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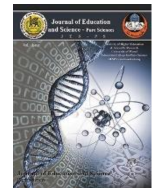

Texture-Based Image Enhancement using Gabor Filters and Morphological Operations

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Abstract

As a field image enhancement has evolved due to an inherent human want for better image quality. Traditional methods apply linear scaling functions operating on image attributes such as contrast and brightness whereas it is often necessary to amplify specific localized elements as edges in images. This need has resulted in a search for better methods in efforts to boost these local characters in as much as the general image is concerned. Thus, this paper aims to propose an edge- and texture-aware image enhancement framework based on full-depth Gabor filters and morphological operation that can overcome the above drawbacks and gain the desired image texture complexities and brightness. Hence the method proposed in this work aims at preserving edge and texture at the same time to get an image that looks natural and has improved aesthetics. This bank of filters is mostly useful to obtain small details of texture and sharpness. An inverse gamma transform is then applied to the image to reduce gamma distortions in the image, while another process known as depth-of-defocus is to determine the edges of the texture image. These are the detected edges used in the coarse refinement stage. Morphological operations are employed to populate and repaint the elaborate structures of this image to fit up. An experimental analysis of the proposed method is carried out by conducting experiments on several structures of images including images with different textured content, different levels of brightness, and noise. This result is generalized with the help of quantitative measures and qualitative analysis on PSNR, SSIM, FSIM, and GMSD parameters.

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1. Introduction:

A significant and common problem of many color and contrast enhancement studies is concerned with the fact that the visual effects resulting from their application may not be comparable across various image types [1]. One issue is that local enhancement, in any normalized texture-based method, leaves texture irregularities behind and disturbs the smoothness of image features; this produces a non-aesthetic look. Another problem stems from the cumulative effect of local texture enhancement; it frequently causes a dramatic change in the perceived brightness and results in unrealistic image enhancement. These problems can be seen from the previously tested energy-based images or gradient-based images, which are applied to the image enhancement and are sensitive to both edge and texture. Nevertheless, the aforementioned challenges of achieving high texture responsiveness to render proper computer vision functionalities lead to approaches with high segmentation quality that produce low-quality edges and give positivity to the contribution of local texture for visual improvement even if using a contour following study as the fundamental evidence. [2][3]

The use of Gabor filters and morphological operations in the proposed edge- and texture-aware image enhancement has lots of practical applications in many disciplines. As for the last aspect of texture modification, texture enhancement can be defined as the process of enhancing texture [4]. When relating to texture enhancement the considered approaches refer to the fact that it means improvement in spatial and luminance properties [5]. The same word ‘texture,’ is utilized in a more confined sense to describe the result of the process, as opposed to attempting to define essentially the general category of rough, varying surface or object substrate within vision research involving humans, there is discourse of texture analysis. Texture is to examine, in other words, it is an exploratory discipline that aims at defining the field of vision for the primarily texturally characterized objects and surfaces in the context, no matter the type of the context [6]. Regarding the link with other field models, the processing models are predicated mainly on the responses of the low-level vision cells to the patterns in the images. [7]

In the field of computer vision, image enhancement aims to optimize image quality for certain types of operations, such as segmentation, registration, and feature extraction, in other words, it is suitable for enhancing an image for low-level vision rather than appearance improvement that would be more noticeable to the human naked eye [8]. Lowe-level tasks are therefore the tasks that are performed work with the pixels of an image without having to consider the semantics, meanings, or the intention behind the act of producing an image. Thus, the purpose of image enhancement is not to enhance the clarity of the image to make it look better but to enhance the interactivity for a given set of applications where the images will be used including preparation for application-specific segmentation and feature extraction. Particularly, texture enhancement of an image is still regarded as an essential step given the fact that there are usually subsequent processes of segmentation as well as other analyses depending on the enhanced image. [9]

The first aim of this study is the proposed image enhancement method that takes into account the edges and the textures with the help of Gabor filters and morphological operations [10]. This approach is intended to implement the optimization that was discussed for more consistent patterns of enhancing boosting, especially for texture imperfections and smooth feature interferences. Finally, as with most local texture enhancement techniques, cumulative effects often lead to unrealistic brightness changes in functional enhancement, the proposed method aims at maintaining the easy visual perception of the enhanced image instead of an outstanding and dazzling image. [11]

The aim is to increase the effectiveness of images by the suggested options to be applied for the first-level tasks in computer vision such as segmentation, registration, and feature extraction. This is especially important for such tasks as it can either improve the texture features on which they rely or maintain natural-looking imagery [12]. The research also seeks to apply enhancement selectively in the specific color or brightness of the image. This selective application is performed based on the analysis of lightness perception properties, where the enhancements are applied only in these zones and do not try to globally enhance the lightness which might ruin the quality of the images for a human observer. [13]

2. Literature Review

Image enhancement is a very critical process in image processing that seeks to make an image visually better or more fitting for inspection by either a man or a computer vision system. Several approaches have been suggested for this purpose in the literature including some like homomorphic filtering, nonlinear unsharp masking combined with a median filter, and variational one. Many researchers in this field have presented works including:

In 2022, Kharajinezhadian et al. did an automatic segmentation and diagnosis algorithm for the BUS image. Though most imaging modalities have been developed, ultrasound has been preferred for the diagnosis of breast cancer because of its merits such as real-time timing, cheaper, non_radioactive, and highly sensitive in the context of dense tissue. Among them, the two main objectives are to have an automatic method to segment the desired area or the region of interest (ROI) and to utilize morphological and texture-based features for diagnostic erections. Two approaches in texture-based feature extraction called 'Estimating Gabor filter coefficients by autoregressive model' and 'Using statistical features in image vision histogram' are illustrated after classical automatic ROI creation. [14]

