TEXTURE CLASS ASSIGNMENT IN TEXSCALE: AN EVALUATION STUDY

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ABSTRACT

This paper describes a methodology termed TEXSCALE for texture analysis.This hierarchical approach is based on the group method which aims to group different textures into super-classes and determine whether a texture belongs in a particular texture super-class in conjunction with a mask tuning scheme to characterize texture features. Unlike the traditional two-step classification operation involving feature extraction followed by classification rule construction, our aim has been to introduce the texture energy computed using texture 'tuned' masks to directly function as a classifier in a single stage. An evaluation study of TEXSCALE classification scheme has been taken via confusion matrix, which examines the extent to which arbitrary texture samples drawn from the total set of sample textures in two seperate studies can be correctly assigned to the classes (15 in the study). One involves 360 samples, the other involves 1440 samples.

1. INTRODUCTION

Texture is a vital element in segmenting images and interpreting scenes. Caelli and Reye[1] have proposed a single unified procedure which integrated colour, texture and shape as features for the vertibrate visual system.

Traditional approaches to texture analysis involves extracting texture features to constitute a feature space and then performing stochastic search within this feature space to determine a complex classifier[2]-[8]. This general description of classifier operation in fact encompasses neural net classification.

Unlike the usual approaches involving feature extraction and classification rule construction, the special interest of our proposed method is to determine a feature, the texture energy computed using texture 'tuned' masks to directly function as a classifier in a single stage by extending both Laws' texture energy concept[9] and Benke *et al*'s mask tuning scheme[10],[11].

The simplicity and roubustness of computation of the derived features of rotated and/or scaled textures by means of our mask tuning scheme has been reported in our previous papers[13], [14]. This paper is concerned to recount an experimental study where the TEXSCALE methodology has been applied to multi-scale and multi-orientation texture classification. The mask tuning scheme for TEXSCALE feature extraction is summarised in Section 2 while the basic concepts of the group method for implementing the hierarchical approach is briefly outlined in Section 3. The simplified classification procedure in TEXSCALE is detailed in Section 4 and the experimental results for this study are presented in Section 5.

2. TEXTURE FEATURE EXTRACTION OVER MASK TUNING

TEXSCALE involves the determination of texture class 'tuned' mask which when applied to a textured image smooth out regions of common texture so that the variance of the convolved image, typically over a $15 * 15$ local window, is (a) reasonably constant over all locations within a region of uniform texture, so that such a region is essentially converted into a region of uniform gray scale, (b) markedly different in value between regions of different texture.

The approach reported here is an extension of the work of Laws and Benke *et al*'s. Note that Laws' approach was limited by the use of a fixed set of masks and Benke-Skinner introduced and applied the adaptive mask concept. The authors have further revised this methodology in a series of papers, which lead to satisfactory segmentation of as 15 distinct textures using a single mask. In our approach the local variance after convolution is well-approximated the sum of squared values of convolved image within the test window, which is expressed as below:

$$TE(i,j) = \frac{\sum_{W_x} \sum_{W_y} (I * A)^2_{rs}}{P^2 W_x W_y}$$

where the rs sum is over all pixels within a square window W of size $W_x * W_y$ centered on the pixel at i, j, A is a zero sum 'tuned' $5 * 5$ convolution mask and P is the parameter normalizer $P^2 = \sum_{i,j} (A_{i,j})^2$.

3. TUNING MASKS IN THE HIERARCHICAL APPROACH

The problem of texture class classification is to find a way of assigning a new texture sample on the basis of a set of measurements to one of a number of possible classes. In this section we show that the conventional two-step procedure by feature extraction and a classification rule selection can be merged into a one-step scheme by introducing the concept of a global texture classifier using a 'tuned' mask.

