ROBUST ROTATION INVARIANT TEXTURE CLASSIFICATION

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ABSTRACT

The importance of texture analysis and classification in image processing is well known. However, many existing texture classification schemes suffer from a number of drawbacks. A large number of features are commonly used to represent each texture and an excessively large image area is often required for the texture analysis, both leading to high computational complexity. Furthermore, most existing schemes are highly orientation dependent and thus cannot correctly classify textures after rotation. In this paper, two novel feature extraction techniques for rotation invariant texture classification are presented. These schemes, using the wavelet transform and Gaussian Markov random field modelling, are shown to give a consistently high performance for rotated textures in the presence of noise. Moreover, they use just four features to represent each texture and require only a 16x16 image area for their analysis leading to a significantly lower computational complexity than most existing schemes.

1. INTRODUCTION

Texture plays an important role in the composition of many natural images and its analysis and classification are essential in a variety of image processing applications. These applications range from remote sensing and crop classification to object-based image coding and tissue recognition in medical images. Approaches such as stochastic [1-3], statistical [4] and spatial-frequency [5, 6] techniques have all achieved considerable success in texture classification. However, there are a number of drawbacks to many of the existing techniques. A large number of features are commonly used to describe each texture which can lead to an unmanageable size of feature space [4]. Furthermore, an excessively large image area is often required for the analysis [4, 6], clearly undesirable if only small texture samples are available or if the features are to be applied to a segmentation problem requiring high resolution. These limitations both lead to techniques that can be computationally very demanding [4]. In addition, the majority of classification schemes cannot maintain a high correct classification rate when the textures for classification have undergone a rotation [5] or when there is noise present.

Here, two novel methods of feature extraction using either wavelet analysis or Gaussian Markov random field (GMRF) modelling on a small area of the image are proposed. It is shown that these schemes require significantly fewer features than most others and provide high performance rotation invariant texture classification. The noise sensitivity and computational complexity of the proposed algorithms are compared, indicating that the wavelet-based approach is superior.

2. ROTATION INVARIANT WAVELET-BASED FEATURE EXTRACTION

In the first approach features are derived from a 3-level wavelet decomposition of a small area (16x16) of the image. The energy levels of the main channels of the wavelet decomposition were found to be highly effective as features for texture segmentation [7]. However, these features are not rotation invariant, since different features are used to represent the texture's horizontal and vertical frequencies. Therefore, in the proposed scheme, rotation invariance is achieved by combining pairs of diagonally opposite wavelet channels to form single features. The LH and HL channels in each level of decomposition are grouped together to produce four main frequency bands, as illustrated in Fig. 1. The HH channels are not used as they tend to contain the majority of noise in the image and thus degrade the classification performance. The energy levels in each of the four chosen bands are calculated as the mean magnitudes of their wavelet coefficients to create a four dimensional feature vector which is then used in the classification algorithm.

3. CIRCULARLY SYMMETRIC GMRF MODEL

The GMRF model has been shown to be a powerful method of texture analysis and classification [1]. The GMRF parameters and noise source variance of a given model can be estimated for a texture using the least squares approach [1] and are often successfully employed as features for texture classification. However, the traditional
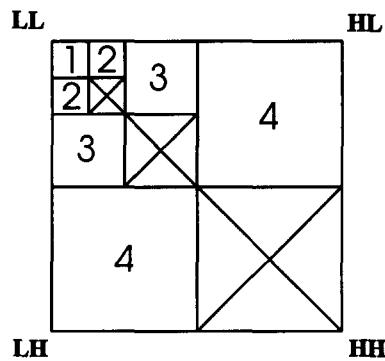
Fig. 1 - Grouping of wavelet channels to form 4 bands used to produce rotation invariant features.
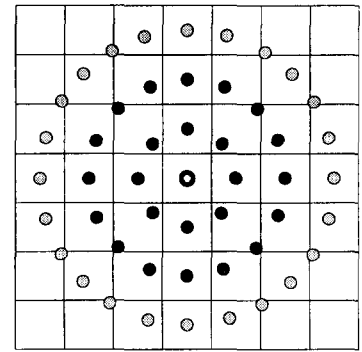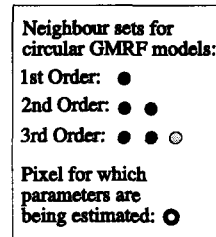

Fig. 2 - Neighbour sets for 1st, 2nd and 3rd order circular GMRFs.

TABLE 1 - TEXTURE CLASSIFICATION RESULTS.

