

Contrast Enhancement Based Image Detection Using Edge Preserved Key Pixel Point Filtering

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Abstract: In existing methods for segmented images, either edge point extraction or preservation of edges, compromising contrast images is so sensitive to noise. The Degeneration Threshold Image Detection (DTID) framework has been proposed to improve the contrast of edge filtered images. Initially, DTID uses a Rapid Bilateral Filtering process for filtering edges of contrast images. This filter decomposes input images into base layers in the DTID framework. With minimal filtering time, Rapid Bilateral Filtering handles high dynamic contrast images for smoothening edge preservation. In the DTID framework, Rapid Bilateral Filtering with Shift-Invariant Base Pass Domain Filter is insensitive to noise. This Shift-Invariant Filtering estimates value across edges for removing outliers (i.e., noise preserving base layers of the contrast image). The intensity values are calculated in the base layer of the contrast image for accurately detecting nearby spatial locations using Shift-Invariant base Pass Domain Filter (SIDF). At last, Affine Planar Transformation is applied to detect edge filtered contrast images in the DTID framework for attaining a high quality of the image. It normalizes the translation and rotation of images. With this, Degeneration Threshold Image Detection maximizes average contrast enhancement quality and performs an experimental evaluation of factors such as detection accuracy, rate, and filtering time on contrast images. Experimental analysis shows that the DTID framework reduces the filtering time taken on contrast images by 54% and improves average contrast enhancement quality by 27% compared to GUMA, HMRF, SWT, and EHS. It provides better performance on the enhancement of average contrast enhancement quality by 28%, detection accuracy rate by 26%, and reduction in filtering time taken on contrast images by 30% compared to state-of-art methods.

Keywords: Rapid bilateral filtering; edge preserved filtering; affine planar transformation; key pixel point localization; shift-invariant base pass domain filter



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1 Introduction

Recent photographs have been used as essential evidence for various beneficial functions. Contrast enhancement is applied in modifying the brightness and contrast of a digital image. It allows the user to alter contrast locally. Contrast enhancement acts as a significant image processing approach that creates different contents of images discernible through an appropriate increase in contrast. Effective contrasting on-edge filtered images have been the subject of research work for the recent development of high-quality video images and rapid advancement in video images (like PC monitors, television, etc.). In images, extraction of edge points minimizes processing time for large-size images. As a result, contrast gets reduced while preserving edges. At the same time, edge-preserving filters have been developed through efficient noise-sensitive, affecting most of the base layer of contrast images while preserving edges. Because of it, edge-preserving filters reduce multiresolution processing. Handling multiresolution becomes a significant challenge to users for controlling over edge filtered contrast images.

Two contrast enhancements based on Forensic Algorithms were designed in [1] including contrast enhancement were identified with manipulation involved in JPEG compressed images and detection of the composite image. However, detecting contrast images was not sufficient. An Automatic Methodology was designed in [2] to classify new objects that include significant differences between normal and malign images with a lesser time duration. However, contrast enhancement quality was not addressed. Automatic detection of Computed Tomography Analysis was performed in [3] to provide an accurate and fast tool for high contrast and low contrast images. However, edge filtering for contrast images remains unaddressed.

An Exact Histogram Specification (EHS) technique was described in [4] for measuring contrast analysis with aid of frequency bands. However, filtering time was not minimized. In several image processing applications, acquiring an image is less probable with a higher number of theoretical and practical problems. Bayesian analysis was introduced in [5] for accurate estimation between images without any parameter tuning. However, super-resolution images were not achieved.

Higher-order derivatives of images were processed in [6] by using a minimization algorithm. Eulers' elastic model not only obtained smooth results but also preserved edges. However, noise removal was not performed efficiently. The Majorize-minimize principle was structured in [7] to preserve edges during image restoration. However, the blurring defect remains unaddressed.

High Resolution (HR) image was mainly developed based on Huber-Markov Random Field (HMRF) model was designed in [8] variational integral for piecewise smoothing nature of HR image. However, image restoration was not performed efficiently. With help of the Fourier domain, mathematical analysis was performed in [9] refers to signal-to-noise ratio. But, if failed to remove noise Generalized Unsharp Masking Algorithm (GUMA) was designed in [10] for enhancing contrast and sharpness through individual treatment of model components and residuals. However, filtering time was not minimized.

To improve contrasting on-edge filtered images, Degeneration Threshold Image Detection (DTID) framework has been proposed. The core idea of the DTID framework is the usage of the Rapid Bilateral Filtering process for filtering edges of contrast images. As a result, contrasting on-edge filtered images is improved. However, the rapid growth of filtering techniques on contrast images and the need for image detection while preserving high contrast edge images remain unsolved issues.

1.1 Novel Contribution

- Degeneration Threshold Image Detection (DTID) framework is developed to enhance the contrast of edge filtered images. DTID framework is designed with the novelty of Rapid Bilateral Filtering process, Shift-Invariant Base Pass Domain Filter, Affine Planar Transformation.

- Rapid Bilateral Filtering process is used in DTID framework to filter edges of contrast image with minimum time. It handles high dynamic contrast images for extracting segmented image key point pixels. Then, the weighted standard distance of intensity values is estimated for preserving edge filtering images.
- Shift-Invariant Base Pass Domain Filter is applied in the DTID framework to significantly remove outliers for noise preservation by detecting intensity values in base layers of the contrast image.
- Affine Planar Transformation is developed in the DTID framework to detect and extract key pixel point localization accurately from multiresolution contrast images. By measuring the value of longitude and latitude angle on edge filtered contrast image, to enhance average contrast enhancement quality.

