IJARSCT

ISSN (Online) 2581-9429

International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

Impact Factor: 7.301

Volume 3, Issue 1, December 2023

Texture Analysis Method – A Survey

Rohan N Khadse[1], Abhishek K Khursange[2], Sumit V Khekare[3],
Rohit R Rathod[4], Prof. Ajay D. Nanure[5]

Third Year Students, Department of Electronics and Telecommunication[1,2,3,4]
Guide, Department of Electronics and Telecommunication[5]
Jagadambha College of Engineering and Technology, Yavatmal, Maharashtra, India

Abstract*: Analysing texture plays a pivotal part in image processing, computer vision, and pattern recognition. It plays a vital part in de ciphering complex visual information by characterizing the spatial arrangement of pixels within an image. This check aims to give a comprehensive overview of colorful texture analysis styles, their operations, and recent advancements in the field. From classic statistical approaches to slice- edge deep literacy ways, this check will claw into the rich geography of texture analysis, offering perceptivity into its significance and eventuality for different disciplines similar as medical imaging, remote seeing, and artificial quality control. "The approaches for analysing texture are veritably different, and differ from each other substantially by the system used for rooting textural features. Four orders can be defined 1) Statistical styles. 2) Structural styles. 3) Model grounded styles. 4) Transfigure- grounded styles.*

Keywords: image processing

I. INTRODUCTION

Analysing texture plays a crucial role in image processing, computer vision, and pattern recognition. It plays a vital role in de ciphering complex visual information by characterizing the spatial arrangement of pixels within an image. This survey aims to provide a comprehensive overview of various texture analysis methods, their applications, and recent advancements in the field. From classic statistical approaches to cutting-edge deep learning techniques, this survey will delve into the rich landscape of texture analysis, offering insights into its significanceand potential for diverse domains such as medical imaging, remote sensing, and industrial
quality control. "The approaches for analysing texture are very diverse, and differ from each other mainly by the method used for extracting textural features.

Four categories can be defined:

1. Statistical methods.
2. Structural methods.
3. Model based methods.
4. Transform-based methods**.**

II. STATISTICAL METHOD

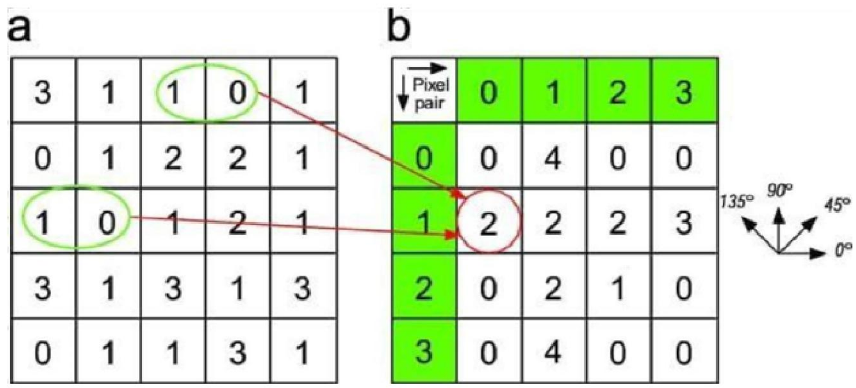
Statistical methods play a significant role in texture analysis. One common statistical method for texture analysis is the Gray-Level Co-occurrence Matrix (GLCM) approach. Here's an explanationof this method:

- **Image Pre-processing:** Start with an image that you want to analyse for texture. You might needto pre-process it to enhance or normalize the texture features, such as applying filters for noise reduction or contrast enhancement.
- **Gray-Level Quantization:** Convert the grayscale image into a discrete set of Gray levels. This step is essential to simplify the analysis and create a matrix of relationships between these Graylevels.
- **GLCM Construction:** The GLCM is a square matrix that quantifies how often pairs of pixel valuesat a certain spatial relationship occur in the image. For each pixel in the image, you look at its neighbouring pixels in a specified direction (e.g., horizontal, vertical, diagonal) and record the combination of Gray levels. For

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.301
Volume 3, Issue 1, December 2023

example, if a pixel has a value of 100, and its neighbour to the right has a value of 110, you would increment the corresponding entry in the GLCM for (100, 110) by 1.

