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Texture Feature Extraction Using Tamura Descriptors and Scale-Invariant Feature Transform

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Abstract

The ability to recognize and distinguish between various textures in an image is made possible by feature extraction, which is a fundamental step in computer vision and image processing. Traditional methods of texture analysis fall short of capturing the perceptual characteristics that give texture its meaning and identity. Because Tamura texture attributes were developed through research into the spatial and frequency components of textures, they offer a more precise and discriminating representation of textures. Tamura features capture significant visual qualities that are crucial for comprehending and interpreting texture. Tamura descriptors enable to characterization and comparison of various textures, enabling tasks like texture classification, segmentation, and retrieval. SIFT processes Tamura descriptors to extract scale-invariant features, enhancing the texture representation's capacity for discrimination. The suggested method was evaluated on numerous benchmark datasets, and the findings revealed that it outperforms conventional texture analysis methods in terms of precision, recall, and other performance measures. The qualitative evaluation further verified the interpretability and perceptual significance of the retrieved texture elements, proving their appropriateness for texture analysis tasks. The evaluation's findings show how well the suggested technique extracts texture features and how it might boost the effectiveness of numerous computer vision and image processing applications.

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1. Introduction

Texture is a fundamental visual attribute that provides vital information for understanding, interpreting and analyzing an image in the field of image processing and computer vision. The ability to extract meaningful texture features is an important part of many image processing and computer vision tasks [1]. Traditional methods of texture analysis (e.g. statistical and spectroscopic methods) are limited when obtaining overlapping and complex texture information. It has become necessary to work on more advanced techniques to produce an accurate and discriminating representation of texture [2].

Extracted textures provide important visual information that makes it easier to identify and understand different regions or elements within the image. In many applications, including medical imaging, object recognition, and image retrieval, texture analysis is an important component of image processing and computer vision. To create effective systems and architectures across a variety of domains, the ability to extract meaningful texture information and discriminative power is required [3].

Efficient and effective texture feature extraction is a crucial step in computer vision and image processing with wide applications in areas including image retrieval and object recognition. Texture interpretation and analysis seek to extract important and discriminative information to capture visual properties of tissues such as spatial organization, color, and density fluctuations [4]. To obtain similar images in a database and classify images into several categories, texture features must be used to discriminately segment regions of interest into images [5].

Integrating different feature extraction methods to increase the reliability and accuracy of texture analysis is an advanced step that has been worked on in recent years. Obtaining additional information from different feature descriptors and integrating it into a more robust texture representation is the aim. Numerous applications, such as face recognition, item identification, and texture categorization, benefit from the effectiveness of this method [6].

A novel approach for joint texture feature extraction is obtained by combining Tamura descriptors with the Scale-Invariant Feature Transform (SIFT) technique [7]. A class of texture features known as Tamura descriptors pinpoint important perceptual aspects of textures, including directionality, contrast, and coarseness. Because their foundation is the way the human visual system interprets texture, they are effective for a wide range of texture analysis tasks [8]. Conversely, SIFT is a well-liked feature extraction method that provides rotation and scale invariant properties that are not affected by changes in lighting or viewpoint. Several computer vision tasks, such as object detection, photo retrieval, and panorama stitching, have been completed with SIFT. Tamura descriptors and the SIFT method together provide a potent framework for texture feature extraction. Many real-world tasks, such as object detection, medical image analysis, and image retrieval, can be accomplished with this framework [9].

The suggested method expands on the corpus of previous research on texture feature extraction and combines two tried-and-true methods to produce a more efficient and reliable solution. Tamura descriptors and the SIFT method are used to create a thorough representation of texture that includes both the image's global and local characteristics [10]. The method is tested against several benchmark datasets, proving its efficacy and superiority over other approaches. One drawback is the method's computing complexity, which may prevent real-time applications from using it [11].

2. Related Works

Many research articles were presented in which issues related to extracting image properties were discussed and addressed, including:

Zhao et al. (2021) presented a paper in which they discussed an approach for detecting asphalt pavement delamination based on aspects of picture texture. A novel unified pattern of texture feature extraction approach called LBP-GLCM is first suggested, based on the conventional algorithms LBP (local binary pattern) and GLCM (gray-level co-occurrence matrix). Second, a SVM (support vector machine) paired with an LBP-GLCM-based detection approach is suggested. Utilizing the Kylbery texture dataset, the suggested detection approach was then verified [12].

Kim et al. (2022) presented a paper in which support vector machines (SVMs) were applied in texture classification. The SVM receives the gray level values of the raw pixels rather than depending on an external feature extractor, allowing the SVM to generalize effectively even in high-dimensional domains. In addition to using the neural network as an arbitrator to perform final classifications from numerous single SVM outputs versus others, decomposition against others is a method for using binary SVMs for the categorization of multiple tissues [13].

Barges et al. (2022) presented a study in which three distinct methods for feature extraction and categorization were suggested. Three classifiers (SVM, KNN, and DA), as well as three different statistical texture feature techniques (GLDM, GLCM, and GLRLM), were provided in the suggested methodologies. As a result, each methodology underwent a very successful accuracy-based comparative study, testing each proposed classifier on each method of acknowledged texture features independently. The main objective of this study is to provide a reliable DR detection approach that will improve accuracy [14].

Gurubelli et al. (2022) presented a paper in which a new color texture extraction method called Modified Local Zigzag Pattern (MLZP) was proposed for effective content retrieval from images of diseased tomato leaves. The descriptor that is being provided uses zigzag sampling to classify textures in a straightforward yet reliable way. This study uses feature descriptors for color, shape, and texture to retrieve images of leaves. First, a Kirsch compass mask was used to determine the texture image's directional edge information in eight different directions. Then, utilizing edge-related data, the local zigzag pattern (LZP) and multilocal zigzag pattern (MLZP) are calculated [15].