The paper is structured as follows: Section 2 relates works on contrast images for effective image processing and several filtering methods to be reviewed. Degeneration Threshold Image Detection (DTID) framework with help of a neat diagram is described in Section 3. Experiments are conducted in Section 4. The corresponding results are provided and discussed elaborately in Section 5. Finally, the concluding work is summarized in Section 6.

2 Related Works

Resolution and contrast enhancement are frequently referred to as significant aspects of the image. Images were being processed for obtaining more enhanced contrast and resolution. Stationary Wavelet Transform (SWT) was efficiently designed in [11] to split an input image into several subbands with the sole purpose of enhancing resolution and contrast in images. SWT has not performed noise ratio. Dynamic Contrast-Enhanced - Magnetic Resonance Imaging (DCE-MRI) was applied in [12] to improve classifier visualization techniques based on SVM. However, the filtering process remains inefficient.

Analysis of images with the aid of computer-aided diagnosis emphasized heavily ovarian cancer imaging despite urgent clinical demands. Tumor Sensitive Matching Flow (TSMF) was performed in [13] contrast-enhanced abdominal CT with the aid of image matching and metastasis classification to reduce the false-positive rate. However, false positives were not minimized. Three-dimensional (3D) Contrast Enhancement-MR Angiography (CE-MRA) examined in [14] the prevalence of Unruptured Cerebral Aneurysms (UCAs) during tertiary comprehensive hospital in china. However, contrast enhancement was not achieved efficiently.

Total Variation (TV) based image restoration was applied in [15] for linear filtering and soft thresholding to deal with images with large sizes. However, the contrasting image remains unaddressed. The Edge Detection Technique was implemented in [16] to perform the edge strength of the original and equalized images. As a result, the effective original image and contrast were enhanced. However, the edge detection accuracy was lower.

The Semi-Supervised Learning Receiver Operating Characteristic (SSLROC) Algorithm was designed in [17] for effective polyp classification with the aid of optimization techniques. However, image quality enhancement was not achieved. A Geometry-Based Correlation Approach was designed in [18] with the purview of obtaining the correlation between the images and multi-view datasets. Joint decoding algorithms and geometric correlation were also derived for effective distributed image processing. However, the enhancement for contrast images was not improved.

A novel algorithm, Contrast-Tone Mapping was presented in [19], for enhancing the contrast in images using a constrained optimization approach. Two types of regularization strategies were described with the aid of a deterministic annealing-based approach in [20] to minimize the noise present in the images. However, motion deblurring issues remain unconsidered. The Least Mean Square Algorithm was applied in [21] for

obtaining better visual quality by reducing the peak signal noise-to-ratio. However, while increasing the size of the images, the noise-to-ratio got increased.

The Intensity Histogram Equalization (IHE) method was a preprocessing method in [22] that removes noise from the image and contrast was enhanced. However, this method deals only with denoising images. A new JPEG-robust Contrast Enhancement forensic method was developed in [23] depending on a modified 6 convolutional neural network (CNN). However, contrast enhancement was not achieved to the desired level.

A novel histogram modification scheme was established in [24] for image contrast enhancement. However, edge preservation remains unaddressed. The Adaptive median-based enhancement method was introduced in [25] to avoid over enhancement and under enhancement during noise suppression. However, real-time image enhancement was not performed. A global sparse gradient-guided variational Retinex model (GSG-VR) was designed in [26] for image enhancement. However, the time complexity remains unaddressed. An approach that seeks candidate matching blocks were developed in [27]. The coefficient of 3D transform was shrinking to carry out denoising. However, the performance efficiency in image enhancement was not improved. Super Resolution-based Sparse Representation has as of late demonstrated in [28] to perform well for picture rebuilding and deblurring. An edge-preserving filtering and principal component analysis (PCA)-based visualization method is proposed in [29] for hyperspectral images. An enhanced affine transformation (EAT) was proposed in [30] for non-rigid IR and VIS image registration. A novel MRI reconstruction algorithm was developed in [31] with edge-preserving filter. A Multi-Compressive Matching Pursuit (MCMP) was developed in [32] for impulse component detection.

Based on the aforementioned techniques and methods, an efficient framework called Degeneration Threshold Image Detection (DTID) has been designed for improving the contrasting on-edge filtered images. DTID framework utilizes the Rapid Bilateral Filtering process for filtering edges of the contrast image.

3 Image Contrast Enhancement Using Degeneration Threshold Image Detection Framework

Degeneration Threshold Image Detection (DTID) framework is introduced to improve the contrasting on-edge filtered images. Besides, the Rapid Bilateral Filtering process is described for filtering edges of the contrast image and handles high dynamic contrast images for smoothing edge-preserving with lesser filtering time. Then, the DTID framework is further divided into three parts, which are contrast image filtering, noise removal with outliers, and detection of objects on multiresolution images.

3.1 Problem Formulation

Object detection is one of the major tasks to be carried out during image processing with high contrast quality. The research work is carried out with different sizes and qualities of multiresolution contrast images to detect the objects. To resolve these issues, a framework named Degeneration Threshold Image Detection is introduced for image enhancement. Degeneration Threshold Image Detection is designed with the implementation of the Rapid Bilateral Filtering process, Shift-Invariant Base Pass Domain Filter, Affine Planar Transformation. DTID framework decreases computation time.