The group method requires in the hierarchical approach a single mask to be tuned so that within each texture class, dispersion of the texture energy (TE) is minimal, while the

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dispersion between classes is maximized. At the same time, it is useful to attempt to restrain the TE to be linear in the numeric rank of the textures. We use figures of merit for mask tuning of the form $D = XY/Z$, where X is the well-known expression for the regression of the least-squares line of best fit line $(x, f(x))$ through the points $(x, TE(x))$

$$X = \frac{\sum_{x=1}^{N} (TE(x)f(x))^2}{\sum_{x=1}^{N} f^2(x) \sum_{x=1}^{N} TE^2(x)}$$

while Y and Z are measure of inter and intra dispersion respectively:

$$Y = \min\{\frac{ABS(TE(x,sx,rx)-TE(y,sy,ry))}{TE(x,sx,rx)+TE(y,sy,ry)}\}$$

$$Z = \max\{\frac{ABS(TE(x,sx,rx)-TE(x,sy,ry))}{TE(x,sx,sx)+TE(x,sy,ry)}\}$$

where sx, sy refer to different scales, rx, ry refer to different rotations while x, y refer to different textures in the given texture set, and $TE(x, sx, rx), TE(y, sy, ry)$ represent the texture energy with certain scale and orientation.

Mask tuning is performed by a combination of random search techniques through the space of mask coefficients, used in combination with dynamic reordering of texture ranking, see [13]. To simplify the process a re-ranking procedure is applied to the two-dimensional texture set in training so that all the texture samples in each trial are ordered in the monotonically increasing sequence of classifier value. Thus for each mask a sorting procedure is called to rank all the texture samples of the given texture set: different textures are linked and ordered from top to bottom while texture samples of one texture in different cases are linked and ordered from left to right, (See Figure 1).

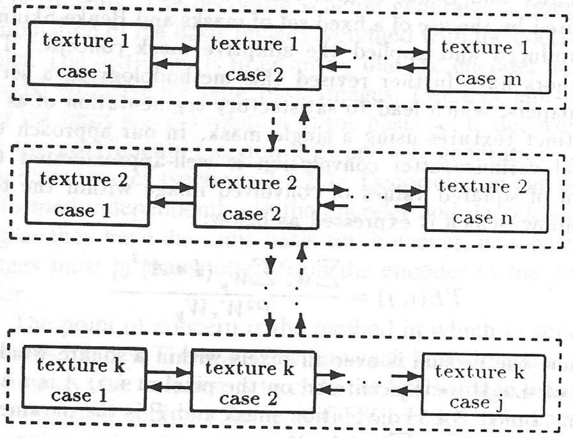

Fig 1: Linked list data structure used so as to permit flexible data entry and handling which facilitates the re-ranking of textures into super-classes
Note that the groups are not the same size

4. THE CLASSIFICATION PROCEDURE

In this section we outline the supervised recognition approach utilized in TEXSCALE, and a block diagram showing our system is presented in Figure 2. The TEXSCALE classification is performed in two stages. The first stage is the training phase where a 'tuned' mask is determined for the linked rotated and/or scaled textures. Such an adaptive mask can be obtained by maximizing the proposed figure of merit $D = XY/Z$ described in Section 3 with the guided random search algorithm introduced in [13]. Using this 'tuned' mask, a set of texture energies TE corresponding to each texture sample in the training texture album are determined. A range-plot is utilized to indicate how packed the texture energy TE is between members (representatives of the same texture under different orientation and scale conditions) of each texture category. The second stage is characterized as the classification stage, where an unknown input texture sample is recognized as belonging to a particular category in the texture album irrespective of scale and rotation. The classification is based on a distance rule which measures the difference between the global texture energy TE of the test image and the reference values TE_i in the range-plot of the training album. The texture is classified to the category for which such a distance $|TE - TE_i|/TE_i$ is minimum.

Two sets of experiments are designed for the classification purpose. In the first set, the training texture album consists of all the possible test samples, and indicates that the classifier 'sees' instances of each texture under each condition. The minimum distance judgement will be directly used to classify the individual input texture samples.

In the second set of experiments it was expected that the test samples not included in the training set could be detected as a new category. The key issue is how to identify the category as new. The implementation can be summarized in four steps:

Step 1: Determine the center of the existing category based on their range-plot produced in the training stage:

$$TE_i = TE_{i(low)} + (TE_{i(high)} - TE_{i(low)})/2$$

where $TE_{i(low)}$ and $TE_{i(high)}$ indicate the boundary of the texture energy distribution of the corresponding category.

