CHAPTER 6
ANALYSIS OF SEGMENTATION BASED IMAGE
CONTRAST ENHANCEMENT

6.1 INTRODUCTION

Contrast development plays a special role in the image processing applications. The image processing application encloses natural digital image photography, remote sensing, and LCD display based images. With the increasing high quality texture images, the application of image segmentation is of greater attention. Although, different methods for automatic image segmentation framework using unsupervised method have been designed; it has been applied only on single-band images with less functionality included for multi-class defined boundary images. Segmented Image performs edge point extraction from the objects using different filtering techniques. With the increasing use of high quality video images and rapid advancement in video images, effective contrasting on edge filtered images has been proposed. An improved trend on image contrast enhancement techniques working with different high quality images.

Enhancement of the overall image contrast and the sharpness of the images are the associated tasks to be performed. The Intensity Histogram Equalization (IHE) method is developed to preprocess the image to remove noise and enhance the image contrast for difference enhancement and in that way introduces intensity to improve the brightness. The preprocessing in IHE method follows the mask production, enlightenment equalization, and color normalization for efficient analysis of the different chosen design parameters. Mask production labels the pixels and Region-of-Interest (ROI) in the entire
image excludes the background of the image to generate a binary image for each band. The histogram threshold rate is mechanically calculated using pixel value statistics for exact relationship maintenance on gradient flow.

Image segmentation is a difficulty of measurement and also significant task for detailed understanding and analysis of images. The Multi-Class Independent Component InfoMax Analysis (MICIA) on multi-class high quality colour images segmentation pattern are employed to improve the efficiency of segmentation. The MICIA method combines the watershed cuts principle and Minimal Spanning Forest method to attain the richer segmentation of color textures with minimal computational time and to evaluate the image at minimum timing interval respectively. Initially, higher quality texture image is segmented using the watershed cuts principle. Watershed cuts principle in MICIA is associated with the regional minima of the map to handle multi-class poorly defined boundary images. Secondly, Independent Component Analysis based on InfoMax achieves the richer segmentation of color textures with maximum likelihood function. ICA based on InfoMax handles multiclass texture images and as a result, the Maximum Likelihood ensures higher independency on segmentation cuts.

Segmented Image presents edge point extraction from the objects using different filtering techniques. The Degeneration Threshold Image Detection (DTID) framework is developed to improve the contrasting on edge filtered images. Initially, DTID framework requires a Rapid Bilateral Filtering process for filtering edges of the contrast image. Rapid Bilateral Filtering handles high dynamic contrast images for smoothed edge preserving with minimal filtering time. Subsequently, the rapid bilateral filtering with shift-invariant base pass domain filter in DTID framework is insensitive to noise. This shift invariant filtering estimates the value across the edges to remove the outliers (i.e., noise preserving base layers of contrast image). Finally, the Affine
Planar Transformation is applied on the edge filtered contrast image in DTID framework to attain high quality of image being detected. Affine Planar Transformation uses the measure value of longitude and latitude angle to detect the image. DTID framework also employs exact key pixel point localization to accurately detect multi-resolution contrast image.

The image contrast enhancement and high quality image segmentation process is implemented in MATLAB coding. Corel Image Features Data Set is used, which contain image features extracted from a Corel image collection. Corel Image Features Data Set holds 68,040 photo images from a mixture of categories. Four sets of features are accessible in Corel Image Features Data Set based on the color histogram, color histogram layout, colour moments, and co-occurrences. Each set of features in Corel Image Features Data Set is stored in a separate file. The initial value is the image ID and the succeeding standards are the feature vector (e.g. color textures) of the image. The similar image has the equivalent ID in all files but the image ID is not the identical as the image filename in Corel Image Features Data Set. Co-occurrence Texture contains 16 dimensions (4 x 4) which are transformed to 16 gray-scale 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.