An effective edge filtering for detecting the objects in the proposed work takes an enormous amount of data. Edge filtering is defined as the process of locating the user-requested objects with sharp edge locations. Edge filtering is followed in the proposed DTID framework using a Rapid Bilateral Filtering process. The Original image after the application of the Rapid Bilateral Filtering process is shown in Fig. 1.

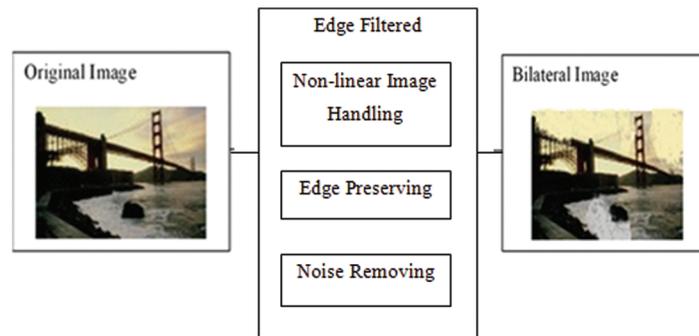


Figure 1: Rapid bilateral filtering process

As shown in Fig. 1, the Rapid Bilateral Filtering process is administered on the original contrast image with multiresolution pixels. Rapid Bilateral Filtering handles the non-linear image intensity value and calculates the weighted standard of the nearby pixels. The computed weighted standard of the nearby pixels helps to preserve the edges on the filtering of the high contrast images in the proposed work. The weight computation in the DTID framework mainly depends on the Euclidean Distance of pixels. The base layer of noise removal is carried out through Shift-Invariant Base Pass Domain Filter. The schematic diagram of the Degeneration Threshold Image Detection (DTID) framework is illustrated in Fig. 2.

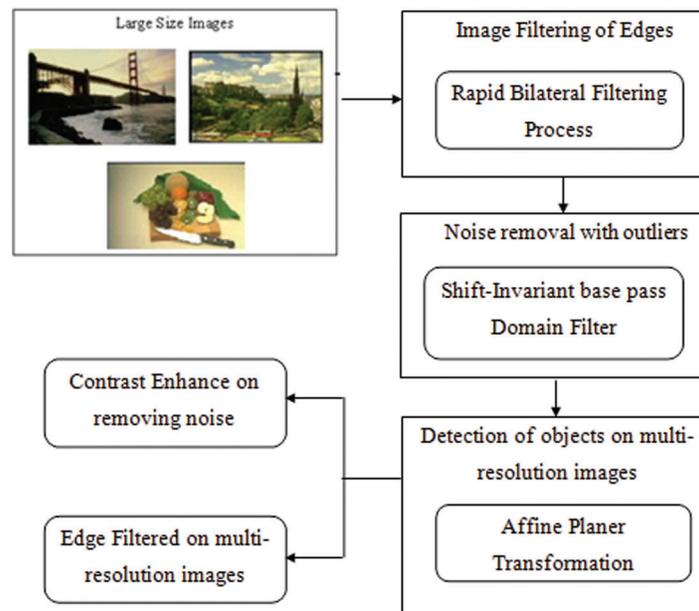


Figure 2: Schematic diagram of DTID framework

Fig. 2 shows the working of the Degeneration Threshold Image Detection framework with the help of pictorial form. The segmented image extracts the key point pixel using the Rapid Bilateral Filtering process. The smoothed edge preserved filtering using the proposed Rapid Bilateral Filtering process to evaluate the weighted standard distance of the intensity values. The intensity values of the base and upcoming layers are measured to identify the noise level deposited on the contrast image.

The DTID framework efficiently deals with the Shift-Invariant base Pass Domain Filter to remove the noise level on the contrast image. Shift-Invariant base Pass Filter enforces both the geometric and photometric locality of the noise level. If the noise gets removed, the contrast multiresolution image utilizes the Affine Planar Transformation for efficient detection of the objects. The efficient detection of objects from the image is provided as input and then the Affine Planar Transformation with latitude and longitude angle values. Finally, the degeneration image threshold is used to detect the objects of high contrast multiresolution images efficiently.

3.2 Contrast Image Filtering

The proposed Degeneration Threshold Image Detection (DTID) framework is designed for contrasting image filtering. Each pixel in multiresolution high contrast images is observed in the image to perform edge filtering with sharp localization. The scene radiance in a multiresolution high contrast image is filtered using the Rapid Bilateral Filtering process. At each pixel point, a high contrast image is mathematically formularized as

$$\text{ContrastImage} = \text{Pixel } (I(x, y)) \quad (1)$$

In Eq. (1), 'I' represents the contrast image at the channel pixel intensity value. It is based on the image between the pixel of interest 'x' and nearer pixel of interest 'y' along with the latitude and longitude axes. The next process is applying rapid bilateral filtering to obtain the space between the 'x' and 'y' pixel. This filter helps to calculate the total mass factor on the intensity values to smooth the pixels. The total mass factor is used to represent the rapid factor (Weighted Standard Measure) on the pixel intensities. This factor is based on the Euclidean distance of the pixel value x, y. This distance represents the smoothness of the pixel values.

The spatial closeness of a high contrast image is filtered through the preserved edges with 'e'. The Euclidean distance 'e' is measured with the pixel x and y where σ denotes the average speed of the edge filtering operation. Then the smoothed edge preserved filtering using the proposed Rapid Bilateral Filtering process measures the weighted standard distance of the intensity values.