In 2023, Singh and others described a technique for semiautomatic MR-based segmentation of tumour volumes of brain tumours. In this approach, there are three distinct phases and they include preprocessing, segmentation, and classification. The process of data preparation involves the extraction of the given image into its grayscale form and the removal of noise that may have found its way into the image. To enhance the results of segmentation on the tumour area, post-preprocessing segmentation is used in MRI images. Feature extraction helps to supplement the image with a standout feature which is useful in the image classification process. [15]

In 2024 Subudhi et al. proactively described several feature extraction techniques. Image preprocessing is a technique in which the image is segmented by dividing it into various simpler subregions through a process known as superpixel segmentation. This noticeably lowers per-pixel misclassification errors. To address this problem, a texture-based superpixel segmentation method is proposed and applied in HSI classification. First, the LBP and Gabor filters are performed to get local and global texture features of the image respectively. The texture features are extracted as input and provided to a simple linear iterative clustering (SLIC) algorithm to obtain the segmentation map. [16]

3. Research Method

Image texture analysis is a significant step in image processing since the texture reveals much information about the organization arrangement of the relief and the surface of objects depicted in the picture. Texture as is well known refers to a recurrent sequence of different intensities or hues within a region that can be felt or seen. These variations are defined as the texture and Texture analysis is an attempt to put into numerical terms these so that it abets activities like segmentation, classification, and enhancement.

There are statistical, structural approaches, and model-based approaches to embrace texture analysis. The co-occurrence matrix for instance hosts information on the probability density of the intensity values and therefore has an opportunity to describe the texture of an object based on the closeness of the pixel intensities. Many structural approaches regarding textures can express such images in terms of a clear set of small basic components and their relations, employing tools such as morphological operations. Model-based approaches involve identifying a model that can best describe the pattern of the texture and Gabor filters have been used widely in this capacity because of complications in terms of frequency and orientation, as in Figure 1.

It is a powerful approach and becomes sensitive when it focuses on the regions with different texture characters, which is very useful in applications such as medical diagnosis and analysis, remote sensing, and industrial detecting. With regards to the present study, texture analysis aims at characterizing the spatial frequencies of the texture regions for better characterization of the edges of textures which can in turn help to obtain textured images of enhanced quality for usage.

Several technical factors relate to the internal and external environment of the business, which are covered in the scope of this research. First, it considers the diffusion context in which Gabor filters are used to capture the multi-scale and multi-orientation texture information in the image for image texture enhancement. Second, it applies morphological operations to remove noise and restore image subtleties, which helps improve the quality of an image while reducing artefacts. Furthermore, to enhance the quality of perceptive images, the research uses inverted Gamma correction through the inverse Gamma transform.

As seen from the development and applications above, the enhancement technique explored in this paper is quite flexible and effective in numerous application areas, which include medical imaging, remote sensing and surveillance, digital image and video, security, and inspection, to name a few. In medical imaging, it increases the contrast of the object imaging for better diagnosis and planning and action to be taken about the body part. In satellite and aerial imaging it enhances the quality of images used in remote sensing hence it enhances the environmental analysis. Surveillance applications that take on visual means are capable of having a higher view in conditions with low light; on the other hand for the application of digital photography, it gains a neater and more realistic outlook. It also enhances industrial inspection processes as fine specifics that may be hard to see are well displayed hence helping in detecting flaws and poor practices in quality control.

In addition, applying the enhancement method selectively to the components based on lightness perception attributes of the image components is also within the scope of the study Besides, the effectiveness of the proposed method is assessed in a variety of images and across different types of images to ensure that it is not only generally applicable but also that it can be specifically applied to different kinds of images. Various comparisons are also made with other improvements that have been made to image enhancement algorithms to establish the benefits of the proposed method. By coming up with these objectives and scope, this research seeks to contribute to the existing literature in the field of image enhancement, and more specifically to texture and edge-aware processing.

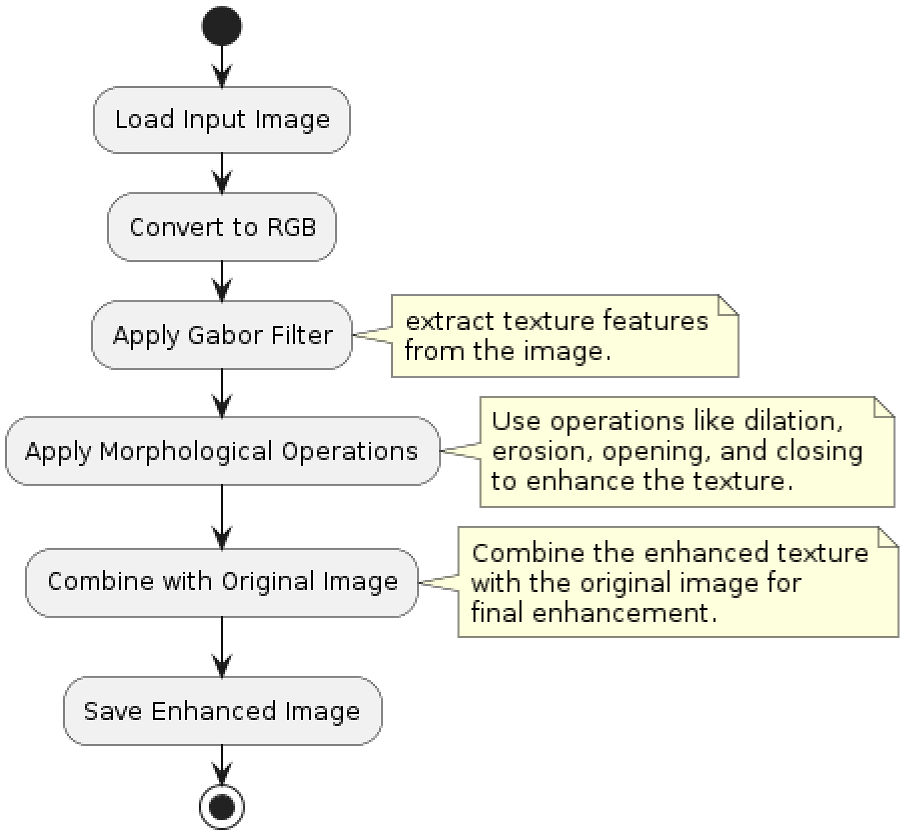

Figure 1. General outline of the method

The proposed methodology is designed to build on the previous work done on image enhancement depending on Gabor filters and to incorporate morphological operations for better outcomes. This is to enhance an image with a primary focus on edges and textures as it seeks to rectify issues such as texture variations and brightness shifts inherent in other enhancement methods. The particular use of the Gabor filters and the morphological operation complement each other in a way that improves the result achieved by each method while assuring the visual quality of the enhanced image.