Li et al. (2023) presented a paper in which a volume-invariant feature transformation method was used to detect all volume-invariant points in a bilateral lung region. The supporting boundary lines are constructed from the boundary points that surround a fixed-sized point. Then, each supporting boundary line was given a literal representation using a Fourier descriptor. Supporting boundaries that need to be rectified are identified by spectrum energy. The supporting boundaries identified by a smooth lateral curve are corrected using the gradient flow snake approach, providing an optimum correction edge in those regions [16].

3. Research Method

Traditional methods often fail to analyze and capture complex and advanced texture features such as statistical and spectroscopic techniques. Traditional methods can often have difficulty displaying complex patterns or capturing visual elements that are important for human interpretation. Therefore, sophisticated methods are needed to extract texture features and elements that are descriptive and perceptually important [17] [18].

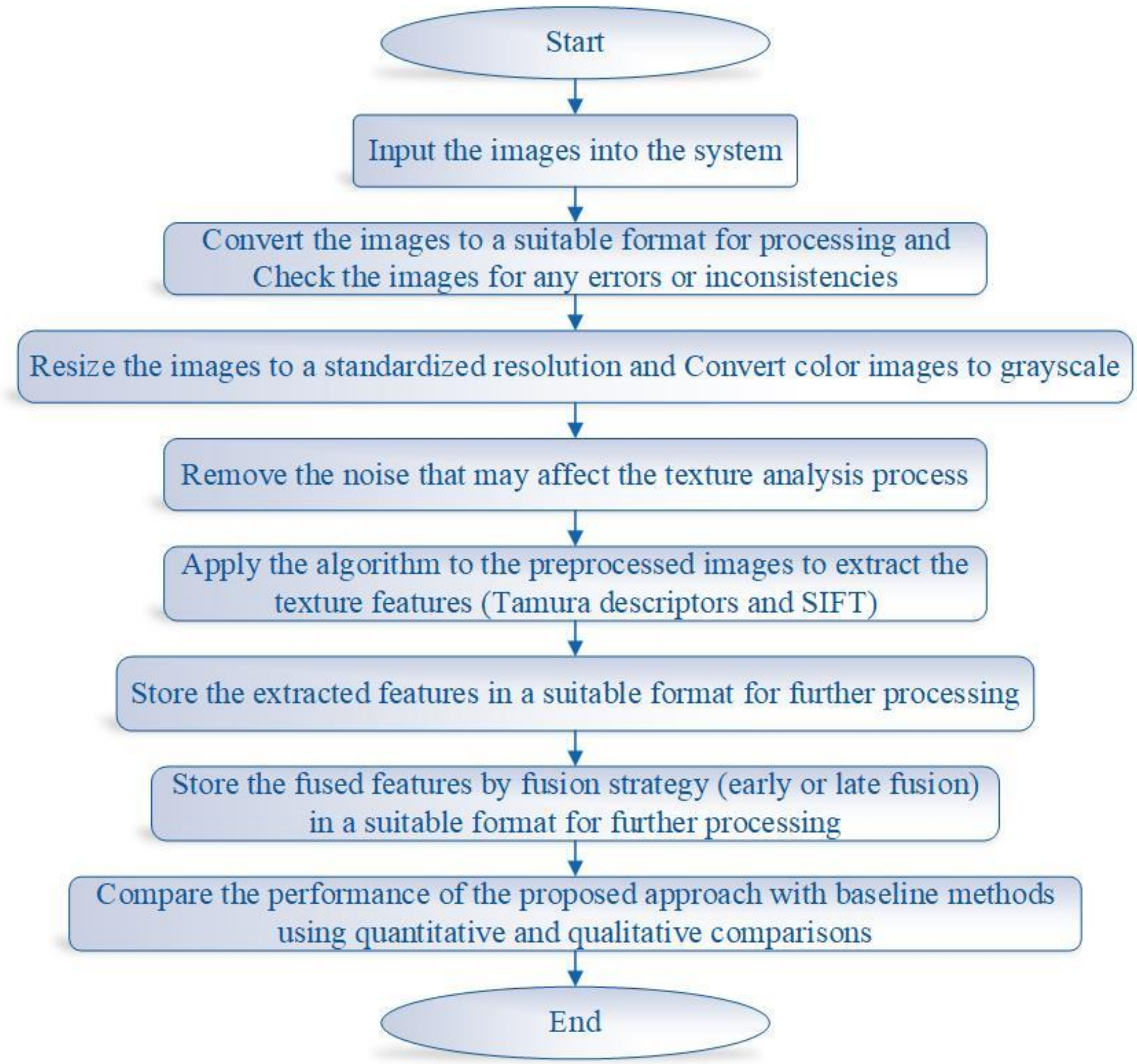

Figure 1. Research Method General Flowchart

The technique for extracting texture features that are suggested in this study combines Tamura descriptors with the Scale-Invariant Feature Transform (SIFT) algorithm. By utilizing the complimentary capabilities of these two methodologies, this method intends to improve the precision and discriminative capability of texture-based image analysis algorithms. The suggested approach entails collecting Tamura descriptors from the image patches before utilizing SIFT to find and match critical locations across various scales and orientations. Following that, classification, retrieval, or other texture-based tasks are performed using the created joint feature vector. Utilizing multiple datasets and performance criteria, as shown in Figure 1, the effectiveness of the proposed method is assessed through a comparison with benchmark techniques and cutting-edge methodologies.

While SIFT offers resistance against image modifications including scaling, rotation, and affine transformations, Tamura descriptors capture key perceptual texture features. Combining these two methods seeks to improve the precision and discriminative capability of texture-based image analysis algorithms [19].

On the other hand, the SIFT algorithm is well known for its resistance to a variety of picture modifications, including scaling, rotation, and affine transformations. Keypoints are local features that SIFT collects that stand out and are invariant to scale and orientation changes. We use a combination of SIFT and Tamura descriptors to enhance the accuracy and discriminative power of texture-based image analysis methods [20].

There are numerous advantages when combining SIFT with Tamura descriptors. First, by capturing features of texture that people see, Tamura descriptions offer a more meaningful depiction of textures. This perceptual-based model can help with improved texture pattern interpretation and comprehension. The second advantage of SIFT is that it can successfully extract texture characteristics even in the presence of numerous distortions due to its robustness against image distortions. When combined, these techniques can improve the efficiency of texture-based applications such as medical image analysis, object recognition, and picture retrieval.