3.3 Rapid Bilateral Filtering Process

Let us assume that the Rapid Bilateral Filtering process for the non-linear term is assumed to attain the solution as, $\emptyset [I(x, y) - I(x)]$. This implies the filtering of edges with the total mass factor. The total mass factor denotes the weighted standard measure with the rapid factor. Therefore, the rapid bilateral filtering computations are measured as,

$$I_{\text{filtered}}(x, y) = \frac{1}{W_E} \sum_{x,y} I(x_i, y_i) S_r [I(x, y) - I(x)] S_c [I(x, y) - I(x)] \quad (2)$$

The bilateral filtering in a rapid form is carried out in the DTID framework, where W_E are the weighted standard measure based on the Euclidean distance with pixel value, (x, y). The Euclidean distance with 'Sr' denotes the range of smoothing on the pixel intensity value whereas 'Sc' denotes the spatial coordinate smoothing for the preserved edge filtered in a smoothing fashion on the original high contrast image I. The image with the pixel values x and y are monitored to filter the edges. The Weighted Standard distance of the intensity values W_E are computed as,

$$\text{Weighted Standard Measure } (W_E) = e^{-\frac{x^2-y^2}{2\sigma^2}} \quad (3)$$

The weighted standard measure of the pixel identifies the closeness between the edge pixels for filtering. The spatial closeness of the high contrast image is filtered through the preserved edges with 'e' being the

Euclidean distance measure on the pixel x and y where σ denotes the average speed of edge filtering operation. The smoothed edge preserved filtering using the proposed Rapid Bilateral Filtering process computed the weighted standard distance of the intensity values.

3.4 Noise Removal with Outliers

The Degeneration Threshold Image Detection (DTID) framework is implemented for removing the noise by preserving the base layers of the contrast image. The intensity values of the base and upcoming layers are measured to identify the noise level deposited on the contrast image. These intensity values are identified with the aid of Shift-Invariant Base Pass Domain Filter (SIDF), which efficiently computes the nearby spatial location and hence removes the noise factor.

The mathematical representation of SIDF filters out the Key Points 'KP'. It has been explained below:

$$SIDF = KP^{-1} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} I(x)S_r(\epsilon)S_c(\epsilon, x)d\epsilon \quad (4)$$

In Eq. (4), SIDF signifies the noise level deposited on the base layer of a high contrast image 'I', which filters out the Key Points with the geometric closeness between pixel intensity 'x' and nearby point 'ε' and 'Sr' denotes the range of smoothing on the pixel intensity value. The distribution of pixel intensities over a multi-resolution image is handled using the standard Base Pass Domain Filter. The algorithmic step of Rapid Bilateral Filtering using DTID framework is given below:

Algorithm 1: Rapid Bilateral Filter

Input: High Contrast Images $\{I_n = I_1, I_2, \dots, I_a\}$, KP , a , n

Output: Smoothed edge preserved filtering

Step 1: For each I_n

Step 2: Compute pixel intensity using (1)

Step 3: Evaluate Weighted Standard Measure based on the Euclidean Distance using (3)

Step 4: Apply Rapid procedural scheme for extraction of Key Points 'KP' using (4)

Step 5: Apply Self-Invariant Base-Pass Domain Filter using (4)

Step 6: Perform noise removal on based layer edge filtering

Step 7: Compute $SBDF = KP^{-1} \int_0^{\infty} \int_0^{\infty} S_r(\epsilon)S_c(\epsilon - x, y)d\epsilon$

Step 8: end for

As shown in Algorithm 1, the Rapid Bilateral Filtering is centered in the proposed work to extract the key points from the edges. The Bilateral Filtering is evaluated with the weighted Euclidean Distance. Besides, Bilateral Filtering helps to extract the sharp localization points with the aid of the DTID framework. The normalization 'KP' extracts the edge points of the specified objects, which ensures the weight for all pixel intensities and performs the smoothed edge filtering. As a result, the Rapid Bilateral Filter removes the noise level on the base layer using the Self-Invariant Base-Pass Domain Filter procedure. As a result, it achieves the smooth edge filtering behavior with high-quality preserved noise-free object detection in a significant manner.

3.5 Multi- Resolution Object Detection

The design of the Degeneration Threshold Image Detection (DTID) framework refers to high-quality object detection or multiresolution object detection. The multiresolution of a high contrast image includes the continuous object detection range of the classes. The object detected in multiresolution contrast image processing uses Affine Planar Transformation in the proposed DTID framework. Then the degeneration image threshold is fixed for detecting the continuous object. The fixed threshold is given below as

$$T(I) = - \sum_{i=1}^{\text{ton}} I(x_i, y_i) \ln \text{Probability}_i \quad (5)$$

In Eq. (5), the Degeneration Threshold of Image 'I' represents the summation of the different probabilistic conditions. Each user detects different objects from high-contrast images as per their need. The threshold determines the value based on the Criterion Affine Function for detecting the objects. The object detection process on high contrast images is illustrated in Fig. 3.