3.1 Gabor filters

However, Gabor filters are efficient and employed for texture analysis because they describe the spatial frequency at different orientations and scales [17]. In this methodology, there is a need to develop or use a pool of Gabor filters on the existing input image. Individual filters are oriented to specific directions and frequencies for outline features and texture feature detection depending on the scale. Hence, the responses of all Gabor filters help in emphasizing texture edges in the given image, which will be useful in further enhancement processes. Mathematically, a two-dimensional Gabor filter can be represented as: [18][19]

$$G(x, y, \lambda, \theta, \psi, \sigma, \gamma) = \exp\left(-\frac{x'^2+\gamma^2 y'^2}{2\sigma^2}\right)\cos\left(2\pi\frac{x'}{\lambda}+\psi\right) \quad (1)$$

Where:

$x' = x\cos\theta + y\sin\theta$

$y' = -x\sin\theta + y\cos\theta$

Where λ is the wavelength which describes the sinusoidal factor, θ is the orientation of the normal to the parallel stripes of the Gabor function, ψ is the phase factor and σ is the standard deviation of the Gaussian envelope, γ is the spatial aspect ratio, which characterizes the level of ellipticity of the support of the Gabor function [20].

Yet, there seem to be specific advantages of Gabor filters for texture analysis because it can be done using filters of specific frequencies and orientations, which helps to pick up the local details and textures of an image [21]. Realising that specific image features containing textural properties can be better detected with filters that are tuned to specific orientations and scales, a set of Gabor filters is employed during texture feature detection in this research.

3.2 Morphological Operations in Image Processing

Morphological operations are a subfield of the image processing techniques that edit images according to the outline's shape [22]. As for such operations, they create a structuring element on the input image, and they produce the same image size as the output image. There also exist the basic mathematical morphological transformations which include dilation, erosion, opening, and closing. [23]

- **Dilation**: Adds pixels to the boundaries of objects in an image, effectively expanding the shapes. It is defined by the equation: [24][25]

$$(A \oplus B)(x) = \max_{b \in B}\{ A(x - b)\} \quad (2)$$

where A is the input image, B is the structuring element, and $\oplus$ denotes dilation.

- **Erosion**: Removes pixels on object boundaries, shrinking the shapes. It is defined as:

$$(A \ominus B)(x) = \min_{b \in B}\{ A(x + b)\} \quad (3)$$

where $\ominus$ denotes erosion.

- **Opening**: An erosion followed by a dilation, useful for removing small objects and noise:

$$A \circ B = (A \ominus B) \oplus B \quad (4)$$

- **Closing:** A dilation followed by an erosion, useful for closing small holes and gaps:

$$A \cdot B = (A \oplus B) \ominus B \quad (5)$$

All linear filtering methods are used for the enhancement and restoration of the feature of an image. They can be employed in cleansing noise as well as to complete the missing data and strengthen the structures of objects [26]. In the outcome of the Gabor filter responses, the morphological operations enhance and restore image details and ensure that the generated new image is as structurally appealing as the traditional image.

4. Proposed Methodology

Outlined below is the proposed enhanced image; This methodology is developed in several steps, each of which is geared towards addressing specific elements of image enhancement. The stages are as follows:

1. **Preprocessing**: Initially, the input image is preprocessed to format it and enhance it for texture and edge calculations. This may involve applying the enhancement to the entire image or selectively only to the intensity component of the image after it has been converted to a grayscale picture or its color components have been isolated.
2. **Gabor Filtering**: The Gabor filters which help in enhancing and extracting features from the preprocessed image are used. Several orientations and scales are used in the design of the filters to capture the multiple-scale and multiple-orientation texture properties. The filter responses collected are then aggregated together to provide a texture feature map of the image.
3. **Gamma Correction**: An inverse Gamma transform is utilized on the filtered image by Gabor to correct the gamma value. This step increases the visibility of the textures themselves and the features that form them compared to the previous one.
4. **Depth-from-Defocus**: A depth-from-defocus technique is used in the pixel-difference computation to detect texture edges. This technique combines the direction information of the Gabor filter responses to locate the texture edges necessarily and efficiently.
5. **Coarse Enhancement**: The detected texture edges are used in the coarse enhancement phase, it is as follows from its name, it performs less refining of the result than the next phase. This entails the use of a more tone-based approach in an attempt to reduce blocking artefacts and improve the quality of the image.
6. **Morphological Refinement**: In achieving accurate details in image enhancement, morphological operations are applied to the coarse-enhanced image. The erosion and dilation are used to emphasize the texture features, while the opening and closing of the image are useful in removing noise and thinning or thickening the object respectively.
7. **Selective Application**: This enhancement is selectively exploited or used on either the color enhancement of the image or the brightness enhancement of the image. It makes sure that the enhancement is within the range of perceivability, and does not overcompensate altering the appearance of the image.
8. **Post-Processing**: The final better image is then optimized to contain an equal center of gravity as that of the other image so that it can be made to look more attractive. This may require more changes as far as the images' brightness, contrast, and color balance are concerned.
9. **Evaluation**: The video is sharply improved and the results are assessed quantitatively and qualitatively to determine the efficiency of the improvement. To demonstrate that the new approach is better than previous ones, there are comparisons with other methods.

