency of excellent success rate. The results are compared with existing literature results which shows that our method outperform the other.

TABLE 1  
Comparison of Proposed method results with Earlier published methods

Texture Classification Methods from Literature	% Correct Classification Rate	Number of Features
Radon Transform features with Mahalanobis Classifier (Cui et al. 2006) [16]	92.2	21
Wavelet packet entropy adaptive network based fuzzy inference system (WPEANFIS) (Avci,2008) [9]	93.12	16
WNN-ANE (Avci,2007)[8]	98.69	76
Proposed Fuzzy logic Classifier system	100	19

- [9] E.Avci, "Comparison of wavelet families for texture classification by using wavelet packet entropy adaptive network based fuzzy inference system", *Applied Soft Computing*, 8, pp.225-231, 2008.
- [10] S.M. Mukane, S.R. Gengaje, and D.S. Bormane, "On Scale Invariance Texture Image Retrieval using Fuzzy Logic and Wavelet Co-occurrence based Features", *International Journal of Computer Applications*, 18(3), pp.10-17,2011.
- [11] S.M. Mukane, D.S. Bormane, and S.R. Gengaje, "On Size Invariance Texture Image Retrieval using Fuzzy Logic and Wavelet based Features", *International Journal of Applied Engineering Research*, 6(6), pp.1297-1310, 2011.
- [12] Cui, P., Li, J., Pan, Q., Zhang, H., "Rotation and scaling invariant texture classification based on Radon transform and multi-scale analysis", *Pattern Recognition Letters*, 27, pp.408-413, 2006.
- [13] Kosko, B., "Fuzzy Engineering", Prentice Hall, New Jersey, 1997.
- [14] P.M. Pawar and R. Ganguli, "Genetic fuzzy system for damage detection in beams and helicopter rotor blades", *Journal of Computer methods in applied mechanics and engineering*, 192, pp.2031-2057, 2003.
- [15] P. Brodatz, "Textures: A Photographic Album for Artists and Designers", Dover, New York, 1966.
- [16] Han, J., and Ma, K., "Rotation-invariant and scale-invariant Gabor features for texture image retrieval", *Image and Vision Computing*, 25, pp.1474-1481, 2007.

## REFERENCES

- [1] R. M. Haralick, K. Shanmugam, and I. Dinstein, "Textural features for image classification", *IEEE Trans. on Systems, Man, and Cybernetics*, 3, pp.610-621, 1973.
- [2] J. Weszka, C. Dyer, and A. Rosenfeld, "A comparative study of texture measures for terrain classification", *IEEE Trans. on Systems, Man, and Cybernetics*, 6(4), 1976.
- [3] Y. Wan, J. Du, D. Huang, Z. Chi, Y. Cheung, X. Wang, G. Zhang, "Bark Texture Feature Extraction Based on Statistical Texture Analysis", In *Proceedings of Int. Sympo. On Intelligent multimedia, Video & Speech processing*, Hong Kong, 2004.
- [4] I. Daubechies, "The wavelet transform, time-frequency localization and signal analysis", *IEEE Trans. on Information Theory*, 36, pp.961-1005, 1990.
- [5] S. G. Mallat, "A theory for multi-resolution signal decomposition: the wavelet representation", *IEEE Trans. on PAMI*, 11, pp.674-693, 1989.
- [6] J. R. Smith and S. F. Chang, "Transform features for texture classification and discrimination in large image databases", In *Proceedings of IEEE International Conference on Image Processing, 1994*.
- [7] R.O. Duda, P.E. Hart, D.G. Stork, "Pattern Classification", John Wiley and Sons, 2006.
- [8] E.Avci, "An expert system based on Wavelet Neural Network-Adaptive Norm Entropy for scale invariant texture classification", *Journal on Experts Systems with Applications*, 32, pp.919-926, 2007.