Step 2: Determine the worst relative error $\triangle$ of the training set:

$$\triangle = \max_i\{(TE_{i(high)} - TE_{i(low)})/TE_i\}$$

Step 3: Calculate the relative error δ_i of the input test texture sample TE and the existing traind categories TE_i in the traing set:

$$\delta_i = (|TE - TE_i|)/TE_i$$

The minimum relative error $\delta = \min_i\{\delta_i\}$ is then used as reference for classification in the next step.

Step 4: Determine the category of the input test sample by comparing sample's minimum relative errors δ with the system worst error $\triangle$: The sample is classified as new if $\delta > \triangle$, otherwise the sample belongs to the existing category corresponding to the minimum relative error.

5. EXPERIMENTAL DESIGN AND RESULTS

Two sets of experiments were completed to assess the classification effectiveness of TEXSCALE. We used 15 different Brodatz textures, with a scale range $(1:2)^2$, $(1:1)^2$, $(2:1)^2$ and a rotation range 0^0, 45^0, 90^0, ..., 315^0. The samples in the training set are histogram equalized and of $256 * 256$ size. In the first set, the training texture album consists of all the possible test samples, and indicates that the classifier 'sees' instances of each texture under each condition. In the second set of experiments it was expected that the test samples not included in the training set could be detected as a new category. Fig 2 lists the 'tuned' masks for the above two sets of classification . M_{15} was tuned in the first set to discriminate over variants of 15 Brodatz textures, while M_8 was tuned in the second set to discriminate over variants of just 8 textures.

The test samples are of four size ($512 * 512$, or $256 * 256$, or $128 * 128$, or $64 * 64$) with three scales and orientations. Therefore, for the first experiment there are 36 test samples of each texture category including all the possible image sizes, scales and orientations. The classification was performed using mask M_{15} and the result is shown in Fig 3 in the form of a confusion matrix. The diagonal row shows how many samples out of 36 test samples for each category were correctly classified. Classification rates for individual categories are listed to the right of each row. Ten of the classes are classified with 100 percent accuracy. The classification results of the other five classes are 96, 80, 78, 66 and 58 percent, respectively. The misclassification of test samples is due to the very close distance differences of texture energy TE between some samples.

In the second experiment there were 96 test samples of each texture superclass. The mask M_8 (above) was used, but test samples were drawn from the 8 classes trained on, together with the other 7 classes available: A sample was either assigned to a class according or classified as new. The classification result is shown in Fig 4 in the form of a confusion matrix.

6. CONCLUSION

TEXSCALE was conceived as a scheme for the hierarchical classification of texture, so that a texture taxonomy could be applied where in the first stage it is determined to what texture class a particular texture sample (or small window into a texture collage) belongs, while in the second stage the actual membership of the texture in that class is determined. More generally, there could be further stages of hierarchical classification. Here we have been concerned with an evaluation of the first stage. The capability of the second stage refers solely to the capability of differentiating individual textures within a single class which was established in our earlier work involving texture tuned masks.

In our experiments, the texture classes have comprised the rotated and scaled variants of 15 Brodatz textures. Hence what was established can be interpreted as providing a rotational and scale invariant texture classification system. In our previous papers detailing the methodology presented here, where the focus was on segmentation capability, that particular interpretation of our experiments was presented. However, in presenting for the first time the data given here on classification/misclassification, we must stress that at the same time the basic concept of TEXSCALE has been established for these particular classes. Future work is planned to involve investigation of the capability of TEXSCALE with regard to the hierarchical classification of model-based textures.

REFERENCES

[1] T.M. Caelli and D. Reye, "On the classification of image regions by colour, texture and shape", *Pattern Recognition*, Vol. 26, No. 4, April, pp. 461-470, 1993.

[2] R.M. Haralick, "Statistical and structural approaches to texture", *Proc. IEEE, 67*, pp. 786-804, 1979.

[3] R.L. Kashyap and A. Khotanzad, "A model based method for rotation invariant texture classification", *IEEE Trans. Pattern Anal. Machine Intell.*, Vol. PAMI-8, pp. 472-481, 1986.

[4] J. Mao and A. Jain, "Texture classification and segmentation using multiresolution simultaneous autoregressive models", *Pattern Recognition*, Vol. 25, No. 2, 1992, pp. 173-188.

[5] M. Pietikäinen, A. Rosenfeld, and L.S. Davis, "Experiments with texture classification using averages of local pattern matches", *IEEE Trans. Syst., Man, Cybern.*, Vol. SMC-13, pp. 421-425, 1983.