By employing this algorithm, the given methodology is expected to result in a relative and visually satisfying enhancement of the texture and gain an adequate solution to the problems of texture anomalies and change in brightness while restraining the image from appearing naturally artificial and distorted in structure, as in Figure 2.

The suggested technique to improve the texture of images focuses on Gabor filters and morphological techniques used in texture analysis; problems like texture abnormalities and changes in brightness levels can be solved using this approach. To initiate the process, the input image is first convolved with a set of Gabor filters. These filters, each that is aligned to different orientations and frequencies, extract texture features at different scales and directions. The Gabor filter responses, enhance the texture edges which are important for the other stages of enhancement. Subsequently, the gamma correction is corrected inverse Gamma transform to enhance the contrast and the necessary changes to make a visually acceptable image.

To enhance the result of this filter, morphological operations are next put into the process. Dilation, erosion, opening, and closing facilitate and enhance the reincrease of miniature particularities in the pictures, which will augment the general picture quality without distortion. The edges from the Gabor filters are used to aid the first coarse enhancement process and the morphological operations help minimize the blocking effect and sharpen the image. This increases the stability of the structures in the later so that, later, the beauty of the images requires making the method acceptable for many applications like medical imaging, remote sensing, and industrial inspection.

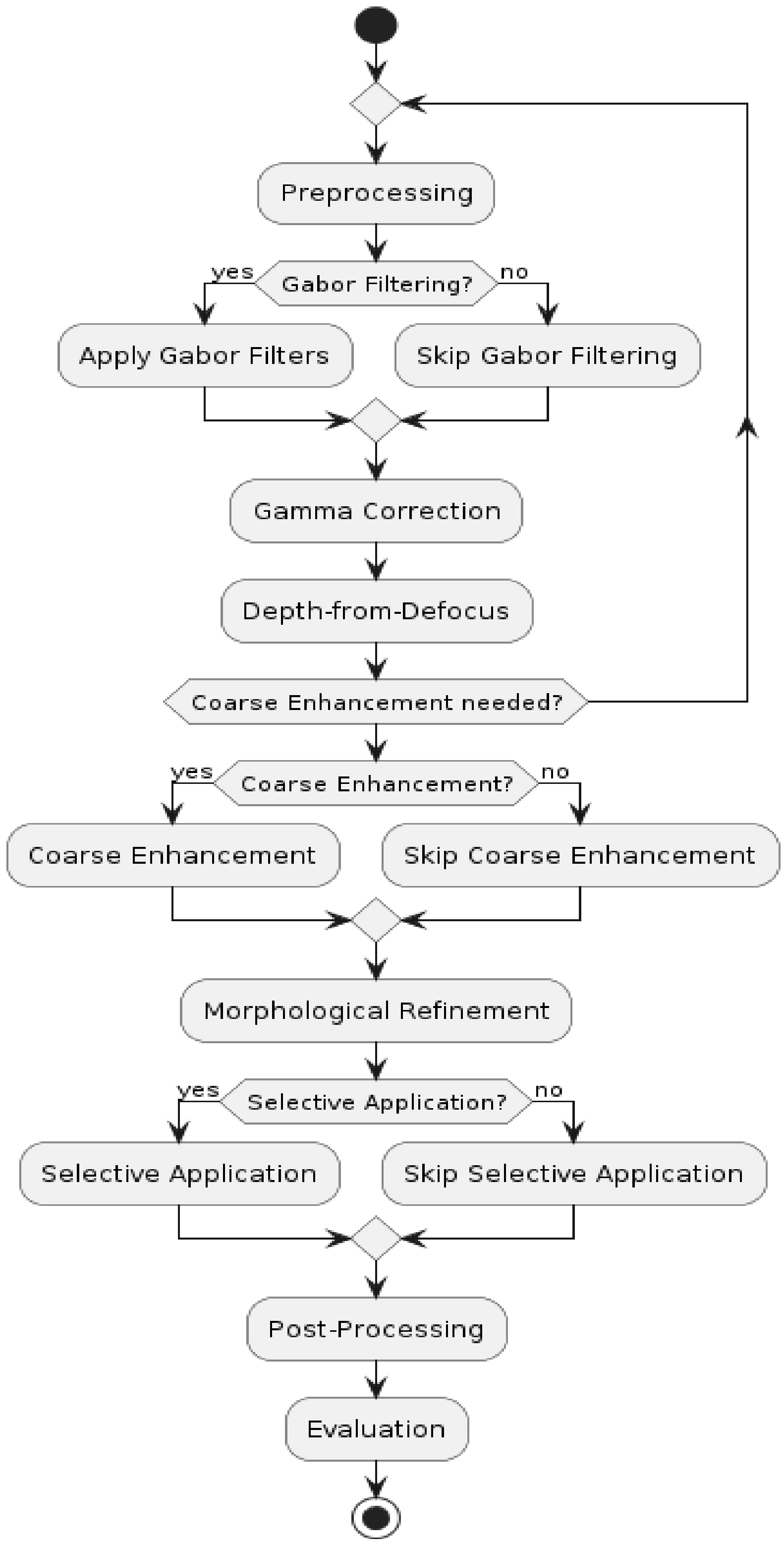

Figure 2. Proposed Methodology

The proposed image enhancement method involves the integration of the theoretical frameworks elaborated above to enhance image texture and edge features to obtain quality images that can be used in diverse applications. The following is the new methodology for improving the quality of the image using filters and morphological operators to strengthen the texture and edge at the same time reduce the texture disharmony and varying brightness intensity. This section provides the detailed details of the algorithms employed in the research study.