FEATURE SET	ORIGINAL TEXTURES	ROTATED TEXTURES	COMPUTATIONAL COMPLEXITY (flops)
3RD ORDER GMRF (7 features)	100.0%	45.8%	16,962
3RD ORDER CIRCULAR GMRF (4 features)	93.8%	95.1%	21,413
WAVELET-BASED FEATURES (7 features)	99.1%	86.5%	4,275
ROTATION INVARIANT WAVELET-BASED FEATURES (4 features)	95.5%	95.8%	4,272

GMRF models are not rotation invariant due to the structure of their neighbour sets. Each GMRF parameter is based on symmetric neighbours and thus can only represent the texture in a single direction. It was found that in order to achieve rotation invariance, the neighbour set should be circularly symmetric so that each GMRF parameter depends on neighbours in all directions. The neighbour sets for the 1st, 2nd and 3rd order circular GMRFs are shown in Fig. 2. The grey levels of neighbours which do not fall exactly in the centre of pixels can be estimated by interpolation. This model is the GMRF equivalent of the autoregressive models in [2] and [3], but was found to give a high classification performance without the need for multiresolution analysis [3] and is thus more computationally efficient. The third order circular GMRF was chosen in the proposed approach since it produced the best performance with a small number of features. The features used for texture classification comprise the three 3rd order circular GMRF parameters and the variance parameter, extracted using the least squares approach from a 16x16 area of the image.

4. CLASSIFICATION RESULTS

Sixteen 256x256 Brodatz textures were used to test the performance of the features. One sample image of each texture was used to provide several 16x16 sub-images with which to train the classification algorithm. A further 7 sample images of each texture were presented to the algorithm in a random order as unknown textures for classification. A minimum distance classifier was employed (using the Mahalonobis distance [6]) to perform the classification. Training and classification were first performed on the original textures, producing the first column of results in Table 1. The training set was then presented at angles of 0, 30, 45 and 60 degrees and the textures for classification at 20, 70, 90, 120, 135 and 150 degrees, yielding the second column of results in Table 1.

The classification results for the two proposed rotation invariant schemes were compared to those using features from the traditional 3rd order GMRF and from the wavelet transform without the combination of channels. Table 1 summarises the results. Although the third order GMRF parameters give 100% correct classification when the textures are presented at their original orientation, they perform very poorly on the rotated textures. This is due to the strong directional dependence of the parameters in the traditional GMRF model. The proposed 3rd order circular GMRF model uses a circularly symmetric neighbour set to remove this directional dependence, resulting in a consistently high classification performance. This can be seen in the confusion matrix in Fig. 3a showing the classification performance on rotated textures. The small number of misclassifications tend to occur either for visually similar textures (paper, sand) or those with a strong directionality which cannot be identified using a circular model (wood, raffia, matting).

The wavelet-based features using seven channels of the wavelet transform also have a strong directional dependence. These features give a high classification performance for the original textures but a mediocre performance for the rotated textures. By combining the directionally dependent wavelet channels, as in the proposed scheme, a high level of rotation invariance is

Accuracy: 95.1%

	CLOTH	COTTON	CANVAS	GRASS	RAFFIA	RATTAN	WOOD	LEATHER	MATTING	WOOL	REPTILE	SAND	STRAW	PIGSKIN	PAPER	WEAVE
CLOTH	42															
COTTON		38			4											
CANVAS			42													
GRASS				42												
RAFFIA					37							5				
RATTAN						42										
WOOD							39		3							
LEATHER								42								
MATTING					1				38	3						
WOOL					5				37							
REPTILE											42					
SAND												38		4		
STRAW													42			
PIGSKIN														42		
PAPER												8			34	
WEAVE																42

(a)

Accuracy: 95.8%

	CLOTH	COTTON	CANVAS	GRASS	RAFFIA	RATTAN	WOOD	LEATHER	MATTING	WOOL	REPTILE	SAND	STRAW	PIGSKIN	PAPER	WEAVE
CLOTH	42															
COTTON		42														
CANVAS			42													
GRASS				42												
RAFFIA					32						10					
RATTAN						42										
WOOD							35		7							
LEATHER								42								
MATTING									31	5		6				
WOOL										42						
REPTILE											42					
SAND												42				
STRAW													42			
PIGSKIN														42		
PAPER															42	
WEAVE																42

(b)

Accuracy: 39.6%

	CLOTH	COTTON	CANVAS	GRASS	RAFFIA	RATTAN	WOOD	LEATHER	MATTING	WOOL	REPTILE	SAND	STRAW	PIGSKIN	PAPER	WEAVE
CLOTH					8							34				
COTTON		32										10				
CANVAS			42													
GRASS				40					2							
RAFFIA	14											28				
RATTAN												42				
WOOD					7		7							28		
LEATHER								42								
MATTING					1					13		28				
WOOL					14						17			11		
REPTILE				41								1				
SAND		6	10								1	25				
STRAW				4								38				
PIGSKIN						40				2						
PAPER									42							
WEAVE																42

(c)

Accuracy: 74.3%

	CLOTH	COTTON	CANVAS	GRASS	RAFFIA	RATTAN	WOOD	LEATHER	MATTING	WOOL	REPTILE	SAND	STRAW	PIGSKIN	PAPER	WEAVE
CLOTH	42															
COTTON		42														
CANVAS			42													
GRASS				42												
RAFFIA					20						6				16	
RATTAN						3					39					
WOOD							2		9					31		
LEATHER								42								
MATTING									16	25					1	
WOOL							7			24				11		
REPTILE					11						25	6				
SAND		1									39				2	
STRAW													42			
PIGSKIN														42		
PAPER								8							34	
WEAVE																42