6.2 ANALYSIS OF SEGMENTATION BASED IMAGE CONTRAST ENHANCEMENT BASED ON IHE, MICIA AND DTID FRAMEWORK

With the Corel Image Features Data Set accessing for image contrast enhancement and segmentation and the experiments conducted for IHE method, MICIA and DTID Framework with existing Generalized Un sharp Masking Algorithm (GUMA) by Guang Deng (2011) in MATLAB. Some of the parameters such as brightness quality efficiency, image contrast reliability,
colour texture segmentation efficiency, multi-class image segmentation time, average contrast enhancement quality, max-flow computational complexity, sub pixel accuracy rate on segmenting, filtering time taken on image contrast, true positive rate, detection accuracy rate are measured to prove the real time usage in practical. Detailed result analyses of these metrics are elaborated in further section.

6.2.1 Measurement of Brightness Quality Efficiency

The brightness quality defines the contrast quality enhancement on the photo image and measured in terms of the pixel rate. The proposed IHE, MICIA and DTID compared with Generalized Unsharp Masking Algorithm (GUMA) by Guang Deng (2011) in MATLAB.

The Brightness Quality Efficiency is described based on three proposed techniques and one existing method. From the table, proposed IHE method evidenced better Brightness Quality Image.

![Brightness Quality Efficiency Measure](image)

**Figure 6.1 Brightness quality efficiency measure**
Figure 6.1 describes the brightness quality efficiency based on the PSNR value. The colored objects are related directly to the inherent properties of the photo imaged objects in IHE method. IHE method presents maximal brightness preservation of images using the intensity rate factor. Lighting geometry and the imaging device are some of imaging conditions considered with pixel value of images to improve the quality ratio. Therefore, the IHE method improves the brightness quality by 22% when compared with the existing Generalized Unsharp Masking Algorithm (GUMA) by Guang Deng (2011) and also improved 14.5% when compared with the proposed MICIA method and 7% improved than the proposed DTID method. Imaging conditions such as lighting geometry and the imaging device scales pixel values in a photo image are used to easily improve the quality ratio.

6.2.2 Measurement of image contrast reliability

The reliability is the ability of the photo image to improve the image contrast under the stated conditions for a specified period of time. Intensity Histogram Equalization (IHE method) for image contrast enhancement is compared against the existing and other proposed models.

The Image Contrast Reliability is described based on three proposed techniques. From the measurement, proposed IHE method recorded high Reliability Image Contrast. The Image Contrast Reliability is improved and measured in terms of percentage (%).
Figure 6.2 Image contrast reliability

Figure 6.2 shows the image contrast reliability of each technique and evaluates the system. The intensity histogram $i[n]$ of a photo image gives the approximate Probability Density Function (PDF) of its pixel intensities to improve the reliability rate. Cumulative Distribution Function (CDF) is attained from image, thus it improves the contrast reliability rate. The discrete mapping function is a leveled version of IHE which uses the image histogram to obtain the higher contrast. The reliability rate is 13% improved when compared with existing Generalized Unsharp Masking Algorithm (GUMA) by Guang Deng (2011). Similarly, the image histogram obtain the higher contrast reliability by 7% when compared with the proposed MICIA method and 6% improved as compared to DTID method.

6.2.3 Measurement of color texture segmentation efficiency

The efficiency of color texture segmentation is measured which evaluates the rate of efficiency of the regions, ‘$c_1, c_2, c_3 \ldots c_n$’ with that of the multi-class distribution point, $p_i$. Multi-Class Independent Component InfoMax Analysis (MICIA) on multi-class high quality color images is
compared against the existing Generalized Unsharp Masking Algorithm (GUMA) by Guang Deng (2011) and other proposed methods shown. Segmentation efficiency is measured in terms of percentage (%).

The color texture segmentation efficiency of MICIA compared with the existing GUMA and proposed two schemes namely IHE method, proposed DTID. The measurement shows that the proposed MICIA recorded high segmentation efficiency.