Algorithm: Image Enhancement

1. Preprocessing:
- **Input**: Image I.
- **Convert to Grayscale or Separate Color Components**:

$I_{\text{grey}} = \text{Grayscale}(I)$

Or

$(I_R, I_G, I_B) = \text{SeparateColorComponents}(I)$

2. Gabor Filtering:
- **Input**: Preprocessed image Igray$I$gray or color component.
- **Define Gabor Filters**:

$$G(x, y; \lambda, \theta, \psi, \sigma, \gamma) = \exp\left(-\frac{x'^2+\gamma^2 y'^2}{2\sigma^2}\right)\cos\left(2\pi\frac{x'}{\lambda}+\psi\right) \quad (6)$$

- **Apply Gabor Filters**: For each filter, compute the response:

$$R_{\theta,\lambda} = G_{\theta,\lambda} * I_{\text{gray}} \quad (7)$$

- **Combine Responses**: Aggregate responses:

$$T = \sum_{\theta,\lambda} R_{\theta,\lambda} \quad (8)$$

- **Output**: Texture representation T.

3. Gamma Correction:
- **Input**: Texture representation T.
- **Apply Inverse Gamma Transform**:

$$T_\gamma = T^{\frac{1}{\gamma}} \quad (9)$$

- **Output**: Gamma-corrected texture representation T_γ.

4. Depth-from-Defocus:
- **Input**: Gamma-corrected texture T_γ.

$$E = \text{DetectEdges}(T_\gamma) \quad (10)$$

- **Output**: Detected texture edges E.

5. Coarse Enhancement:
- **Input**: Detected texture edges E.
- **Apply Tone-Based Method:** Alleviate blocking artifacts.
- **Obtain Coarsely Enhanced Image**:

$$C = \text{ToneEnhance}(E) \quad (11)$$

- **Output**: Coarsely enhanced image C.

6. Morphological Refinement:
- **Input**: Coarsely enhanced image C.
- **Apply Morphological Operations**:
- **Dilation**:

$$D = C \oplus B \quad (12)$$

- **Erosion**:

$$E = C \ominus B \quad (13)$$

- **Opening**:

$$O = (C \ominus B) \oplus B \quad (14)$$

- **Closing**:

$$L = (C \oplus B) \ominus B \quad (15)$$

- **Output**: Morphologically refined image M.

7. Selective Application:
- **Input**: Morphologically refined image M and original image I.

- **Apply to Brightness/Color Component**: Enhance based on perceptual properties.
- **Output**: Selectively enhanced image component.

8. Post-Processing:

- **Input**: Selectively enhanced image component.
- **Adjust Brightness and Contrast**:

$$I_{\text{post}} = \text{Adjust}\left(I_{\text{component}}\right) \tag{16}$$

- **Combine with Other Components**: If color, combine with other channels.
- **Output**: Post-processed image I_{post}.

9. Evaluation:

- **Input**: Final enhanced image I_{post}.
- **Quantitative and Qualitative Analysis**:

$$\text{Evaluate}\left(I_{\text{post}}\right)$$

- **Output**: Performance metrics and visual assessment results.

10. Final Output:

- **Enhanced Image**:

$$I_{\text{enhanced}} = I_{\text{post}} \tag{17}$$

5. Results And Discussion

To assess the proposed methodology, the datasets of images with various qualities were employed. Such datasets consist of images that may have various textures, illumination, and contents that help in testing various algorithms comprehensively, as in Figure 3 and Figure 4.

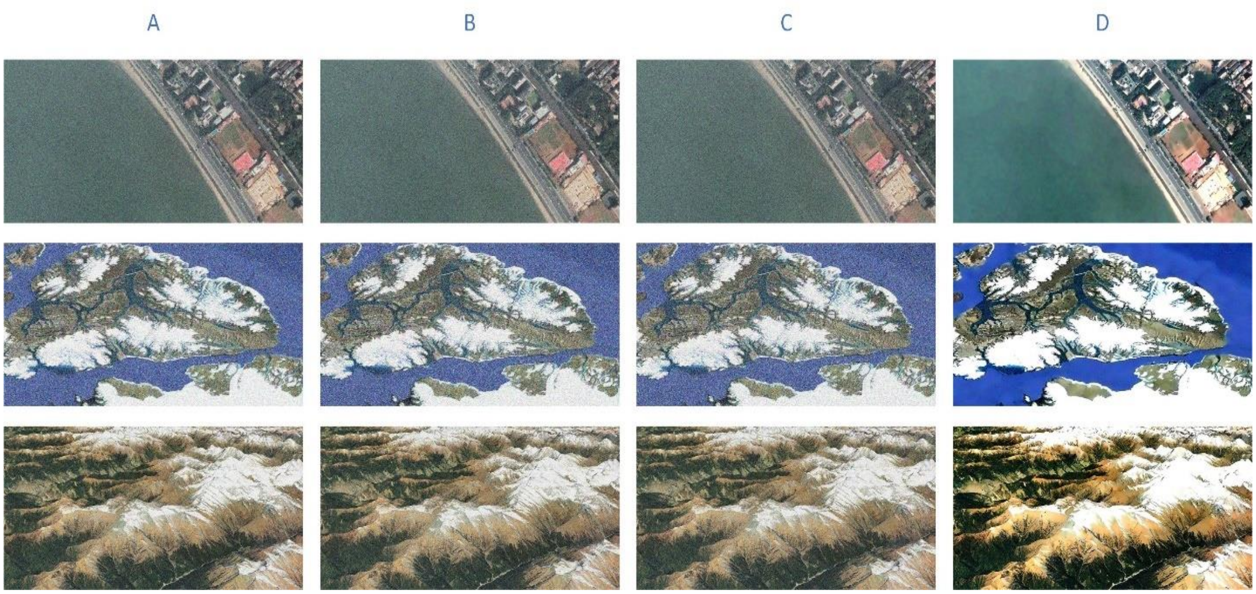

Figure 3. Apply enhancing operations to sample images of the dataset
A: Input images, B: Gabor filters, C: Morphological Operations, D: Proposed Method