(d)

Fig. 3 - Confusion matrices for (a) circular GMRF and (b) rotation invariant wavelets on rotated textures without noise and (c) circular GMRF and (d) rotation invariant wavelets on rotated textures with a signal-to-noise ratio of 10dB

achieved, as demonstrated by the confusion matrix in Fig. 3b. Some misclassifications occur for the highly directional textures such as raffia, wood and matting, due to the loss in directional information when the wavelet channels are combined. However, the overall classification accuracy for rotated textures is very high (95.8%).

For each of the proposed schemes, there is a slight degradation in their performance on the original textures compared to the non-rotation invariant approaches. There is an inevitable trade-off between classification performance and rotation invariance due to the information loss on making the schemes rotation invariant. Confusion matrices showing the performance of the non-rotation invariant schemes were presented in [8].

The computational complexity of each approach is also given in Table 1. This is measured by the number of floating point operations (flops) required to perform the extraction of a single set of features. It can be seen that the wavelet-based approaches are computationally much less expensive and are thus preferable to the GMRF approaches given their similar classification performance.

5. PERFORMANCE ON NOISY IMAGES

Real images often contain a certain level of random noise, incurred either during the imaging process or due to a noisy communications link. It is important that any texture classification scheme can operate successfully with a given level of noise. To test the noise performance of the proposed rotation invariant classification schemes, various levels of noise were introduced to the classification set of textures by adding additive white Gaussian noise with zero mean and a variance dependent on the required signal-to-noise ratio. Six levels of noise were used, ranging from a
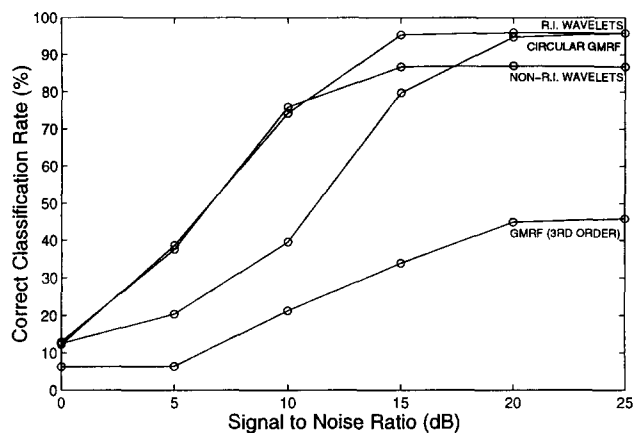
Fig. 4 - Noise performance of schemes on rotated textures

barely visible 25dB signal-to-noise ratio to a very obvious 0dB. The degradation in performance of the rotation invariant schemes with the addition of noise is emphasised in Figs. 3c and 3d while the noise performances of the four schemes on the rotated textures are compared in the graph in Fig. 4.

Fig. 4 shows that for a high signal-to-noise ratio (20-25dB) all the feature extraction techniques have approximately the same performance as for the original noise-free images. It can be seen that the performance of the GMRF-based features begins to deteriorate once the signal-to-noise ratio drops below 20dB whereas the wavelet-based features remain insensitive to noise until the signal-to-noise ratio is below 15dB. The greater noise sensitivity of the GMRF approaches can be explained by their strong dependence on the intensity values of particular pixels: should any of a pixel's neighbours be affected by noise, the GMRF parameter estimates for that pixel will change substantially leading to an uncharacteristic set of features and hence a misclassification. Fig. 3c shows how badly the circular GMRF is affected by noise.

The wavelet-based approaches are not so adversely affected by small amounts of noise due to the averaging effect of measuring the energy within relatively large frequency bands. Fig. 3d emphasises the superior noise performance of the rotation invariant wavelet-based scheme. The addition of high frequency noise to the textures mainly causes the low frequency textures (rattan, wood, wool) to be misclassified as textures with higher spatial frequencies (sand, pigskin). Although the number of misclassifications has increased considerably, the main diagonal remains clearly defined.

6. CONCLUSION

Two novel texture classification schemes have been proposed, the first using the wavelet transform and the second using Gaussian Markov random fields. These schemes exhibit comparable performances to existing methods but both use a significantly smaller feature space. Furthermore, the features are robust and computationally inexpensive (both methods are amenable to fast implementation) and only a small analysis area for feature extraction is required. In addition, unlike most existing techniques, the proposed schemes are invariant to rotations of the textures to be classified, attaining the same high classification performance on the textures at all orientations. The wavelet-based approach was found to be superior to the GMRF approach due to its higher performance, lower computational expense and greater robustness to noise. Its features are also easily derived from those of its non-rotation invariant counterpart, unlike the GMRF approach.

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