3.1 Tamura Descriptors

The Tamura descriptors offer a thorough framework for texture analysis founded on the ideas of human texture perception. The goal of these descriptors is to identify and measure the visual properties of textures, like their directionality, contrast, and coarseness. Compared to traditional methods, Tamura descriptors provide a more accurate and realistic representation of textures by accounting for these perceptual factors [21].

Tamura descriptor extraction is a multi-step procedure. Before conducting the texture analysis process, the input image or region of interest is preprocessed to enhance its quality and remove any noise or artefacts. After that, the image is divided into smaller, overlapping blocks or windows, which serve as the Tamura feature extraction local regions. To compute the Tamura descriptors (coarseness, contrast, and directionality) for each window, the autocorrelation function, the statistical distribution of gray-level differences, and the Fourier spectrum are analyzed separately. The results of these computations are numerical values that characterize each window's perceptual attributes. The computed Tamura features from each window are ultimately combined or integrated to produce a complete representation of the texture [22].

Several benefits resulted from the incorporation of Tamura descriptors in texture analysis. The representation is made more meaningful and comprehensible in the first place by the fact that it captures perceptual properties that are pertinent to how people perceive textures. It also makes it possible to characterize textures at various scales while accounting for changes in coarseness. To improve the accuracy and discriminative capacity of texture-based tasks, Tamura descriptors can be employed alone or in combination with other texture analysis techniques.

The perceptual characteristics of textures, such as roughness, contrast, and directionality, are acknowledged, as well as their connection to Tamura and SIFT descriptions. These perceptual characteristics are crucial for capturing the visual characteristics that characterize textures and permit their meaningful representation [23].

Tamura texture features are derived from the analysis of the spatial and frequency properties of textures. The working principles of Tamura texture features can be summarized as follows:

A. Coarseness characteristic: This characteristic gauges how rough or fine a texture is judged to be. It describes the size of the repeated patterns that are visible in the texture. The texture image is examined in the frequency domain to calculate the coarseness feature. The autocorrelation function is calculated to assess the texture's self-similarity at various ranges. A high autocorrelation number indicates a finer texture, while a low value denotes a larger degree of repetition. Autocorrelation Function (ACF):

$$ACF(r) = \frac{1}{MN}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}[I(x,y)-\mu][I(x+r,y)-\mu] \tag{1}$$

Where r is the distance between pixel pairs, $I(x,y)$ is the intensity at pixel (x,y), M and N are the dimensions of the image, μ is the mean intensity of the image.

B. Contrast Feature: The contrast feature measures the subtle differences in local intensity that occur within a texture. It describes how abruptly or smoothly a texture's various sections or elements change from one another. The texture image is examined in the spatial domain to calculate the contrast feature. Calculated is the statistical distribution of the variations in gray levels between adjacent pixels. A high-contrast texture shows a wide variety of gray-level variations, signifying prominent borders and strong transitions. The distribution of gray-level variations is narrower in low-contrast textures, indicating smoother transitions. The statistical distribution of gray-level disparities is used to calculate it. Gray-Level Difference Distribution:

$$\text{Contrast} = \sqrt{\sum_{i=0}^{L-1} p(i)\cdot(i-\mu)^2} \tag{2}$$

Where L is the number of gray levels, $p(i)$ is the probability of gray level i, μ is the mean gray level.

C. Directionality Feature: This feature identifies the predominant alignment or orientation of texture pieces. It describes the texture's apparent pattern, such as its alignments along the horizontal, vertical, or diagonal axes. The Fourier spectrum is used to conduct a frequency domain analysis of the texture image to compute the directionality feature. To determine the dominating frequencies and orientations within the texture, the power spectrum is studied. Utilizing the Fourier spectrum, it is calculated. Power Spectrum:

$$P(u,v) = |F(u,v)|^2 \tag{3}$$

Where $F(u,v)$ is the 2D Fourier transform of the texture image.

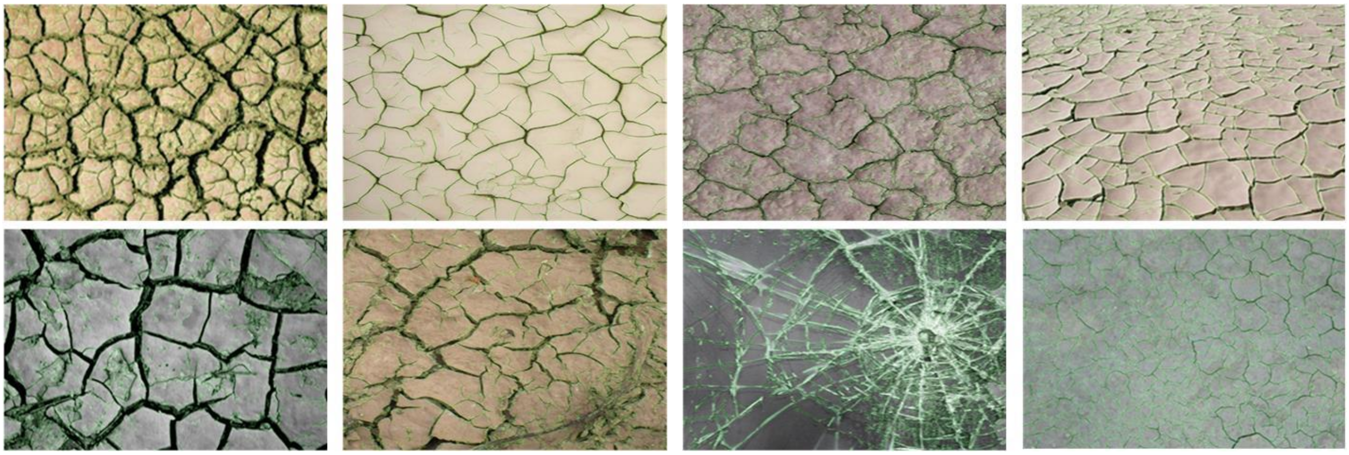

Figure 2. Tamura Descriptors for Extracting Features

The paper proposes to represent textures based on their perceptual properties by extracting these Tamura texture elements. These traits record crucial visual characteristics that are necessary for analyzing and comprehending textures. Tasks like texture classification, segmentation, and retrieval are made possible by the use of the computed Tamura texture characteristics, which may be utilized to describe and compare various textures [24].