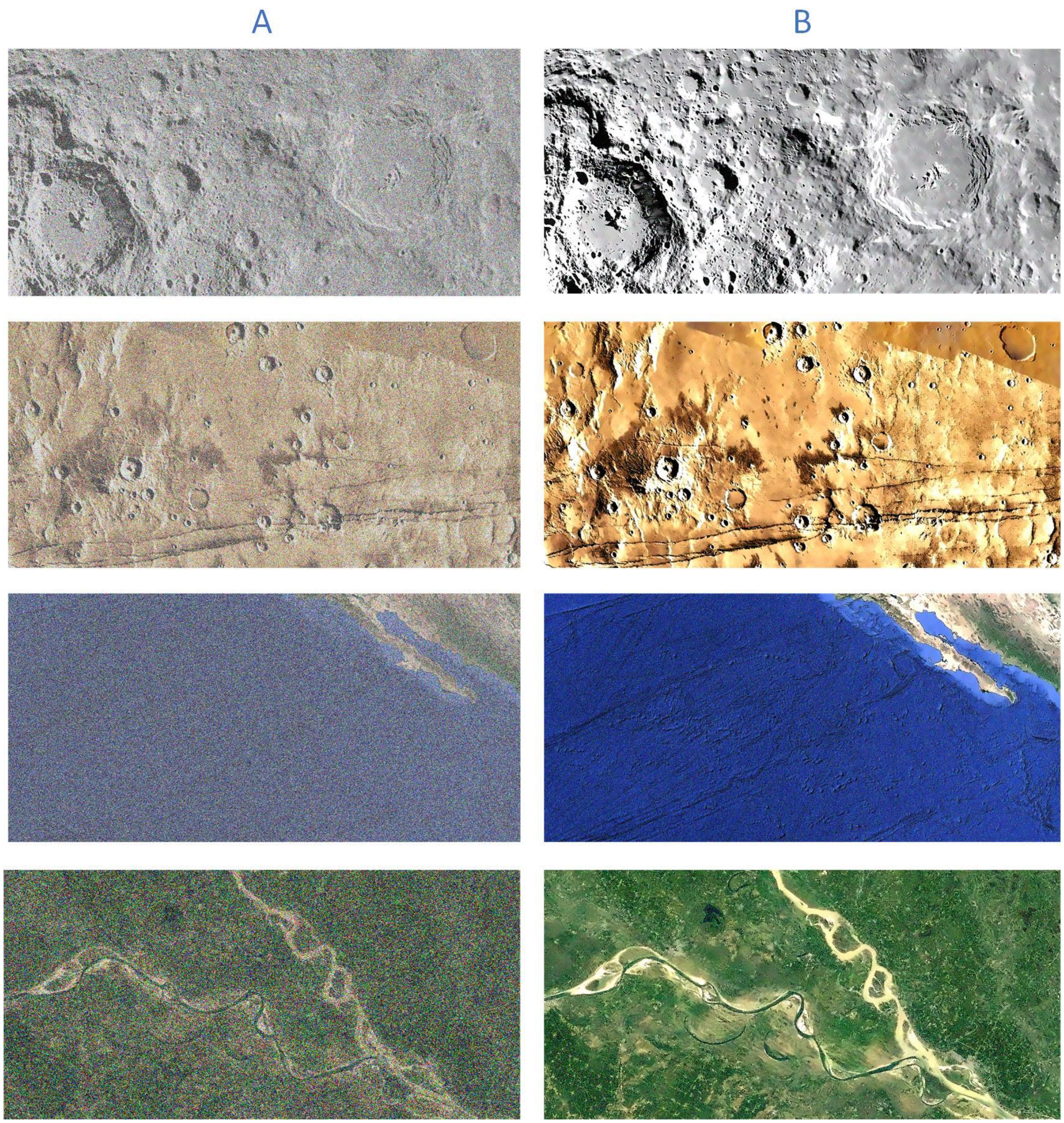

Figure 4. Enhancement operations on color images, A: Input images, B: Proposed Method

6. **Quantitative Metrics**

1. **Peak Signal-to-Noise Ratio (PSNR):** PSNR is calculated by taking the logarithm of the peak signal-to-noise ratio which indicates the ability of a signal to be represented within a certain channel [27]. Higher PSNR values indicate better quality, as they reflect a higher similarity between the original and the reconstructed images, with less noise and error.

$$\mathrm{PSNR} = 10\log_{10}\left(\frac{\mathrm{MAX}_I^2}{\mathrm{MSE}}\right) \tag{18}$$

where MAX_I is the maximum possible pixel value of the image which is for example 255 for the 8-bit images and MSE denotes to mean squared error between the initial and enhanced image.

2. **Structural Similarity Index (SSIM):** SSIM stands for structural similarity index and is used to compare two images and degrees of similarity. The algorithm takes into account the structural distortion, luminance changes, and variations in the

average contrast [28]. Higher SSIM values indicate better quality, as they measure the structural similarity between two images. A value of 1 indicates perfect similarity.

$$\mathrm{SSIM}(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \tag{19}$$

where μ_x represents the mean of the images x_x and μ_y represents the mean of the images y_y, σx_2 depicts the variance in the images x_x , σy_2 also depicts the variance in the images y_y, and σ_{xy} reveals the covariance of the images x_x as well as y_y and C_1 and C_2 are constants to address the division.