![Figure 6.3 Measure of color texture segmentation efficiency](image)

**Figure 6.3 Measure of color texture segmentation efficiency**

Figure 6.3 shows the rate of color texture segmentation efficiency with respect to the number of regions. From the Figure 6.3 it is illustrative that with the increase in the number of regions, the color texture segmentation efficiency is improved using proposed MICIA method when compared to the two other methods namely IHE method, DTID. The watershed cut principle in proposed MICIA method is used for segmenting region based texture similarity. The independent component analysis is used to improve the texture segmentation region. The minimum spanning forest method in MICIA use watershed cut principle for segmentation processes. They process the multi-class images with minimal computational time. Therefore, the color texture segmentation efficiency is improved by 22% when compared to Generalized
Unsharp Masking Algorithm (GUMA) by Guang Deng (2011). ICA based on InfoMax handles multiclass texture images and as a result, the Maximum Likelihood ensures higher independency on segmentation cuts improving the color texture segmentation efficiency by 12% when compared to IHE method and 7% as compared to proposed DTID.

6.2.4 Measurement of Multi-Class Image Segmentation Time

The multi-class image segmentation time is defined as the time taken to perform multi-class image segmentation using watershed gradient on two dimensions. The multi class segmentation time measured between proposed Multi-Class Independent Component InfoMax Analysis (MICIA), Intensity Histogram Equalization (IHE), Degeneration Threshold Image Detection (DTID) framework and existing Generalized Unsharp Masking Algorithm (GUMA) by Guang Deng (2011). The multi-class image segmentation time is measured in terms of milliseconds (ms).

The multi-class image segmentation time and comparison made with one existing method and three proposed methods. Therefore, the proposed MICIA method reduce the segmentation time as compared to other methods as shown in below graph.

Figure 6.4 describes the multi-class image segmentation time based on the number of regions taken into consideration for experimental purpose in the range of \( c_1 \) to \( c_7 \).
Figure 6.4 Measure of multi-class image segmentation time

Above figure 6.4 shows the measure of multi-class image segmentation time with three different proposed methods and existing Generalized Unsharp Masking Algorithm. With the application of Watershed Cuts Principle richer segmentation of color textures is obtained with minimal computational time and as a result improvement over multi-class image segmentation time is achieved by 75% when compared to Generalized Unsharp Masking Algorithm (GUMA) by Guang Deng (2011). The existing GUMA method was performed with different spectral content, applied only to single-band images segmentation and it also consumed more segmentation time. However, Watershed Cuts Principle in MICIA is associated with regional minima of the map to handle multi-class poorly defined boundary images reducing the multi-class image segmentation time by 31% when compared to proposed IHE method and 11.5 % as compared to proposed DTID framework.

6.2.5 Measurement of Average Contrast Enhancement Quality

The average contrast enhancement is the average of the summation of intensity values for the base and the values for the upcoming layer. It is measured in terms of percentage (%). The contrast enhancement quality is
measured between the three proposed methods and one existing method namely Generalized Unsharp Masking Algorithm (GUMA) by Guang Deng (2011).

In order to increase the average contrast enhancement quality for both the base and upcoming layer, over multi-resolution image is considered. In the experimental setup the number of images ranging from 4 to 28 is considered. The average contrast enhancement quality using the framework DTID provides comparable values than the other methods. The targeting results to improve the contrast on edge filtered images to measure the contrast enhancement quality using DTID framework is compared with other methods is shown in Figure 6.5, presented for visual comparison based on the number of images provided as input. The proposed DTID differs from the GUMA by Guang Deng (2011) and MICIA, IHE method in that using incorporated Shift-Invariant Base Pass Domain Filter that employ intensity values to improve the contrast on edge filtered images. With the objective of increasing the average contrast enhancement quality in DTID framework, the intensity values of the base and upcoming layer are measured with the help of Shift-Invariant Base Pass Domain Filter.

![Figure 6.5 Measurement of average contrast enhancement quality](image_url)
By applying, Shift-Invariant base Pass Domain Filter in DTID framework significantly evaluates the nearby spatial location resulting in increase in the average contrast enhancement quality. Furthermore, the distribution of pixel intensities over multi-resolution image with the aid of standard base pass domain filter helps in increasing the average contrast enhancement quality by 30 % compared to GUMA by Guang Deng (2011) and 15 % compared to proposed IHE method, 8.5 % as compared to proposed MICIA.