3.2 Scale-Invariant Feature Transform (SIFT)

The local texture information that is resistant to numerous picture transformations including scale changes, rotations, and affine distortions is crucially captured using the Scale-Invariant Feature Transform (SIFT) feature extraction procedure [25] [26]. In this paper, the SIFT feature extraction process is utilized alongside Tamura descriptors to enhance the representation of textures. The working of the SIFT feature extraction process can be described in detail as follows:

A. Scale-Space Extrema Detection: The method of SIFT feature extraction begins with the identification of potential interest points or keypoints in the image at various scales. The difference-of-Gaussian (DoG) images are searched for local extrema to do this. To create the DoG pictures, the source image is convolved with several Gaussian filters set to various scales. Comparing the pixel values of the present scale with those of its neighboring scales enables the identification of the extrema. Apply Gaussian filters at various scales to build the scale-space pyramid as shown in equations (4) and (5). To generate DoG pictures, compute the difference of smoothed images at neighboring scales.

$$L(x,y,\sigma) = G(x,y,\sigma) * I(x,y) \tag{4}$$

Where L is the smoothed image, G is the Gaussian kernel, σ is the scale parameter, and I is the original image.

$$D(x,y,\sigma) = L(x,y,k\sigma) - L(x,y,\sigma) \tag{5}$$

Where k is a constant factor determining the scale difference.

B. Keypoint Localization: The algorithm then runs a precise localization step to filter out unstable keypoints and exclude those with low contrast or poor localization accuracy. The intensity values and gradients surrounding each keypoint are taken into account to achieve this. Keypoints that don't fit a specific set of requirements, such as low contrast or unstable edge responses, are eliminated. Using equation (6) as a guide, determine the picture gradients in both the x and y dimensions. Using equation (7) to calculate the gradient's strength and direction at each pixel, Using a 3D quadratic function to refine keypoint locations as an equation (8) by fitting it to neighboring samples in the DoG space, Equation (9), which use a Taylor series expansion to determine the keypoint's location with sub-pixel accuracy, Taking the equations (10) and (11) to remove keypoints with low contrast and uncertain structure, respectively.

$$I_x(x,y) = \frac{\partial I}{\partial x},\ I_y(x,y) = \frac{\partial I}{\partial y} \tag{6}$$

$$\begin{gathered} M(x,y) = \sqrt{I_x^2(x,y) + I_y^2(x,y)} \\ \theta(x,y) = \arctan\ 2\big(I_y(x,y), I_x(x,y)\big) \end{gathered} \tag{7}$$

$$\begin{gathered} D(\mathbf{x}) = D + \frac{\partial D}{\partial \mathbf{x}}\mathbf{x} + \frac{1}{2}\mathbf{x}^T \frac{\partial^2 D}{\partial \mathbf{x}^2}\mathbf{x} \\ \text{where } \mathbf{x} = (x,y,\sigma)^T \end{gathered} \tag{8}$$

$$\mathbf{x}' = \mathbf{x} - \frac{\partial^2 D^{-1}}{\partial \mathbf{x}^2}\frac{\partial D}{\partial \mathbf{x}} \tag{9}$$

$$D(\mathbf{x}') \geq \text{ contrast threshold} \tag{10}$$

$$|D(\mathbf{x}')| < \frac{(\text{ edge threshold } + 1)^2}{\text{edge threshold}} \tag{11}$$

C. Orientation Assignment: To make sure the generated descriptions are independent of image rotation, each keypoint is given a dominant orientation. To accomplish this, gradient orientations near the keypoint are computed. The dominant orientation is indicated by the histogram's greatest peak, which is constructed from a gradient of orientations. Then, depending on this dominating orientation, the keypoints are given an orientation. Using equation (12) to calculate a histogram of gradient orientations at the keypoint, Equations 13 and 14 describe how to identify the dominant orientation as the histogram's peak and how to assign the keypoint an orientation depending on the dominant orientation.

$$H(\theta) = \sum_{\mathbf{x} \in \text{ neighborhood}} M(\mathbf{x})\delta(\theta - \theta(\mathbf{x})) \tag{12}$$

$$\theta_{\text{dominant}} = \arg \max_{\theta} H(\theta) \tag{13}$$

$$\theta_{\text{keypoint}} = \theta_{\text{dominant}} \tag{14}$$

In this paper, the Scale-Invariant Feature Transform (SIFT) feature extraction procedure for texture analysis includes a critical step called keypoint localization. Keypoint localization tries to remove unstable keypoints and fine-tune the locations of possible keypoints found during scale-space extrema detection. Invariant with standard picture modifications, the SIFT feature extraction approach is quite good at capturing distinguishing local texture information. It makes it possible to represent textures according to their local structures, which helps with tasks like texture classification, texture-based object recognition, and image retrieval. To offer a thorough representation of textures that contain both global perceptual qualities and local distinguishing information, the SIFT features are retrieved in this research along with Tamura descriptors, improving the overall capabilities of texture analysis.