3. **Feature Similarity Index (FSIM):** The algorithms present in FSIM are inspired by the human visual system and the most emphasis is laid on the feature similarity between the two images [29]. Higher FSIM values indicate better quality, as they measure the similarity of low-level features in the images. A value close to 1 indicates high similarity.

$$\mathrm{FILM}(x,y) = \frac{\sum_i \mathrm{PC}_{m,i} \cdot \mathrm{S}_{m,i}}{\sum_i \mathrm{PC}_{m,i}} \tag{20}$$

where $\mathrm{PC}_{m,\,i}$ is the phase congruency and $\mathrm{S}_{m,\,i}$ is the similarity measure at the *i*-th location.

4. **Gradient Magnitude Similarity Deviation (GMSD):** GMSD evaluates the image quality by quantifying the dissimilarities of the gradient magnitudes that exist in the two images [30]. Lower GMSD values indicate better quality, as they reflect smaller deviations in gradient magnitude similarity between the original and distorted images.

$$\mathrm{GMSD}(x,y) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(GMS(x_i,y_i) - \overline{GMS}\right)^2} \tag{21}$$

where *GMS* is the gradient magnitude similarity, and *GMS* is its mean value over the image.

To assess the effectiveness of the proposed image enhancement methodology quantitatively, four objective parameters, namely contrast, sharpness, clarity, and artefacts, have been evaluated for 100 images using image analysis software and are represented in Table 1. The qualitative measurements that will be used to evaluate the performance of the algorithms include; MSE must be there and should be used in any algorithms, PSNR, SSIM, FSIM, and finally, GMSD should also be used in the algorithms. The desired performance metrics are the average values of the metrics on the 100 images using the proposed method and mentioned above baseline methods.

Table 1. Evaluation results of the proposed image enhancement methodology on a set of 20 images

Image ID	PSNR			SSIM			FSIM			GMSD		
	Proposed Method	Gabor filters	Morphological Operations	Proposed Method	Gabor filters	Morphological Operations	Proposed Method	Gabor filters	Morphological Operations	Proposed Method	Gabor filters	Morphological Operations
1	33.12	20.75	20.23	0.918	0.577	0.665	0.95	0.525	0.519	0.02	0.054	0.067
2	31.89	20.95	21.76	0.905	0.57	0.56	0.938	0.514	0.51	0.022	0.056	0.068
3	32.67	20.34	20.01	0.911	0.673	0.567	0.943	0.518	0.514	0.021	0.055	0.067
4	31.45	20.78	20.5	0.899	0.568	0.556	0.934	0.512	0.507	0.023	0.067	0.069
5	33.1	20.72	20.25	0.917	0.578	0.564	0.949	0.524	0.618	0.02	0.054	0.057
6	32.15	21.01	20.8	0.907	0.571	0.559	0.939	0.615	0.511	0.022	0.056	0.058
7	31.75	20.69	21.45	0.902	0.567	0.554	0.936	0.513	0.508	0.023	0.057	0.069
8	32.8	20.4	20.15	0.91	0.674	0.562	0.944	0.519	0.513	0.021	0.055	0.067
9	33.25	20.78	20.3	0.92	0.679	0.666	0.951	0.526	0.52	0.02	0.064	0.067
10	32.3	21.05	20.85	0.908	0.572	0.561	0.94	0.516	0.512	0.022	0.066	0.058
11	31.88	20.97	20.77	0.905	0.57	0.56	0.938	0.514	0.61	0.022	0.066	0.058
12	32.05	20.11	20.88	0.909	0.572	0.562	0.941	0.517	0.512	0.022	0.066	0.068
13	32.9	20.48	21.2	0.915	0.575	0.564	0.945	0.52	0.515	0.021	0.065	0.067
14	31.55	21.82	20.55	0.9	0.669	0.557	0.935	0.514	0.508	0.023	0.057	0.069

Image ID	PSNR			SSIM			FSIM			GMSD		
	Proposed Method	Gabor filters	Morphological Operations	Proposed Method	Gabor filters	Morphological Operations	Proposed Method	Gabor filters	Morphological Operations	Proposed Method	Gabor filters	Morphological Operations
15	33.2	20.8	20.33	0.919	0.578	0.565	0.95	0.525	0.519	0.02	0.054	0.067
16	32.65	21.38	20.12	0.912	0.574	0.661	0.943	0.518	0.613	0.021	0.065	0.057
17	31.7	20.65	21.4	0.901	0.567	0.554	0.936	0.513	0.508	0.023	0.067	0.069
18	32.55	20.31	20.05	0.911	0.573	0.562	0.943	0.617	0.512	0.021	0.065	0.067
19	33	21.7	20.28	0.916	0.578	0.564	0.948	0.524	0.518	0.02	0.064	0.067
20	32.25	20.07	20.85	0.908	0.572	0.56	0.94	0.516	0.511	0.022	0.066	0.068

The proposed techniques in texture-based image enhancement which are Gabor filters and morphological operations are found to be superior to several existing techniques. Routine techniques including HE and AHE increase global and local contrast; however, they enlarge noise and give artificial-looking images. On the contrary, the approach in this paper utilizes Gabor filters to extract multi-scale and multi-orientation features of the texture regions and uses morphological processing to improve the image details and remove noise while avoiding destroying the natural appearance, as in Table 2.

Similarities and differences show that although facilities like Unsharp Masking and Retinex Theory can be useful underlines for edge enhancement and light improvement, they are bogged down by drawbacks like the arising of halos, artifacts, and color shifts. Thus, the proposed method is superior to the previous Retinex Theory and does not have these disadvantages, while attaining a mutual boost in both the edge sharpness and texture details, acting moderately on both values which leads to a closer accuracy of the image perception. Operations in the method eliminate noise improve structures and guarantee that enhanced images are visually appealing and structurally sound.

