Feature Fusion for Image Texture Segmentation

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Abstract

A design-based method to fuse Gabor filter and grey level co-occurrence probability (GLCP) features for improved texture recognition is presented. Feature space separability and unsupervised image segmentation are used for testing. The fused features are robust with respect to the curse of dimensionality and additive noise. Feature reduction methods are typically detrimental to the segmentation performance. Overall, the fused features are a definite improvement over non-fused features and are advocated in texture analysis applications.

1 Introduction

Texture segmentation is the task of identifying regions with similar patterns in an image. A common strategy is to extract features pixel-by-pixel and then classify the extracted features. To improve the overall quality of image texture segmentation, either the quality of the texture features or the quality of the classification algorithm must be improved. *This paper focuses on the improvement of the quality of the texture features for the purpose of image segmentation.* Many papers analyze individual texture feature methods, however, few papers consider the fusion of texture features. Also, published texture comparison papers tend to use pure texture samples as opposed to mixed texture samples found in segmentation.

There exists limited research on the topic of fusing texture features. For a fixed number of samples, increasing the feature space dimension will eventually cause the classification accuracy to decline (the "curse of dimensionality"), [9], [7], [1]. Published demonstration of the curse of dimensionality in unsupervised texture segmentation is unknown to the authors. Normalization is used for scaling so that certain features do not dominate the distance calculations during classification [5]. Normalization is important, yet the authors are not aware of any papers that study normalization in the context of texture segmentation. Also, papers that compare different methods for unsupervised texture segmentation are rare.

This paper uses a novel design-based approach to fuse Gabor filtered [7] and grey level co-occurrence probability (GLCP) [6] texture features. Whereas other research papers generally fuse features blindly, a rationale is provided here for the fusion of these particular features. The fused feature set is demonstrated to be an improvement over using the non-fused feature sets. The roles of the curse of dimensionality, image noise, feature space normalization, and feature space reduction are investigated.

2 Texture Feature Fusion

2.1 Texture Feature Extraction Methods

An experimentally supported preferred Gabor feature set is used [4]. Four octave-separated frequency bands and six orientations (30^o spacing) are chosen. The feature set excluding the highest frequency is F_{G18}, and the feature set using all 24 Gabor filter features is F_{G24}.

The GLCP method [6] is a popular technique. First, co-occurring probabilities of all pairwise combinations of quantized grey levels in the fixed-size spatial window given inter-pixel distance and orientation are determined. Second, preferred statistics (contrast, entropy, and correlation) are applied to the co-occurring probabilities [3]. A 9×9 window is used. Two inter-pixel distances ($\delta = 1, \delta = 2$) and 4-neighbor orientations produce eight sets of GLCPs. A quantization level of

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64 is used. Each pixel is represented by a 24-d feature vector, denoted by F_{C24}.

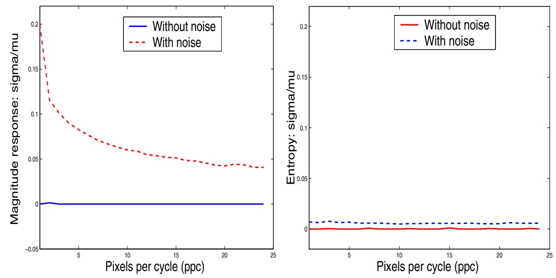
2.2 Parameter Selection

A tuned Gabor filter applied to a sinusoid will generate a consistent magnitude response, preferable for pattern recognition. In the presence of point noise, Gabor filters are able to generate consistent measurements in low and medium frequencies but generate inconsistent measurements for higher frequencies. To replace the high-frequency Gabor filter features with some other more suitable features is appropriate. The GLCP features are able to play such a role. If the inter-pixel distance is set to 1 or 2, the corresponding GLCP features measure high frequency information.

An example of the impact of noise on the feature extraction ability of Gabor filters and GLCPs as a function of signal frequency is presented. Long duration unit sinusoids set to 2.0 to 25.0 pixels per cycle (ppc) were created and zero mean Gaussian noise (σ = 0.2) was added to each signal. A magnitude response of each signal to a matched complex Gabor filter was determined. GLCP feature measurements are also applied. Let σ and μ denote the standard deviation and mean of the feature measurement. The ratio $\frac{\sigma}{\mu}$ reflects the variation over the entire signal. The Gabor value of $\frac{\sigma}{\mu}$ was determined for each frequency and plotted in Fig. 1(a) and that for entropy is plotted in Fig. 1(b). With higher local frequencies (corresponding to decreasing ppc), $\frac{\sigma}{\mu}$ increases. However, Fig. 1(b) indicates that the GLCP features (with similar figures for constrast and correlation) have consistent measurements across all signal frequencies, which is preferable.

