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Texture analysis and classification: methods, challenges, and research directions

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ABSTRACT

Texture analysis plays an important role in image processing and computer vision because it provides discriminative information about spatial patterns, surface characteristics, and local intensity variations. This review critically examines four major approaches to texture analysis and classification: statistical, structural, model-based, and transform-based methods. Statistical approaches characterize texture through intensity distributions and spatial relationships, while structural methods represent patterns using repetitive primitives and their spatial arrangements. Model-based approaches describe texture through probabilistic or mathematical representations of spatial dependencies, whereas transform-based methods extract frequency, orientation, and multiscale information using techniques such as Fourier, Gabor, and wavelet transforms. The review compares these approaches in terms of their fundamental principles, representative techniques, strengths, and limitations. Particular attention is given to their suitability for regular and irregular textures, computational requirements, feature representation, and sensitivity to variations in scale, rotation, illumination, and noise. The discussion also identifies persistent challenges in developing reliable texture classification systems, particularly the integration of complementary features, dimensionality reduction, computational efficiency, and generalization across different image conditions. Finally, several research directions are highlighted to support the development of robust, efficient, and application-oriented texture analysis and classification methods.

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1. INTRODUCTION

The Texture is a fundamental visual property that describes the spatial arrangement and repetition of patterns within an image. It provides useful information for distinguishing image regions that may have similar intensity or color characteristics but different surface appearances. Consequently, texture analysis has been widely applied in medical imaging, remote sensing, industrial inspection, material recognition, and image retrieval.

The development of texture analysis has produced several approaches based on different representations of image patterns. Statistical methods characterize texture through the distribution and spatial relationships of pixel intensities, whereas structural methods describe textures using repetitive primitives and their spatial arrangements. Model-based and transform-based methods provide alternative representations by describing texture generation processes or analyzing image information across spatial frequencies and scales.

Although these approaches have contributed substantially to texture classification, no single method performs optimally across all image conditions. Their effectiveness depends on factors such as texture regularity, image resolution, scale, rotation, illumination, and computational requirements. This review critically examines the four approaches and discusses their comparative characteristics, practical limitations, and potential research directions.

2. STATISTICAL TEXTURE ANALYSIS

Statistical texture analysis represents texture through measurable distributions and spatial relationships among image pixels. It is particularly effective for describing irregular or stochastic textures that do not exhibit clearly identifiable structural primitives. The approach is attractive because its features can be computed directly from image intensities without requiring an explicit model of texture construction.

The gray-level co-occurrence matrix (GLCM), introduced by Haralick *et al.* [1], is one of the most established statistical techniques. It describes the frequency of pairs of gray levels occurring at specified spatial distances and orientations, from which features such as contrast, correlation, energy, and homogeneity can be derived. Tamura *et al.* [2] proposed perceptually motivated features, including coarseness, contrast, and directionality, to represent texture characteristics more closely related to human visual perception.

Other statistical approaches examine different aspects of spatial intensity distributions. Gray-level run-length methods characterize consecutive pixels with the same gray level and provide information about texture coarseness and directional organization [3]. These methods can distinguish textures with different local patterns, although their performance may depend on quantization, spatial direction, and the selected neighborhood configuration.

The main advantage of statistical methods is their relatively straightforward implementation and interpretability. However, conventional statistical features may lose important spatial information when complex textures are represented only by global statistics. Their sensitivity to rotation, scale, illumination, and image resolution also limits their reliability when images are acquired under varying conditions.

3. STRUCTURAL TEXTURE ANALYSIS

Structural texture analysis describes texture as an arrangement of basic elements, commonly called texture primitives or texels. These elements may represent repeated shapes, lines, regions, or local patterns that form a larger visual structure. The method is particularly suitable for regular and periodic textures in which the primitives and their spatial relationships can be identified.

A structural representation generally involves identifying texture primitives and describing the placement rules that govern their arrangement. These rules may include spatial repetition, orientation, distance, and neighborhood relationships. Structural descriptions can therefore provide meaningful information about the organization of textures that may not be sufficiently represented by statistical distributions alone.

An important contribution to structural texture analysis was presented by Zucker and colleagues through research on structural texture analysis using statistical and geometric principles. Van Gool *et al.* [4] also discussed structural approaches alongside statistical techniques and emphasized the importance of texture primitives and placement rules. Their discussion illustrates that structural and statistical descriptions are not necessarily independent, because statistical measurements can sometimes provide evidence about underlying texture organization.

Despite its conceptual advantages, structural analysis has practical limitations. Identifying meaningful primitives becomes difficult when textures are irregular, noisy, or contain overlapping patterns. Furthermore, structural methods may require complex preprocessing and feature extraction, making them less suitable for highly stochastic textures or images with substantial variations in scale and orientation.

4. MODEL-BASED TEXTURE ANALYSIS

Model-based texture analysis represents image texture through mathematical or probabilistic models that describe the relationships among pixels or the processes that generate texture patterns. Rather than relying exclusively on manually selected descriptive features, these methods attempt to capture the underlying behavior of texture. They are particularly useful when spatial dependencies and local interactions are important for distinguishing image regions.

Markov random field (MRF) models are among the established approaches in this category. Cross and Jain [5] investigated MRF-based texture models by treating texture as a stochastic image field in which pixel values depend on neighboring pixels. This representation provides a systematic way to describe local spatial dependencies and can support both texture classification and synthesis.

Other model-based approaches use autoregressive models and related stochastic representations to characterize local intensity relationships. These models can capture texture properties through a relatively compact set of parameters, allowing different texture patterns to be compared according to their estimated statistical behavior. Their effectiveness, however, depends on whether the selected model adequately represents the actual texture characteristics.