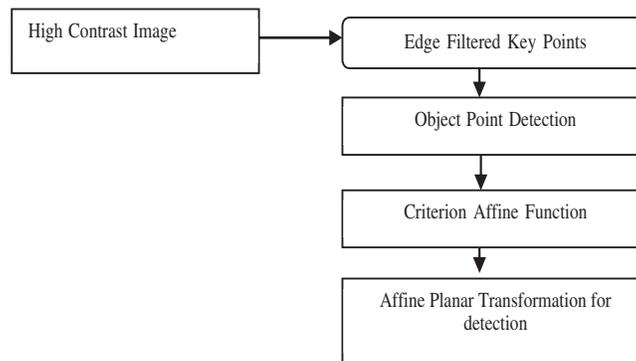


Figure 3: Object detection process on high contrast images

Fig. 3 shows the object detection process on high-contrast images. The criterion function (i.e., threshold) is fixed for detecting the object from the continuously placed objects. The planar transformation with the longitude and latitude angles detects and extracts the Key Pixel Point localization on multiresolution contrast images in an efficient manner. Therefore, there is an improvement in the detection accuracy. The planar transformation based on the Affine Property is briefly explained in Section 3.4.1 for description.

3.6 Affine Planar Transformation

Each image taken for the detection of objects in the DTID framework is simulated with all possible affine distortion sources with respective changes of the longitude and latitude angles. The longitude and latitude angle simulates the Affine Property for detecting and localizing the Key Pixel Points from multiresolution contrast images. Hence, it improves the detection accuracy. To efficiently detect the extracted edge, filtered planar-based angle measurement is designed. The key points are localized and extracted in the DTID framework without any invariant scale changes. A criterion affine function is the scale-space of the image, which is used to obtain the simplicity of extracting the objects from high contrast images.

The image to be processed for object detection is repeatedly carried out with these steps to enhance the detection accuracy efficiently. The image obtained is subtracted (i.e., filtered) from the overall image to attain the user-needed object with lesser processing time. For obtaining more accuracy in the DTID framework, each intensity value of the pixel is checked with the closest neighborhood for the sharp localization of multiresolution images with high quality in a significant manner.

4 Experimental Evaluation

In this section, the experiment is conducted in MATLAB coding using Corel Image Features Dataset extracted from the UCI repository to evaluate the performance of the proposed Degeneration Threshold Image Detection (DTID) framework for increasing the contrast on edge filtered images. High Contrast Image Filtering using Degeneration Threshold Image Detection (DTID) framework is compared with the existing methods including Generalized Unsharp Masking Algorithm (GUMA), Huber-Markov Random Field (HMRF) model, Stationary Wavelet Transform (SWT), Exact Histogram Specification (EHS) technique and multi-level histogram shape segmentation methods.

4.1 Dataset

The main reason for selecting the Corel Image Features Dataset based on the proposed Degeneration Threshold Image Detection (DTID) framework helps to detect efficiently object with different image resolutions. The multiresolution images are also processed in the DTID framework to measure performance. The image dataset holds 68,040 photo images from a mixture of categories such as high-quality and low-quality images. Each set of features in the Corel Image Features Data Set <https://archive.ics.uci.edu/ml/datasets/corel+image+features> is stored in a separate file and each line corresponds to a single image used for detecting the objects after edge filtering. The initial value has the image ID and the succeeding standards are the feature vector (e.g., color textures) of the image. A similar image has an equivalent ID in all files, but the image ID is not identical to the image filename in Corel Image Features Data Set. Co-occurrence Texture contains 16 dimensions (4×4) which are transformed into 16 grayscale images. The co-occurrence in 4 directions is worked out horizontal, vertical, and two diagonal directions. The 16 values are Second Angular Moment, Contrast, Inverse Difference Moment, and Entropy.

4.2 Metrics

Three widely adopted metrics are used in the experiments, which include filtering time (Ftime) taken on contrast images, Average Contrast Enhancement (ACE), quality, and Detection Accuracy Rate (A). The filtering time is defined as the time taken to filter contrast images as given below. It is measured in terms of milliseconds (ms), where I_n refers to 1 to 'a' contrast image. If the filtering time taken on contrast images is lower, then the method is said to be more efficient.

$$F_{\text{time}} = \text{Time} \sum_{n=1}^a I_n \quad (6)$$

The Average Contrast Enhancement for the DTID framework is defined as the average summation of the intensity values for the base and the values for the upcoming layer. It is measured in terms of percentage (%). When the average contrast enhancement is higher, then the method is said to be more efficient.

$$ACE = \frac{\text{Base}_{\text{val}} + \text{Upcominglayer}_{\text{val}}}{n} \quad (7)$$

The Detection Accuracy Rate using the DTID framework measures the ratio of the difference between the image being sent and the image being detected (i.e., in terms of pixels). The Detection Accuracy Rate is measured in terms of percentage (%). While the Detection Accuracy Rate is higher, then the DTID framework is said to be more efficient.

$$A = \frac{I_S - I_D}{I_S} \quad (8)$$

5 Results and Discussions

The performance of the proposed Degeneration Threshold Image Detection (DTID) framework is evaluated and compared with the existing methods, namely, Generalized Unsharp Masking Algorithm (GUMA) [10], Huber-Markov Random Field (HMRF) [8] model, Stationary Wavelet Transform (SWT) [11], Exact Histogram Specification (EHS) [4] technique and multi-level histogram shape segmentation method [25]. The simulation analysis is carried out on different parameters such as filtering time taken on contrast images, average contrast enhancement quality, and detection accuracy rate when compared with the state-of-the-art works. The performance is evaluated according to the following metrics with the help of tables and graph values.

5.1 Impact of Filtering Time Taken to Contrast Images

Fig. 4 shows the result of filtering time taken on contrast images vs. the varying number of images. To optimize the efficient detection of the proposed DTID framework, substantial experimental results are illustrated in Fig. 4 and compared with the existing GUMA [10], HMRF [8], SWT [11], EHS [4], and multilevel histogram shape segmentation method [25] respectively.