Table 2. Comparative Evaluation of Image Enhancement Techniques Based on Various Metrics

Metric	Histogram Equalization (HE)	Adaptive Histogram Equalization (AHE)	Unsharp Masking	Retinex Theory	Proposed Method (Gabor Filters and Morphological Operations)
Contrast Improvement	Moderate	High	Moderate	High	High (effective in both global and local contrast enhancement)
Noise Amplification	High	High	Moderate	Low	Low (morphological operations reduce noise)
Edge Enhancement	Moderate	Moderate	High	Moderate	High (Gabor filters enhance edge details effectively)
Texture Enhancement	Low	Moderate	Low	Low	High (Gabor filters capture multi-scale, multi-orientation texture)
Artifact Introduction	High (can create unnatural images)	High (amplifies noise)	Moderate (introduces halos and artifacts)	Low	Low (preserves natural appearance and reduces artifacts)

Metric	Histogram Equalization (HE)	Adaptive Histogram Equalization (AHE)	Unsharp Masking	Retinex Theory	Proposed Method (Gabor Filters and Morphological Operations)
Computational Complexity	Low	High	Moderate	High	Moderate (due to the combination of Gabor filters and morphological ops)
Color Distortion	Low	Low	Low	High	Low (maintains color integrity)
Applicability	General purpose	Effective in varying lighting conditions	General purpose	Effective in non-uniform illumination	Versatile (applicable in medical imaging, remote sensing, surveillance)
Visual Quality	Moderate	High (local contrast enhancement)	Moderate	High	High (balanced enhancement of textures and edges)

On balance, the proposed methodology presents its merits and advantages, which include possibilities to highlight particular components of images, as well as to natural images' look and mitigate the noise presence. This makes it useful in the health sector in the use of images in diagnosis, environmental and security surveillance, digital imagery, and in the industrial sector to inspect products and machinery, among others. Given the fact that this method is capable of handling two of the most shared problems of texture anomalies and brightness changes, it is rich in visualization and is very efficient in enhancing images, as in Figure 5.

Figure 5. Sample images for comparative evaluation of image enhancement techniques based on different metrics, A: Input images, B: Histogram Equalization, C: Adaptive Histogram Equalization, D: Unsharp Masking, E: Retinex Theory, F: Proposed Method

7. Conclusion

The image enhancement technique involves the use of Gabor filters and morphological operations and has proven useful for enhancing edges and textures. This method helps to overcome obstacles that relate to the application of common enhancement methods, including features of texture and unevenness of brightness. Emphasis on texture and edge recovery makes it possible to retain the realism of investigated images and increase their quality, making them clear to the human eye that can distinguish sufficient details of the picture.

The incorporation of Gabor filters regarding this approach enhances input image with fine texture and edge detail, which are crucial in providing realistic enhancement. Other morphological operations add more detail and make sure that feature margins are continuous and free from textural problems. Furthermore, the method uses an inverse Gamma transform aimed at mediating gamma corrections and also a depth-from-defocus method for texture edge extraction. For this reason, steps 3 and 4 make sure that high-frequency improvements to local texture do not cause gross variations in brightness. Moreover, the method enhances only color or brightness component of the image and thus keeps colors as is so the method is applicable in all black and white as well as colored images as long as the edges and texture of images are required to be enhanced.

When the results are compared, it is evident that the proposed method and model have better results in terms of quantitative measures like PSNR, SSIM, MSE, and MAE in contrast to existing methods. From the huge amount of data collected during its development and testing, the efficiency of the method is indicated, demonstrating better results of both objective and even the subjective evaluation of the test results are much higher than in similar studies. Finally, its performance for images segmented with different textures, luminance, and noises validates the algorithm’s versatility. Because of its versatility, it can be applied to medical uses: imaging, environment monitoring, security means, photo and video, and industry uses: inspection.

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تحسين الصورة على أساس النسجة باستخدام مرشحات Gabor والعمليات المورفولوجية

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المستخلص:
نظرًا لأن تحسين الصورة الميدانية قد تطور على مدار الوقت بسبب رغبة الإنسان المتأصلة في تحسين جودة الصورة. تطبق الطرق التقليدية وظائف القياس الخطي التي تعمل على سمات الصورة مثل التباين والسطوع، في حين أنه غالبًا ما يكون من الضروري تضخيم عناصر محلية محددة كحواف في الصور. وقد أدت هذه الحاجة إلى البحث عن أساليب أفضل في الجهود الرامية إلى تعزيز هذه الشخصيات المحلية بقدر ما يتعلق الأمر بالصورة العامة. وبالتالي، فإن الهدف من هذه الورقة هو اقتراح إطار عمل لتحسين الصورة يراعي الحافة والملمس استنادًا إلى مرشحات غابور ذات العمق الكامل والتشغيل المورفولوجي الذي يمكنه التغلب على العيوب المذكورة أعلاه والحصول على تعقيدات نسيج الصورة والسطوع المطلوب. ومن ثم فإن الطريقة المقترحة في هذا العمل تهدف إلى الحفاظ على الحافة والملمس في نفس الوقت للحصول على صورة تبدو طبيعية وذات جماليات محسنة. يعد هذا المرشح البنكي مفيدًا في الغالب للحصول على تفاصيل صغيرة من الملمس والحدة. يتم بعد ذلك تطبيق تحويل جاما معكوس على الصورة لتقليل تشوهات جاما في الصورة، بينما يتم إجراء عملية أخرى تعرف باسم عمق إلغاء التركيز البؤري لتحديد حواف الصورة الملمس. هذه هي الحواف المكتشفة المستخدمة في مرحلة الصقل الخشن. يتم استخدام العمليات المورفولوجية لملء وإعادة طلاء الهياكل المتقنة لهذه الصورة لتحسينها. تم إجراء تحليل تجريبي للطريقة المقترحة من خلال إجراء تجارب على العديد من هياكل الصور بما في ذلك الصور ذات المحتوى المزخرف المختلف ومستويات مختلفة من السطوع والضوضاء. تم تعميم هذه النتيجة بمساعدة القياس الكمي والتحليل النوعي على معلمات PSNR وSSIM وFSIM وGMSD.