The principal strength of model-based methods is their ability to describe spatial dependencies that may not be adequately captured by simple statistical features. Nevertheless, model selection and parameter estimation can be computationally demanding, particularly for complex or heterogeneous textures. Model assumptions may also restrict their applicability when real-world textures do not follow the assumed stochastic process.

5. TRANSFORM-BASED TEXTURE ANALYSIS

Transform-based texture analysis examines image information in alternative domains to reveal spatial-frequency characteristics that may be difficult to observe directly in the spatial domain. These methods are particularly useful for textures containing patterns at different frequencies, orientations, and scales. Fourier, Gabor, and wavelet transforms are among the widely investigated techniques.

Fourier-based analysis represents texture through its frequency distribution and is useful for identifying periodic patterns and dominant spatial frequencies. However, the conventional Fourier transform provides limited spatial localization, making it less effective when texture characteristics vary across image regions. Gabor filters address this limitation by analyzing localized frequency and orientation information, allowing different directional patterns to be distinguished.

Jain and Farrokhnia [6] demonstrated the use of Gabor filter banks for unsupervised texture segmentation. Their approach extracts texture information from multiple frequency and orientation channels and combines the resulting features for region separation. This approach is effective for textures with distinguishable directional and frequency characteristics, although selecting appropriate filter scales and orientations remains an important design consideration.

Wavelet transforms provide a multiresolution representation that captures texture information at different spatial scales. Unser [7] demonstrated the use of wavelet frames for texture classification and segmentation, highlighting the benefits of an overcomplete representation for reducing sensitivity to image translation. Compared with single-resolution approaches, wavelet-based methods can provide richer descriptions of textures with variations in spatial scale.

Transform-based methods offer a flexible representation of texture characteristics, but their performance depends on transform selection, filter configuration, and feature aggregation. A large number of transform coefficients may also increase computational and storage requirements. Consequently, dimensionality reduction and feature selection are important considerations when designing efficient classification systems.

6. COMPARATIVE ANALYSIS

The four approaches represent different perspectives on texture description and therefore offer complementary capabilities. Statistical methods emphasize measurable intensity relationships, structural methods focus on primitive arrangements, model-based methods describe underlying spatial dependencies, and transform-based methods capture frequency and multiscale characteristics. Their advantages and limitations should be considered in relation to the texture properties and classification requirements of a particular application.

Table 1 summarizes the principal characteristics of the four approaches. The comparison indicates that the suitability of a method depends not only on its feature representation but also on the regularity, complexity, and variability of the target texture. A method that performs well on periodic textures may not necessarily be effective for irregular natural textures or images acquired under changing conditions.

Table 1. Comparative analysis of texture analysis approaches

Approach	Main representation	Major strengths	Main limitations
Statistical	Pixel distributions and spatial relationships	Simple, interpretable, effective for stochastic textures	Limited structural representation; sensitive to configuration
Structural	Texture primitives and placement rules	Describes regularity and spatial organization	Difficult primitive extraction; less suitable for irregular textures
Model-based	Probabilistic or mathematical texture models	Captures spatial dependencies and local interactions	Model selection and parameter estimation can be complex
Transform-based	Spatial-frequency and multiscale information	Captures orientation, frequency, and scale characteristics	Filter selection, computational cost, and feature dimensionality

The comparative evaluation of texture features by Ohanian and Dubes [8] demonstrated that classification performance varies among feature families and that no single feature subset is universally

optimal. This finding reinforces the importance of application-specific feature selection and experimental evaluation. Therefore, selecting a texture analysis method should involve considering both the characteristics of the image data and the operational requirements of the classification task.

7. CHALLENGES AND RESEARCH DIRECTIONS

Despite extensive research, texture classification continues to face challenges related to variations in scale, rotation, illumination, noise, and image acquisition conditions. These variations can significantly change the extracted features even when the underlying material or object remains the same. Developing representations that remain reliable under such variations is therefore an important research objective.

A second challenge concerns the representation of complex textures that contain both regular and irregular patterns. Statistical methods may capture local intensity relationships but overlook structural organization, whereas structural methods may struggle to describe stochastic variations. Combining complementary representations could provide a more comprehensive description, provided that the resulting feature set remains computationally manageable [9].

Another important direction is the development of efficient feature selection and classification strategies. High-dimensional feature representations can introduce redundancy and increase computational requirements, particularly when multiple statistical descriptors, model parameters, and transform coefficients are combined. Future research should therefore investigate feature selection, dimensionality reduction, and classifier design as integrated components of texture classification rather than treating feature extraction as an isolated process.

Finally, texture classification requires more rigorous and application-oriented evaluation. Comparisons should consider not only classification accuracy but also computational complexity, robustness to acquisition changes, generalization across datasets, and sensitivity to parameter settings. Such evaluations can help determine whether a proposed method provides meaningful advantages beyond performance on a single benchmark dataset [10].

8. CONCLUSION

Texture analysis provides essential information for image classification by describing spatial patterns and relationships that cannot always be captured by color or intensity features alone. Statistical, structural, model-based, and transform-based approaches offer different but complementary ways to represent texture characteristics. Each approach has specific strengths and limitations, making the selection of an appropriate method dependent on texture properties and application requirements. The review indicates that robust texture classification requires more than selecting an individual feature extraction technique. Future research should emphasize complementary feature representations, computational efficiency, robustness to variations in image acquisition, and reliable evaluation across different datasets. These directions are important for developing texture classification systems that are both technically effective and suitable for practical applications.

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