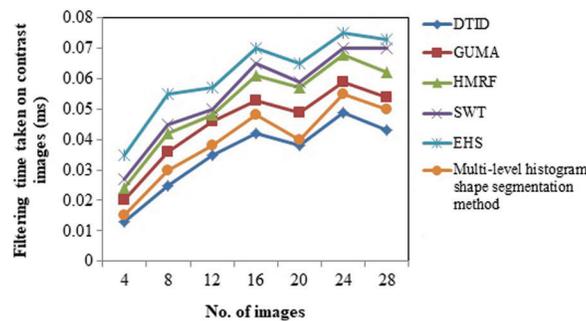


Figure 4: Measure of filtering time taken on contrast images

Results are presented for a different number of images that cover a mixture of categories such as high-quality and low-quality images. The filtering time taken to contrast images for several images is performed at different time intervals are shown below. The results reported here confirm that with the increase in the number of images, although the filtering time increases comparatively, the filtering time has taken on contrast images is reduced when compared to the other methods. The process is repeated for 28 images for conducting experiments.

The investigation of the filtering time taken on contrast images for the different number of images using the DTID framework is compared with the existing GUMA, HMRF, SWT, EHS, and multilevel histogram shape segmentation methods for different implementation runs. As illustrated in Fig. 4, the proposed DTID framework efficiently reduces the time taken for filtering on contrast images when compared to four other methods, GUMA, HMRF, SWT, EHS, and multilevel histogram shape segmentation methods.

Therefore, the filtering time taken on contrast images is drastically reduced due to the proposed DTID framework. Removal of noise is considered one of the important tasks in computer vision and image enhancement processing. Some filter techniques are used to enhance the efficiency of a digital image. However, it failed to protect the image edges by eliminating noise and reduce the filtering time. This is achieved in the proposed method by employing the Rapid Bilateral Filtering process. The Rapid Bilateral Filtering process holds the nonlinear image intensity value and the weighted standard of the nearby pixel value. This weighted standard value aids to maintain the edges on the filtering of the high contrast images. Therefore, the sharp edge location for diverse scene characteristics is successfully obtained with

minimum time. Besides, the filtering time is reduced. The contrast images compromise the contrast while preserving the edges. Moreover, evaluating weighted standard measures using the DTID framework efficiently identifies the closeness between the edge pixels for filtering. Furthermore, the DTID framework minimizes the filtering time taken on contrast images by 24% compared to GUMA, 34% compared to HMRF, 38% compared to SWT, 45% compared to EHS, and 11% compared to a multilevel method.

5.2 Impact of Average Contrast Enhancement Quality

To increase the average contrast enhancement quality for both the base and upcoming layers over the multiresolution image is considered. In the experimental setup, the number of images ranging from 4 to 28 is illustrated in Fig. 5. The average contrast enhancement quality using the DTID framework provides comparable values to the state-of-the-art methods.

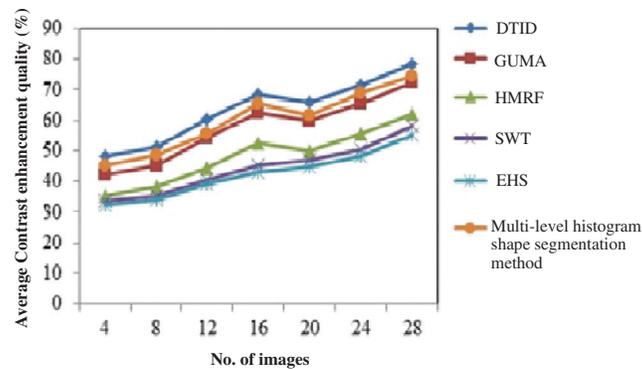


Figure 5: Measure of average contrast enhancement quality

The targeting results to improve the contrast on edge filtered images to measure the contrast enhancement quality using the DTID framework is compared with four state-of-the-art methods like GUMA, HMRF, SWT, EHS, and multilevel histogram shape segmentation methods. Fig. 5 is presented for visual comparison based on the number of images provided as input. DTID framework differs from the existing GUMA, HMRF, SWT, EHS, and multilevel histogram shape segmentation methods. Contrast enhancement is an important part in the image processing approach. Image quality enhancement is a method of enhancing the contrast and edge sharpness of the image. Improving the image quality and minimizing the noise is an essential process in image processing. There are several contrast enhancement methods used to create better images. But, it failed to obtain contrast enhancement. To overcome the issue, the proposed DTID incorporates a Shift-Invariant Base Pass Domain Filter that employs intensity values to improve the contrast of edge filtered images. At first, the input image is decomposed into a number of base layers using the Rapid Bilateral Filtering process. Then the intensities of the base layer and other layers are calculated using Shift-Invariant Base Pass Domain Filter. To increase the average contrast enhancement quality in the DTID framework, the intensity values of the layers are measured successfully.

Shift-Invariant Base Pass Domain Filter in the proposed DTID framework significantly evaluates the nearby spatial location, resulting in increasing the average contrast enhancement quality. Furthermore, the distribution of pixel intensities over the multi-resolution image with the aid of a standard Base Pass Domain Filter helps in increasing the average contrast enhancement quality by 11% compared to GUMA, 32% compared to HMRF, 43% compared to SWT, 50% compared to EHS and 6% compared to multi-level histogram shape segmentation methods. In contrast, in the existing method, only the

histogram equalization procedure is followed. They are highly sensitive to noise for the enhancement of quality.