- **Normalization:** Normalize the GLCM by dividing each element by the total number of pixel pairs considered. This ensures that the GLCM represents probabilities.
- **Feature Extraction:** From the GLCM, various statistical features can be calculated to describe thetexture, including:
- **Contrast:** Measures the difference in intensity between neighbouring pixels.



a				
3	1	1	0	1
0	1	2	2	1
1	0	1	2	1
3	1	3	1	3
0	1	1	3	1

Pixel pair	0	1	2	3
0	0	4	0	0
1	2	2	2	3
2	0	2	1	0
3	0	4	0	0

III. STRUCTURAL METHODS

Structural methods for texture analysis are techniques used to analyse and describe the structural properties of textures in images. Here's a brief survey of some common structural texture analysis methods:

- **Co-occurrence Matrix (Haralick Texture Features):** This method involves computing a cooccurrence matrix that captures the probability of pairs of pixel intensity values occurring at various spatial relationships within the image. From this matrix, various statistical measures likecontrast, energy, and entropy can be derived to describe texture.
- **Run-Length Encoding:** Run-length encoding is used to characterize textures by counting the number of consecutive pixels with the same intensity value along rows or columns in the image.
- These counts can provide information about texture regularity and homogeneity.
- **Local Binary Patterns (LBP):** LBP is a technique that defines a binary code for each pixel in an image based on the comparison of its intensity value with the values of its neighbouring pixels. Patterns formed by these binary codes are used to describe texture properties like uniformity and coarseness.
- **Gabor Filters:** Gabor filters are a family of linear filters that are sensitive to texture variations at different orientations and scales. By applying Gabor filters at multiple scales and orientations, one can extract features that describe the texture's frequency and orientation characteristics.
- **Texture Energy Measures:** These methods calculate the energy or variance of local texture patterns, such as the sum of squared gradients or the eigenvalues of the texture covariance matrix. These measures are used to capture the texture's overall complexity and detail.
- **Fractal Analysis:** Fractal-based methods assess texture by examining its self-similarity or self affinity at different scales. Fractal dimensions or Hurst exponent values are often used to quantify the irregularity and complexity of textures

IV. MODEL-BASED METHODS

Model-based methods for texture analysis are a set of techniques used in computer vision and image processing to characterize and understand the texture patterns present in an image. These methods are based on the idea of modelling the statistical properties or structural aspectsof textures to describe and analyse them. Here's an overview of how model based texture analysis works:

- **Texture Modelling:** Model-based methods begin by creating a mathematical or statistical modelthat represents the texture of interest. These models can be simple or complex, depending on the nature of the texture being analysed.
- **Texture Classification:** These extracted texture features can be used for classification tasks, such as distinguishing between different types of textures or materials in an image. Common classification techniques include machine learning algorithms like Support Vector Machines (SVMs) or neural networks.
- **Segmentation:** Model-based methods can also be employed for texture segmentation, where the goal is to partition an image into regions or objects based on their texture characteristics.
- This is particularly useful in medical imaging and remote sensing applications.
- **Texture Synthesis**: In some cases, model-based approaches can generate synthetic textures thatclosely resemble the texture model. This is useful for texture synthesis tasks, such as generatingrealistic textures for computer graphics and rendering.
- **Statistical Analysis:** Model-based methods often involve statistical analysis of texture properties. Common statistics include mean, variance, co-occurrence matrices, and higher ordermoments, which provide insights into the texture's distribution and structure.
- **Parametric and Non-parametric Models:** Model-based methods can use parametric models (e.g., Gaussian, Markov Random Fields) or non-parametric models (e.g., histogram-based or wavelet-based) depending on the texture's characteristics and the complexity of the analysis required

V. TRANSFORM-BASED METHODS

Transform-based methods for texture analysis refer to a class of techniques used to analyse andcharacterize textures in digital images. These methods rely on mathematical transformations toextract meaningful information from textures. Here's a brief overview:

- **Fourier Transform:** The Fourier Transform is a common approach in texture analysis. It decomposes an image into its frequency components. Texture information is encoded in the amplitudes and phases of different frequency components. By analysing these components, you can characterize the texture's periodicity and orientation.
- **Wavelet Transform:** Wavelet Transform is another widely used method. It decomposes an image into different scales and orientations. This allows for the capture of texture details at different levels of granularity. Wavelet coefficients are often used as texture features for analysis.
- **Principal Component Analysis (PCA):** PCA can be applied to transform texture data into a lowerdimensional space, where the most significant variations in texture are retained. This can simplify texture analysis and visualization.
- **Sparse Coding and Dictionary Learning:** These techniques involve representing textures as sparse linear combinations of basis functions (dictionary atoms). Learning the dictionary from data can be useful for texture classification and Denoising.
- **Convolutional Neural Networks (CNNs):** While not traditional transforms, CNNs have become popular for texture analysis. They automatically learn hierarchical features from textures and have achieved state-of-the-art results in various texture-related tasks. In survey on Transform- based texture analysis methods, researchers typically review and compare these techniques in terms of their strengths, weaknesses, and applicability to different texture analysis tasks

Categories	Sub-categories	Method
Statistical	Image Pre-processing	Binary Gabor pattern
	Gray-Level Quantization	GLCM and Gabor filters
	GLCM Construction	Gabor and LBP
	Normalization	wavelet transform and GLCM
	Feature Extraction	local binary patterns and significant point'sselection
	Contrast	Energy variation

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.301
Volume 3, Issue 1, December 2023

		Combination of primitive pattern units and statistical features Hybrid colour local binary patterns
Structural	Co-occurrences Matrix Run-Length Encoding Local Binary Patterns Gabor Filters Texture Energy Measures Fractal Analysis	Energy variation Edge-based texture granularity detection Morphological filter Skeleton primitive and wavelets
Model-Based	Texture Modelling Texture Classification Segmentation Texture Synthesis Statistical Analysis Parametric and Non-parametric Models	Multifractal Analysis in Multi-orientation Wavelet Pyramid Markov Random Field Texture Models simultaneous autoregressive models
Transform-Based	Fourier Transform Wavelet Transform Principal Component Analysis Sparse Coding and Dictionary Learning Convolutional Neural Networks	Binary Gabor Pattern wavelet channel combining and LL channel filterbank GLCM and Gabor Filters Gabor and LBP wavelet transform and GLCM SVD and DWT domains Skeleton primitive and wavelets

Table: Categorization of Texture Classification Methods

VI. CONCLUSION

In conclusion, the comprehensive survey on texture analysis methods has provided a nuanced understanding of the current landscape in this domain. The findings showcase a rich tapestry of approaches, spanning classical methods to cutting-edge deep learning techniques. Notably, there is a discernible trend towards the integration of advanced computational methods, especially within the realm of convolutional neural networks (CNNs) and recurrent neural networks (RNNs).The survey illuminates the versatility of texture analysis across various domains, including medical imaging, satellite imagery, and industrial applications. Traditional methods such as statistical and structural approaches persist, but the dominance of deep learning methods is unmistakable, driven by their ability to automatically extract intricate features and discern complex patterns.

Moreover, the survey underscores the ongoing challenges in texture analysis, including the need for labelled datasets, interpretability of deep learning models, and adaptability across diverse domains. Future research directions may likely focus on overcoming these challenges, fostering interdisciplinary collaborations, and exploring novel applications for texture analysis in emerging fields. In essence, the survey paints a dynamic picture of the evolving landscape of texture analysis methods, highlighting both the successes and the persistent challenges that researchers and practitioners face in harnessing the full potential of this crucial aspect of imageanalysis.

REFERENCES

[1]. Haralick, R. M., Shanmugam, K., & Din stein, I. (1973). Textural features for imageclassification. IEEE Transactions on Systems, Man, and Cybernetics, (6), 610-621.

[2]. Tuceryan, M., & Jain, A. K. (1998). Texture analysis. In The Handbook of Pattern Recognitionand Computer Vision (Vol. 2, pp. 207-248). World Scientific.

[3]. Amadasun, M., & King, R. (1989). Textyral features corresponding to textural properties. IEEE Transactions on Systems, Man, and Cybernetics, 19(5), 1264-1274

IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.301
Volume 3, Issue 1, December 2023

[4]. Gebejes, A., & Huertas, R. (2013). Texture characterization based on grey-level co-occurrencematrix. Databases, 9(10), 375-378.

[5]. Ojala, T., Pietikainen, M., & Maenpaa, T. (2000, June). Gray scale and rotation invariant texture classification with local binary patterns. In European conference on computer vision (pp. 404-420). Springer, Berlin, Heidelberg.