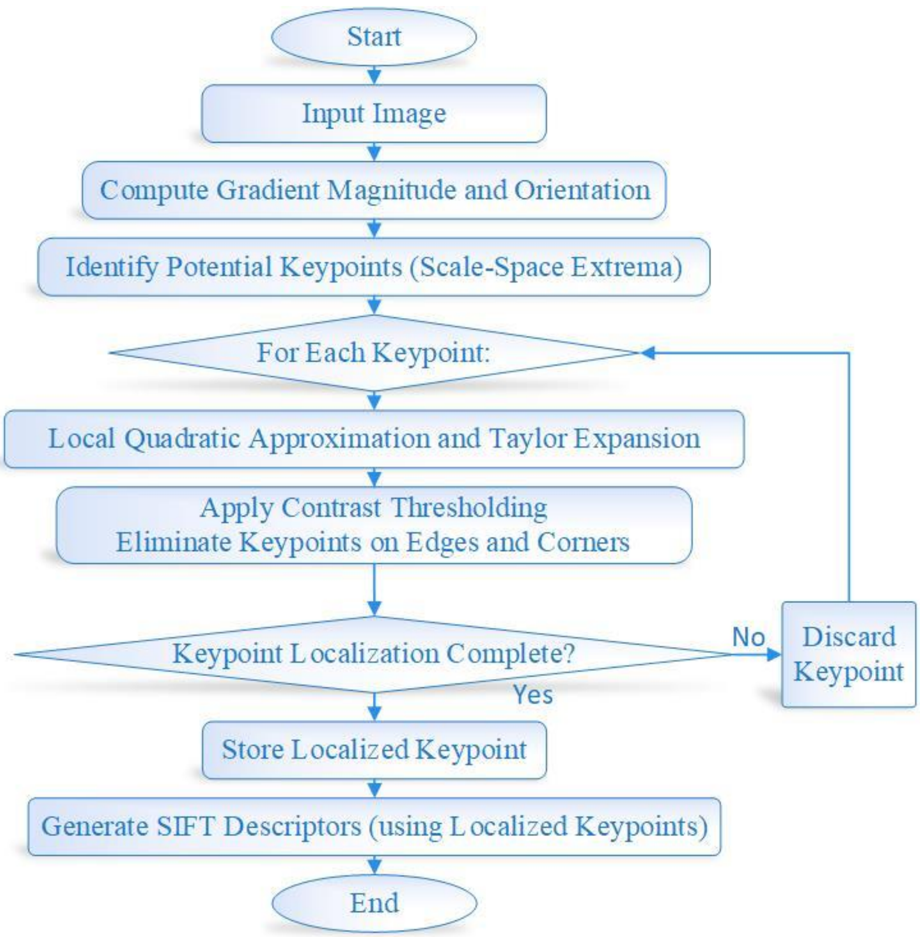

Figure 3. Flowchart for Enhancing Texture Analysis through Keypoint Localization and SIFT Feature Extraction

Figure 4. Feature extraction using SIFT

3.3 Orientation Assignment

In this study, the Scale-Invariant Feature Transform (SIFT) feature extraction approach for texture analysis includes a crucial phase called Orientation Assignment. The objective of the orientation assignment is to give each keypoint a dominant orientation, rendering the resulting descriptors rotation-invariant. The orientation assignment process can be described in detail as follows:

1. Start
2. Determine Gradients
3. Determine Each Pixel's Gradient Magnitude and Orientation
4. For Each Keypoint:
   a. Create Keypoint Neighborhood (Circular Region)
   b. Construct an Orientation Histogram within the Neighborhood
   c. Accumulate Gradient Magnitudes in Histogram Bins
   d. Identify Dominant Orientations (Peaks) in Histogram
   e. Select Dominant Orientation(s)
   f. Assign Orientation(s) to Keypoint
   g. Loop through Keypoints
5. End Keypoint Loop
6. Ensure Descriptor Rotational Invariance
7. End
8. Descriptor Invariance to Image Rotation is Guaranteed by the SIFT Algorithm
9. Directions Around keypoints, align local texture information
10. Enhance Feature Matching and Recognition
11. Improve SIFT Features Robustness
12. Facilitate Accurate Texture Analysis and Knowledge
13. End

The SIFT technique performs orientation assignment to guarantee that the resultant descriptors are rotation-invariant. By aligning the local texture data around the keypoints according to the specified orientations, following feature matching and identification tasks are made easier. The orientation assignment technique improves the SIFT features' robustness and makes it possible to reliably comprehend and analyze textures.

3.4 Integration of Tamura Descriptors and SIFT

In this paper, an integration approach of Tamura descriptors and Scale-Invariant Feature Transform (SIFT) is proposed for texture analysis. The integration aims to leverage the complementary strengths of both techniques to enhance the effectiveness of texture characterization, as shown in Figure 5.

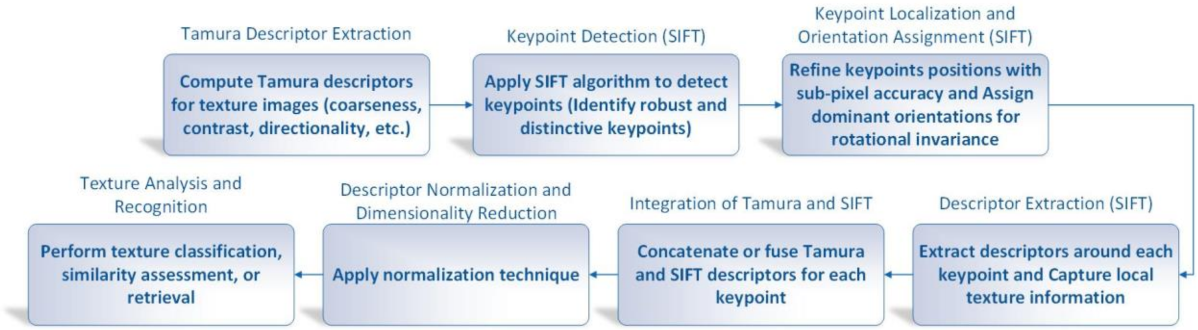

Figure 5. Integrating Tamura Descriptors with SIFT: A Fusion of Texture Analysis Techniques

There are several methods, such as Early Fusion (combining before processing), Late Fusion (combining after separate processing), Feature-level Fusion (applying statistical measures on extracted descriptors), Decision-level Fusion (combining classifier outputs), and Hybrid Fusion (a combination of methods). Depending on the dataset, objectives, and available computing power, different texture tasks including classification, segmentation, and retrieval can be optimized using these methodologies. Tamura descriptors and SIFT are combined in the proposed method, as shown in Figure 6, to combine the robustness and invariance offered by SIFT with the perceptual texture features recorded by Tamura descriptors. A more thorough and efficient texture analysis is now possible in a variety of applications, including image processing, computer vision, and pattern recognition. This integration improves the texture characterization capabilities.