5.3 Impact of Detection Accuracy Rate

Fig. 6 shows the detection accuracy rate for the proposed DTID framework and existing methods such as GUMA, HMRF, SWT, and EHS techniques versus seven different image sizes. The Detection Accuracy Rate returned over the DTID framework increases gradually, although not linear for differing sizes of images because of the dynamic changes observed.

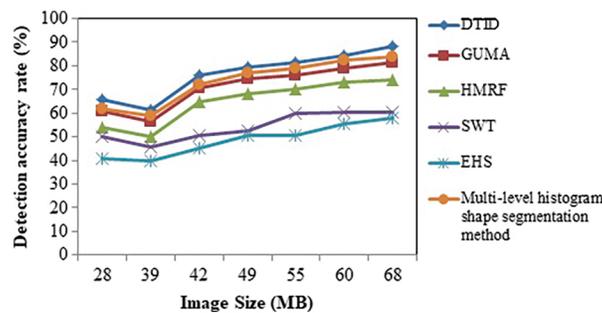


Figure 6: Measure of detection accuracy rate

Fig. 6 illustrates that the detection accuracy rate is improved using the proposed framework DTID. For example, for an image size of 42 MB, the Detection Accuracy Rate using the DTID framework is 75.88 percent, whereas GUMA records 70.86 percent; HMRF records 64.83 percent; SWT records 50.5, EHS records 45 percent and multilevel histogram shape segmentation method records 72.33 percent. The enhancement process is used to enhance the quality and features of the image such as edges, and contrast are identified. Numerous existing methods are employed to provide improved images. However, it failed to achieve detection accuracy. To address the issue, the proposed DTID framework improves the Detection Accuracy Rate with the application of the Affine Planar Transformation. Affine Planar Transformation is used to discover and localize the relevant pixel and hence improves the detection accuracy efficiently.

Detecting a continuous object in the DTID framework using Degeneration Image Threshold includes the summation of different probabilistic conditions for high contrast images. DTID framework helps in improving the Detection Accuracy Rate by 7% compared to GUMA. Besides, the Planar Transformation with both longitude and latitude angle helps to easily detect the extracted edge filtered objects and thereby improves the Detection Accuracy Rate by 18% compared to HMRF, 41% compared to SWT, 58% compared to EHS, and 4% compared to multilevel histogram shape segmentation methods.

5.4 Qualitative Analysis

The Qualitative Analysis of the proposed framework is designed. Fig. 7 shows the impact of Qualitative Analysis of average contrast enhancement quality and Detection Accuracy Rate are performed using the proposed DTID framework and existing methods like GUMA, HMRF, SWT, EHS.

As shown in Fig. 7, the Qualitative Analysis of the average contrast enhancement quality and Detection Accuracy Rate is measured with the help of an input image (a), (b). The contrast-enhanced quality image was obtained using DTID, GUMA, HMRF, SWT, and EHS. They are provided as (d), (e), (f), (g), and (h), respectively with the input image as in (c). Furthermore, the Detection Accuracy Rates using DTID, GUMA, HMRF, SWT, and EHS are provided in (j), (k), (l), (m) and (n) with the input image as in (i).