[6] M. Unser, "Local linear transforms for texture measurements", *Signal Processing*, Vol. 11, pp. 61-79, 1986.

[7] H. Wechsler and T. Citron, "Feature extraction for texture classification", *Pattern Recognition*, Vol. 12, pp. 301-311, 1980.

[8] J.S. Weszka, C.R. Dyer and A. Rosenfeld, "A Comparative study of texture measures for terrain classification", *IEEE Trans. Syst., Man, Cybern.*, Vol. SMC-6, pp. 269-285, 1976.

[9] K.I. Laws, "Textured Image Segmentation", *Ph.D Thesis*, University of Southern California, January 1980.

[10] K.K. Benke and D.R. Skinner, "Segmentation of visually similar textures by convolution filtering", *The Australian Computer Journal*, Vol. 19, No. 3, pp. 134-138, 1987.

[11] K.K. Benke, D.R. Skinner and C.J. Woodruff, "Convolution operators as a basis for objective correllates for texture perception", *IEEE Trans. Syst., Man, Cybern.*, Vol. SMC-18, pp. 158-163, 1988.

[12] P. Brodatz, *Textures: A Photographic Album for Artists and Designers*, Dover Publications, New York, 1966.

[13] H.A. Cohen and J. You, "A multi-scale texture classifier based on multi-resolution 'tuned' mask", *Pattern Recognition Letters*, Vol. 13, Number5, 1992, pp. 599-604.

[14] J. You and H.A. Cohen, "Classification and Segmentation of Rotated and Scaled Textured Images Using Texture 'Tuned' Masks", *Pattern Recognition*, Vol. 26, No. 2, Feb., pp. 245 - 258, 1993.

[15] R. Picard, "Finding similar patterns in large databases", Paper WA2.1, *Proc. of IEEE ICASSP'93*, April 27-30, 1993, Minneapolis, Minnesota.

[16] C.Y.C Bie, H.C Shen and D.K.Y Chiu, "Hierarchical maximum entropy partitioning in texture image analysis", *Pattern Recognition Letters*, Vol. 14, pp. 421-429, 1993.

$$M_{15} = \begin{bmatrix} 19 & -11 & -32 & 15 & 9 \\ 33 & 48 & -23 & 0 & -58 \\ -27 & 24 & -2 & -6 & 11 \\ -12 & 6 & -10 & 29 & -13 \\ -25 & 1 & 10 & 40 & -26 \end{bmatrix} \qquad M_8 = \begin{bmatrix} 40 & 49 & 26 & -52 & -63 \\ 42 & 37 & 39 & -48 & -70 \\ 0 & 76 & 32 & -9 & -99 \\ 80 & 81 & -52 & -69 & -40 \\ 31 & -21 & 54 & -42 & -22 \end{bmatrix}$$

Fig 2: New 'tuned' masks as computed

Texture Sample	Assigned Class 1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	Classification Rate %
1. calfd24	36															100
2. canvd20		34												2		96
3. canvd21			36													100
4. corkd4				36												100
5. grassd9					36											100
6. paperd57						21					12		3			58
7. pebbled54							36									100
8. pigskind92								36								100
9. raffiad84	3								24				9			67
10. sandd28										36						100
11. sandd29											36					100
12. strawd15												36				100
13. wired6						2			6				28			78
14. wired14		6						1						29		80
15. woold19															36	100
															Total	92

Fig 3: Confusion matrix showing the class assignment accuracy for the 540 texture samples

Texture Sample	Assigned Class 1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	new	Classification Rate %
1. calfd24	96																100
2. canvd20									4				2			90	93
3. canvd21			96														100
4. corkd4	6			88											2		91
5. grassd9	5			14		12									1	64	68
6. paperd57				5		80										11	83
7. pebbled54			1			2				23			2			68	60
8. pigskind92	1			4		2									11	78	81
9. raffiad84			4						92								96
10. sandd28										96							100
11. sandd29	11			14		18										53	55
12. strawd15																96	100
13. wired6													96				100
14. wired14				5					8				8			75	77
15. woold19															96		100
																Total	88

Fig 4: Confusion matrix showing the classification accuracy with untrained texture classes