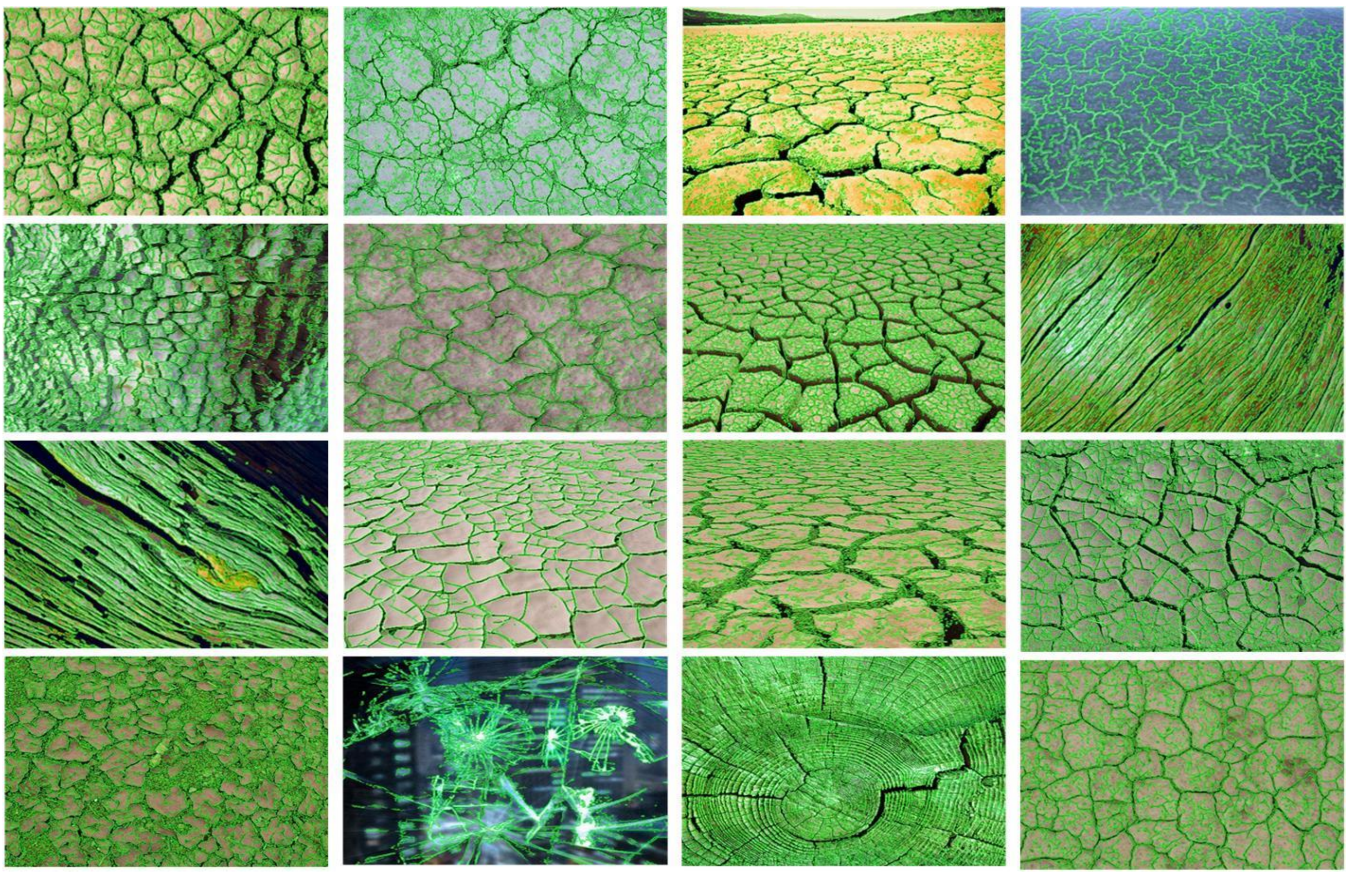

Figure 6. Feature extraction using the integration of Tamura descriptors and SIFT

4. Results Evaluation Metrics

The performance and efficacy of the suggested joint texture feature extraction strategy, which combines Tamura descriptors with Scale-Invariant Feature Transform (SIFT) descriptors, are evaluated in this research using a variety of assessment measures. These evaluation metrics offer numerical measurements and perceptions of how well the method performs when applied to various texture analysis tasks.

MSE (Mean Squared Error) is a measure of the average squared difference between the pixel values of the original and distorted images. It's a commonly used metric for assessing image quality, the equation:

$$MSE = \frac{1}{N \cdot M} \sum_{i=1}^{N} \sum_{j=1}^{M} (I(i,j) - \hat{I}(i,j))^2 \quad (15)$$

Where $I(i,j)$ is the pixel value of the original image, $\hat{I}(i,j)$ is the pixel value of the distorted image, and N and M are the dimensions of the images. A smaller MSE indicates better image quality, as it means the pixel values of the distorted image are closer to the original image.

Peak signal-to-noise ratio (PSNR) is a metric used to assess how well an image has been compressed or reconstructed. It measures the power of corrupting noise that degrades the signal's quality about the signal's maximum achievable power (the original image). Formula: Typically, MSE between the original and warped images is used to determine PSNR. Since there is a lower difference in pixel values between the original and deformed images, a higher PSNR denotes greater image quality. The formula:

$$psnr = 10 \cdot log_{10} \left(\frac{MAX^2}{MSE} \right) \quad (16)$$

Where MAX represents the maximum possible pixel value (e.g., 255 for 8-bit images).