2.3 Feature Fusion

If GLCPs are preferred to Gabor filters for detecting higher frequency signals, why not use this method exclusively for texture feature extraction? To exhaustively select all GLCP parameters is computationally prohibitive. There is a high degree of correlation for preferred GLCP features and matched Gabor filters, negating the need to calculate low and mid-frequency GLCP texture features. Finally, larger GLCP window sizes will capture information with respect to many frequencies. For Gabor filters, the larger spatial bandwidth is automatically associated only with lower frequency signals. To substitute for the high frequency band, F_{G18} can be



(a) (b)

Figure 1: $\frac{\sigma}{\mu}$ ratio for (a) Gabor and (b) GLCP features noisy and noise-free sinusoids.

combined with F_{C24} (F^{C24}_{G18}). To supplement, F_{G24} can be fused with F_{C24} (F^{C24}_{G24}).

3 Discriminant Analysis Testing and Results

A 256 $\times$ 256-size image for each of thirteen Brodatz textures are used to extract features for discrimination. These texture samples are: field stone (D002), wire (D006), canvas (D021), netting (D034), water (D038), shaw cloth (D052), straw matting (D055), paper (D057), wood grain (D068), fiber cloth (D076), cotton canvas (D077), straw cloth (D078), and loose burlap (D104).

Hypothesis 1: *The fused feature sets (F^{C24}_{G24}, F^{C24}_{G18}) will have higher feature space separability between classes compared to the individual feature sets (F_{G24}, F_{G18}, F_{C24}).* The Fisher criterion (τ) [5] is used is used as a non-parametric means of assessing class feature space separability. The average τ for each feature set and its relative value to the feature set with the largest average τ (F^{C24}_{G24}) are reported (Table 1). The fused feature sets have considerably stronger separability than any of the individual feature sets.

Hypothesis 2: *Feature reduction is expected to erode the class feature space separability.* Principal components analysis (PCA) (98% energy retained) and the feature contrast (FC) method [8] (a recently defined technique) are applied to the two fused feature sets. Both feature reduction methods cause dramatic reductions in feature space separability. The results for the first two

Table 1: Class feature space separability average class-pairwise Fisher linear criterion values.

Feature Set	Average (τ_{avg})	Ratio to F_{G24}^{C24}
F_{G24}^{C24}	173.09	1
F_{G18}^{C24}	163.69	0.946
F_{G24}	113.94	0.658
F_{G18}	106.74	0.617
F_{C24}	23.74	0.137
F_{G24}^{C24} by PCA	16.99	0.098
F_{G24}^{C24} by FC	61.01	0.353
F_{G18}^{C24} by PCA	16.64	0.096
F_{G18}^{C24} by FC	57.18	0.330

hypotheses suggest that these fused feature sets will produce higher segmentation accuracies and that feature reduction should decrease segmentation performance.

4 Segmentation Testing

The standard K-means method [5] is used for clustering. Linear normalization is used. Three 256×256 Brodatz mosaic images are used for testing. Fig. 3(a) illustrates the image originally published by Bigun and Du Buf [2]. The second image (Fig. 3(c), referred to as the "Patch" image) contains five textures in six patches. The third image (Fig. 3(e), referred to as the "Star" image) contains five textures.

Hypothesis 3: *The curse of dimensionality should not be apparent when using the 48-d texture feature set.* Three curves (one for each image) are used to illustrate that the curse of dimensionality is generally not significant using the 48-d feature set (Fig. 2). Each curve is produced by randomly adding features and then reporting the maximum accuracy obtained from 25 K-means runs. The curse of dimensionality is not apparent for the Patch or Star images, and is barely apparent for the Bigun image. Note that the Bigun image is an extreme case, having seven distinct textures with numerous texture boundaries. Other authors are cautious about the curse of dimensionality with respect to image segmentation [8], [9], [7], [1], but this caution has been historically derived from classification problems where individual textured samples are selected and must be classified.