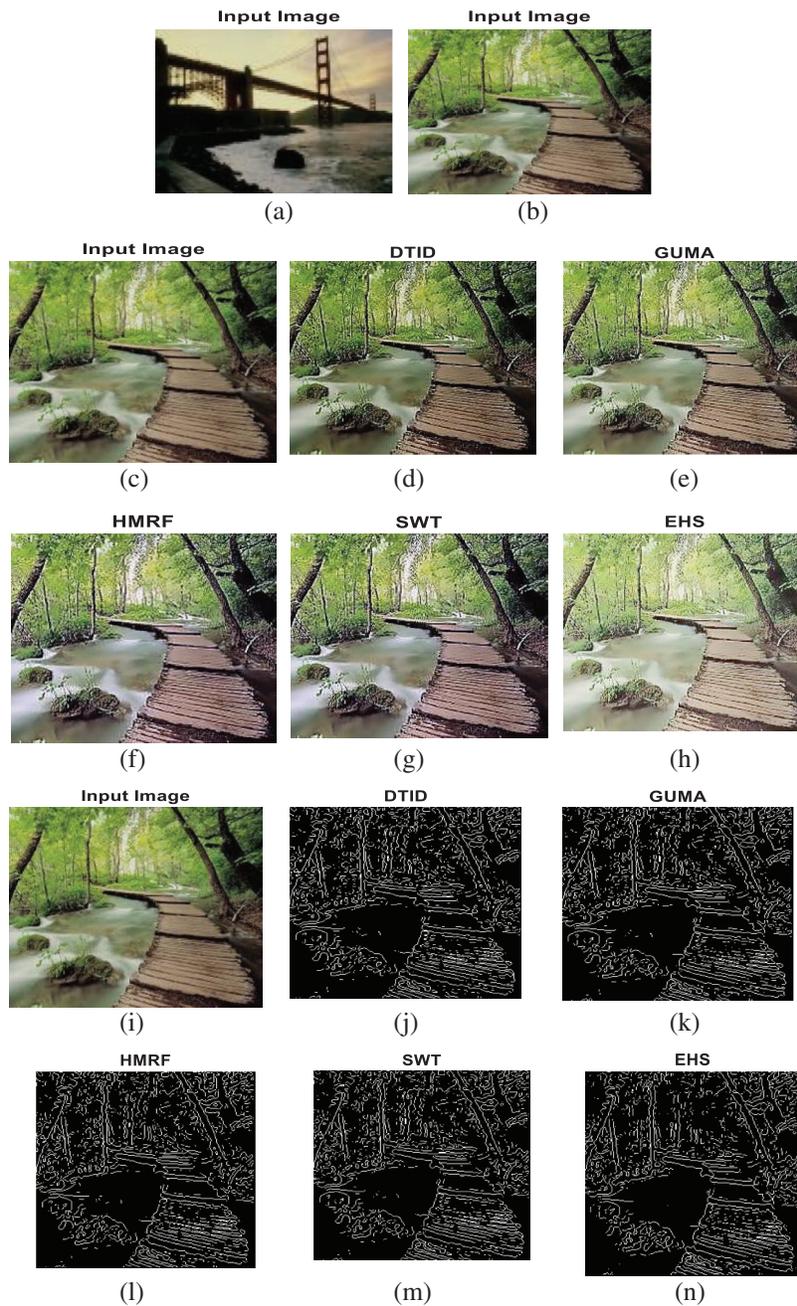


Figure 7: Qualitative analysis on average contrast enhancement quality and detection accuracy rate using DTID, Existing GUMA, HMRF, SWT and EHS, (a) Input image 1 (b) Input image 2 (c) Input image (d) contrast-enhanced quality using DTID (e) contrast-enhanced quality using GUMA (f) contrast-enhanced quality using HMRF (g) contrast-enhanced quality using SWT (h) contrast-enhanced quality using EHS (i) Input image (j) detection accuracy rate using DTID (k) detection accuracy rate using GUMA (l) detection accuracy rate using HMRF (m) detection accuracy rate using SWT (n) detection accuracy rate using EHS

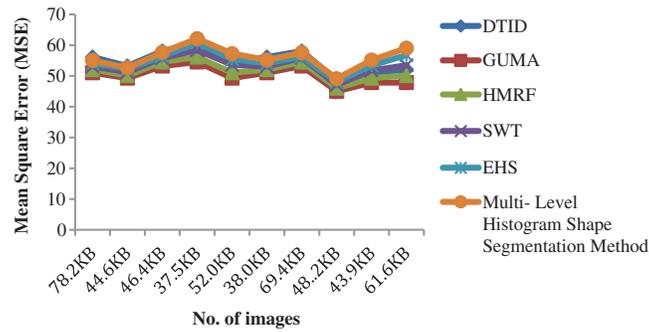


Figure 8: Mean square error rate

5.5 Mean Square Error (MSE)

Mean Square Error (MSE) is defined as the Mean or Average of the square of the difference between actual and estimated values is shown in the Fig. 8.

$$ms_{er} = [Size_d - Size_o]^2 \quad (9)$$

ms_{er} denotes mean square error. From (9), $Size_d$ be denoised image size, $Size_o$ signifies the original image size.

Detecting a continuous object in the DTID framework using Degeneration Image Threshold includes the summation of different probabilistic conditions for high contrast images. DTID framework helps in improving the Mean square Error by 9% compared to GUMA. Besides, the Planar Transformation with both longitude and latitude angle helps to easily detect the extracted edge filtered objects and thereby improves the Mean square Error by 6% compared to HMRF, 3% compared to SWT, 1% compared to EHS, and 4% compared to multilevel histogram shape segmentation methods.

5.6 Correlation Coefficient (CR)

The correlation coefficient is used for calculating a strong relationship among two variables. The correlation coefficient illustrates how one variable moves in relation to another. A positive correlation represents which two move in the same direction, with +1.0 correlations when they move in random. A negative correlation coefficient tells you that they instead move in opposite directions.

$$\rho_{x,y} = \frac{Cov(x, y)}{\sigma_x \sigma_y} \quad (10)$$

$\rho_{x,y}$ Represents Pearson product-moment correlation coefficient $Cov(x, y)$ indicates covariance of variables x and y σ_x denotes the standard deviation of x and σ_y represents the standard deviation of y.

6 Conclusion

A Degeneration Threshold Image Detection (DTID) framework has been designed to improve the contrasting on-edge filtered images. Besides, the Rapid Bilateral Filtering process is performed for efficiently filtering the edges of the contrast image. The edges of the contrast images are filtered to higher accurate detection results. These accurate results have been attained by determining the weighted standard distance with the aid of the Rapid Bilateral Filtering process for the nonlinear term. This in turn increases the closeness between the edge pixels for filtering using weighted standard distance. Next, Shift-Invariant Base Pass Domain Filter is introduced for significantly removing the outliers across the edges. Finally, the Affine Planar Transformation in the DTID framework is used for detecting and

extracting the Key Pixel Point localization from multiresolution contrast images. DTID framework improves the Detection Accuracy. Then the Affine Planar Transformation employs the longitude and latitude angle values with the aid of degeneration image threshold. Furthermore, it detects the continuous object as per the user's requirement. Simulation results are performed to compare in terms of filtering time taken on contrast images, average contrast enhancement quality, and detection accuracy rate. They evaluate the effectiveness of the DTID framework. Moreover, the proposed DTID framework presents a contrast enhancement quality with filtering time for efficiently contrasting on-edge filtered images. The performance results demonstrate the proposed DTID framework. It provides better performance on the enhancement of average contrast enhancement quality by 28%, detection accuracy rate by 26%, and reduction in the filtering time taken on contrast images by 30% when compared to state-of-art methods.

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