The Universal Image Quality Index (UQI) measures how structurally comparable two distorted images are to their original counterparts. It accounts for brightness, contrast, and structure data. Usually, it is specified as a number between 0 and 1, with 1 denoting complete likeness. A higher UQI denotes better image quality since it reflects a closer structural relationship between the original and distorted images. The Normalized Absolute Error (NAE) is a measurement of the difference in pixel values between the original and warped images. The equation: offers a quantitative evaluation of image quality.

$$NAE = \frac{1}{N \cdot M} \sum_{i=1}^{N} \sum_{j=1}^{M} \frac{|I(i,j) - \hat{I}(i,j)|}{I(i,j)} \quad (17)$$

Where $I(i,j)$ is the pixel value of the original image, $\hat{I}(i,j)$ is the pixel value of the distorted image, and N and M are the dimensions of the images.

The Structural Content Quality Index (SC-QI) is a tool for evaluating the quality of distorted images that determines how closely their structural content resembles that of the original image. For the SC-QI formula, structural information-related calculations are used to provide a result between 0 and 1, with 1 denoting complete similarity. A higher SC-QI denotes stronger structural content similarity between the original and deformed images, which suggests superior image quality.

Table 1. Applying metrics to samples of digital images

metrics before and after feature extraction															
Img.	**PSNR metric**			**MSE metric**			**UQI metric**			**NAE metric**			**SC-QI metric**		
	Tamura Descriptor	SIFT	Integration	Tamura Descriptor	SIFT	Integration	Tamura Descriptor	SIFT	Integration	Tamura Descriptors	SIFT	Integration	Tamura Descriptor	SIFT	Integration
001	30.58	29.50	33.50	53.37	54.43	27.26	0.74	0.78	0.80	0.40	0.41	0.24	0.57	0.54	0.77
002	32.15	31.24	34.31	39.66	40.55	24.11	0.77	0.76	0.81	0.30	0.31	0.14	0.58	0.53	0.72
003	30.74	28.55	33.80	49.39	51.26	24.44	0.71	0.74	0.85	0.36	0.33	0.21	0.49	0.45	0.73
004	29.49	27.65	32.55	73.13	74.62	36.11	0.74	0.77	0.86	0.60	0.63	0.46	0.22	0.25	0.57
005	33.38	30.41	35.15	29.89	30.77	19.87	0.79	0.74	0.88	0.22	0.24	0.09	0.76	0.74	0.84
006	32.78	31.72	35.99	29.37	31.18	14.02	0.71	0.76	0.89	0.24	0.25	0.20	0.50	0.56	0.73
007	31.15	27.81	34.02	49.88	51.82	25.78	0.69	0.68	0.74	0.43	0.45	0.30	0.57	0.54	0.76

008	33.25	31.43	36.64	29.59	30.25	13.56	0.69	0.67	0.87	0.21	0.26	0.18	0.52	0.55	0.77
009	31.55	30.21	34.15	43.02	45.46	23.63	0.77	0.75	0.85	0.33	0.35	0.19	0.62	0.65	0.78
010	29.90	25.44	32.78	58.97	60.73	30.40	0.70	0.71	0.81	0.46	0.44	0.26	0.44	0.47	0.68
011	29.65	26.55	32.61	69.35	70.31	35.12	0.74	0.76	0.89	0.66	0.63	0.51	0.39	0.35	0.67
012	30.52	31.66	33.54	57.62	60.62	28.78	0.79	0.78	0.86	0.64	0.66	0.45	0.60	0.67	0.79
013	33.67	30.39	36.01	27.74	30.31	16.15	0.81	0.82	0.87	0.19	0.20	0.09	0.69	0.65	0.81
014	31.92	29.64	33.89	41.75	40.65	26.54	0.73	0.76	0.84	0.34	0.35	0.15	0.65	0.64	0.76
015	31.04	28.36	34.39	50.36	49.37	23.31	0.71	0.74	0.81	0.41	0.44	0.33	0.45	0.46	0.73
016	33.38	27.03	35.97	29.83	27.63	16.44	0.78	0.75	0.89	0.37	0.38	0.27	0.75	0.74	0.86
017	31.18	30.65	34.01	48.36	46.37	25.23	0.74	0.76	0.82	0.35	0.37	0.19	0.55	0.56	0.75
018	31.74	31.42	34.46	43.23	45.87	23.08	0.81	0.82	0.89	0.60	0.65	0.43	0.73	0.73	0.86
019	32.43	33.21	36.00	34.84	33.54	15.32	0.65	0.64	0.87	0.24	0.24	0.16	0.45	0.45	0.73
020	29.54	27.72	32.86	43.12	45.86	20.09	0.61	0.63	0.82	0.32	0.35	0.28	0.33	0.31	0.67
021	29.42	26.59	32.22	74.23	76.38	38.96	0.78	0.79	0.86	0.67	0.65	0.47	0.40	0.44	0.66
022	30.37	30.94	33.33	58.72	59.49	29.74	0.70	0.72	0.82	0.60	0.64	0.53	0.32	0.33	0.65