Hypothesis 4: *Fused feature sets will achieve higher segmentation accuracies than non-fused feature sets.*

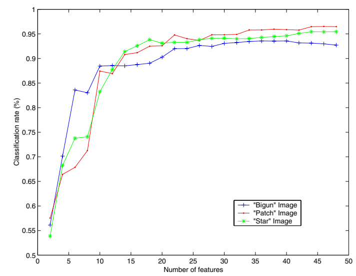


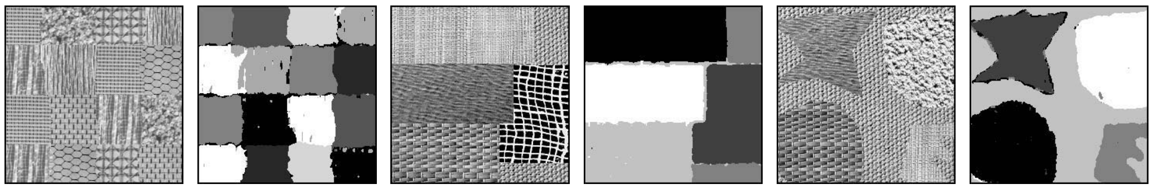
Figure 2: Randomly selected texture features (from the set F_{G24}^{C24}) versus segmentation accuracy (%) for all three images.

Table 2: Average segmentation accuracy (%) using K-means (25 runs). NN - features not normalized, PCA - features reduced by PCA, FC - feature contrast [8].

Test	Bigun	Patch	Star
F_{G18}	75.8	74.1	80.2
F_{G24}	77.2	75.2	82.3
F_{C24}	57.4	82.5	89.5
F_{G18}^{C24}	84.9	89.0	93.5
F_{G24}^{C24}	83.9	90.0	93.6
$F_{G18}NN$	79.7	82.3	80.5
$F_{G24}NN$	87.2	79.7	83.5
$F_{G18}^{C24}PCA$	83.5	90.3	89.2
$F_{G24}^{C24}PCA$	81.0	88.0	88.8
$F_{G18}^{C24}FC$	74.7	62.3	56.3
$F_{G24}^{C24}FC$	68.2	56.3	64.7

Table 2 shows that the fused feature sets (F_{G18}^{C24} and F_{G24}^{C24}) have higher segmentation accuracies (statistically significant) relative to the non-fused feature sets (F_{G24},F_{G18},F_{C24}). Each entry represents the average of 25 K-means runs.

Hypothesis 5: *Linear normalization of pure Gabor filtered texture features will reduce their segmentation ability.* Normalization is not expected to be necessary when using only Gabor filtered magnitude features since each Gabor feature dimension has the same unit. As a result, the relative strength of magnitude responses is considered important for texture identification. Table 2 includes the segmentation accuracies across all three images for normalized and non-normalized (indicated by NN) Gabor features. In every case, the segmentation accuracies for the non-normalized Gabor features



(a) (b) (c) (d) (e) (f)

Figure 3: (a) Bigun image and (b) its segmentation (c) Patch image and (d) its segmentation (a) Star image and (b) its segmentation. All results using feature set F_{G24}^{C24}.

are higher than the normalized features. Paradoxically, linear normalization does not modify the Fisher critерions, however, the same linear normalization is detrimental to the segmentation accuracy.

Hypothesis 6: *Feature reduction of non-fused and fused texture feature sets will lead to poorer segmentation ability.* Table 2 indicates the accuracies of the two fused feature sets and their feature space reduction using PCA and FC [8]. Overall, the PCA method produces effective segmentation results. There is an indication that the PCA transform was inappropriate for feature reduction prior to clustering due to undesired interaction between classes [1], however, in contrast, the results here indicate that the PCA transform is quite adept at this task. The feature contrast (FC) method consistently reduced the segmentation accuracy.

5 Conclusions

The paper produces a number of significant contributions. A design-based method to fuse Gabor filter texture features and GLCP features is described and implemented. Discriminant analysis indicates that the fused texture features are more separable relative to the individual feature sets and feature reduction dramatically decreases the separability. The curse of dimensionality does not affect the segmentation performance, given the proposed feature set. Fused feature sets consistently outperform independent feature sets in segmentation accuracy. Linear normalization reduces the segmentation capability of Gabor features. Feature reduction using PCA slightly reduced the segmentation accuracy and feature reduction using FC dramatically reduces the segmentation accuracy.

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