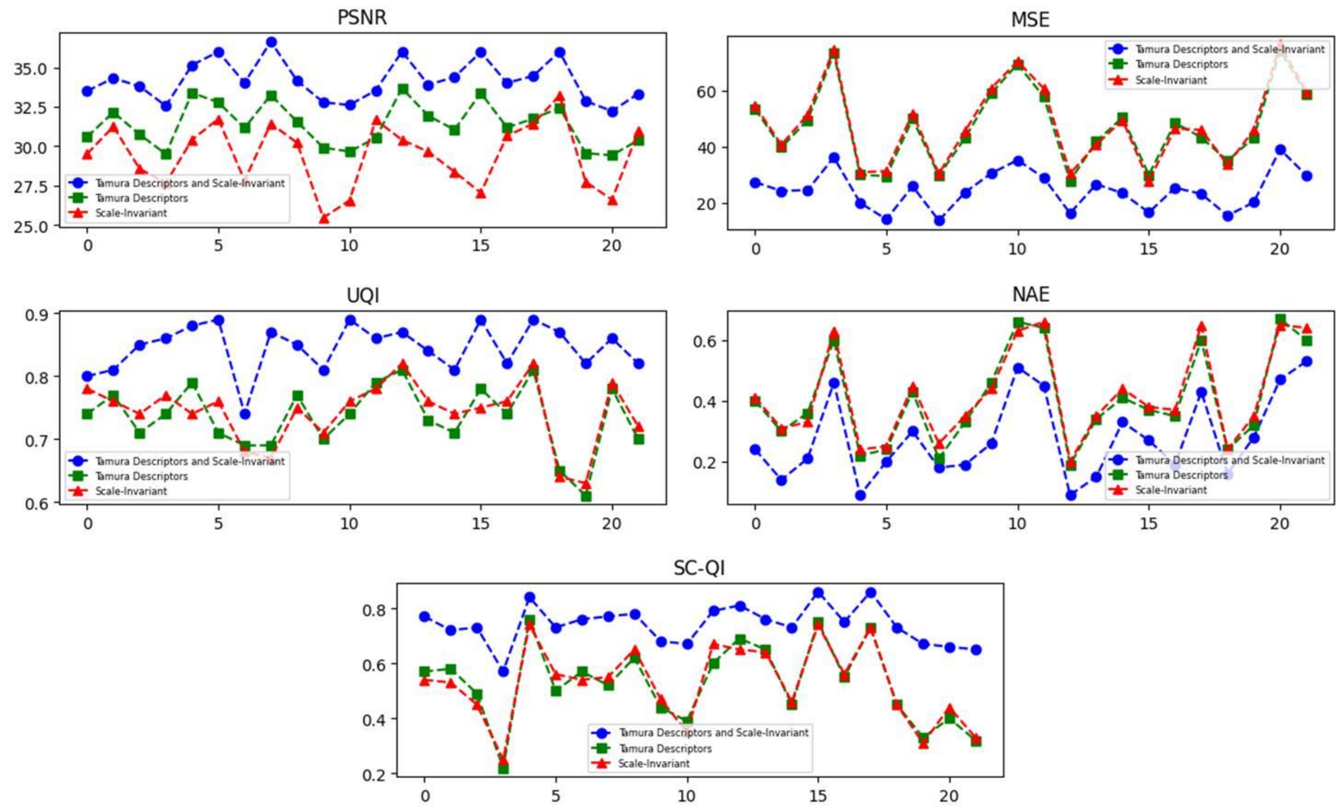

Figure 7. Histogram of applying metrics to sampled digital images

5. Conclusion

The significance of texture analysis in computer vision and image processing has been thoroughly covered in this paper, as well as how traditional approaches to texture analysis, such as statistical and spectral methods, have limitations in capturing complex and high-level texture characteristics. To get around these drawbacks, the suggested technique in this study combines Tamura descriptors with the Scale-Invariant Feature Transform (SIFT) algorithm to extract texture features.

The basis of Tamura descriptors consists of the three perceptual texture properties of directionality, contrast, and coarseness. These qualities are applied to describe an image's texture in a way that is both meaningful to the eye and perceptual. Tamura descriptors make it possible to extract texture features that are more in line with human perception. They can also be used to capture minute patterns and perceptual details that are essential to understanding for humans. SIFT is used to increase the texture representation's discriminating power. Finding and comparing critical points at different scales and orientations can be accomplished efficiently with the help of SIFT.

By integrating Tamura descriptors with SIFT, the proposed method can potentially extract both discriminative and descriptive texture features, which can be useful for a variety of texture-based applications. This concept enhances texture-based image analysis algorithms' precision and discriminative power by harnessing the complementary qualities of these two methodologies. The suggested approach initially extracts Tamura descriptors from the image patches to locate and match critical areas across different scales and orientations.

By comparing the effectiveness of the proposed method with state-of-the-art methodologies and a range of datasets and performance indicators, it is determined to be effective. The results show that compared to traditional texture analysis approaches, the suggested method performs better in terms of accuracy and recall. The ability to recognize and differentiate between different textures in an image further demonstrates the efficacy of the proposed technique.

For researchers and practitioners in computer vision and image processing who wish to extract texture characteristics using Tamura descriptors and SIFT, the proposed method is a helpful resource. The proposed method can be used for multiple tasks such as object detection, texture-based segmentation, image retrieval, and image recognition. It has shown promising results in recognizing and differentiating between different textures in an image.

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Conflict of interest

The author has no conflict of interest.

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استخراج ميزة النسجة باستخدام واصفات Tamura وتحويل الميزة غير المتغيرة

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المستخلص:

أصبحت القدرة على التعرف على الأنسجة المختلفة في الصورة والتمييز بينها ممكنة من خلال استخراج الميزات، وهي خطوة أساسية في رؤية الحاسوب ومعالجة الصور. الأساليب التقليدية لتحليل النسيج لا تتمكن من التقاط الخصائص الإدراكية التي تعطي النسيج معناه وهويته. نظرًا لأنه تم تطوير سمات نسيج تامورا من خلال البحث في المكونات المكانية والتكرارية للأنسجة، فإنها توفر تمثيلًا أكثر دقة وتمييزًا للأنسجة. تلتقط ميزات Tamura صفات بصرية مهمة تعتبر ضرورية لفهم الملمس وتفسيره. تتيح واصفات Tamura إمكانية وصف ومقارنة الأنسجة المختلفة، مما يسهل المهام مثل تصنيف الأنسجة وتقسيمها واسترجاعها. تقوم SIFT بمعالجة واصفات Tamura لاستخراج ميزات ثابتة الحجم، مما يعزز قدرة تمثيل النسيج على التمييز. تم تقييم الطريقة المقترحة على العديد من مجموعات البيانات المرجعية، وكشفت النتائج أنها تتفوق على طرق تحليل النسيج التقليدية من حيث الدقة والتذكر ومقاييس الأداء الأخرى. كما تحقق التقييم النوعي من قابلية التفسير والأهمية الإدراكية لعناصر النسيج المسترجعة، مما يثبت ملاءمتها لمهام تحليل النسيج. تظهر نتائج التقييم مدى نجاح التقنية المقترحة في استخلاص ميزات النسيج وكيف يمكن أن تعزز فعالية العديد من تطبيقات رؤية الحاسوب ومعالجة الصور.