6.2.6 Measurement of Max-Flow Computational Complexity

Max-Flow Computational complexity in image contrast enhancement measurement based on the three proposed methods. The multi class segmentation time measured between proposed Multi-Class Independent Component InfoMax Analysis (MICIA), Intensity Histogram Equalization (IHE), Degeneration Threshold Image Detection (DTID) framework and the existing Generalized Unsharp Masking Algorithm (GUMA) by Guang Deng (2011). Max-Flow Computational complexity is measured in terms of percentage (%).

The Max-Flow Computational Complexity based on Normalized Spatial Frequency shows in Intensity Histogram Equalization method and it reduces the computational complexity compared to other methods.
Figure 6.6 Measure of max-flow computational complexity

Figure 6.6 demonstrates the computational complexity based normalized spatial frequency. The complexity is reduced in IHE method using the distinct mapping $D[n]$ to modify the pixel values. Mapping function is developed in proposed IHE method for detecting the computational complexity. The identical distribution of images is performed by attaining the mapping function from the histogram with their dynamic range. Hence, IHE max-flow computation takes image pixels with certain level of contrast for each color band. Therefore, the computational complexity is 43% improved when compared with the Generalized Unsharp Masking Algorithm (GUMA) by Guang Deng (2011). In IHE method, mapping function is obtained from the histogram to easily detect the computational complexity. IHE finds a mapping to obtain an image with a histogram that is as close as possible to a uniform distribution to fully exploit the dynamic range and to have a 26% lesser complexity in Max-Flow computation as compared to proposed MICIA method and also the complexity is reduced 12% as compared to DTID.

6.2.7 Measurement of Sub Pixel Accuracy Rate on Segmenting

The sub pixel accuracy rate on segmenting is the maximum allowed value in two dimensional images with the samples to be considered left and right
of the sub pixel. The Sub Pixel accuracy is measured between the proposed IHE, MICIA and DTID method compared with existing GUMA by Guang Deng (2011).

The evaluation of the sub pixel accuracy rate is measured in terms of percentage (%) achieved with the different number of sub pixel ranging from 100 to 700 and comparison is made with the existing schemes namely GUMA and the proposed IHE, MICIA and DTID. As a result, the sub pixel accuracy rate is high in proposed Multi-Class Independent Component InfoMax Analysis (MICIA).

![Figure 6.7 Measure of sub pixel accuracy rate with respect to number of sub pixel](image)

Figure 6.7 describes the sub pixel accuracy rate based on the number of sub pixel being measured in the range of 100 and 700 taken for experimental purpose. The application of mathematical morphology on High Quality texture image reduce the computational time on multi-class images and improves the sub pixel accuracy rate on segmenting by 33.5 % when compared to Generalized Unsharp Masking Algorithm (GUMA) by Guang Deng (2011). Furthermore with the application of colour dilation and erosion of points on two
dimensional multi-class images separately increases the sub pixel accuracy rate by 18% and 9.5% when compared to proposed IHE and DTID respectively.

6.2.8 Measurement of filtering time taken on image contrast

The filtering time is the time taken to filter contrast images are measured in terms of milliseconds (ms). The comparison operation performed between the proposed Degeneration Threshold Image Detection (DTID) framework, Multi-Class Independent Component InfoMax Analysis (MICIA), Intensity Histogram Equalization (IHE) method and the existing Generalized Unsharp Masking Algorithm (GUMA).

The result of filtering time taken on contrast images versus varying number of images is performed. To better recognize the efficiency of the proposed DTID framework, substantial experimental results are illustrated in Figure 5.4 and compared against the existing GUMA and HMRF respectively. Results are presented for different number of images that cover mixture of categories such as high quality and low quality images.

The filtering time taken on contrast images for several images are performed at different time interval is shown below. The results reported here confirm that with the increase in the number of images, though the filtering time increases, but comparatively the proposed framework shows an improvement compared to the other methods. The process is repeated for 28 images for conducting experiments.
In order to investigate the filtering time taken on contrast images for different number of images evaluated with DTID framework and the existing GUMA. As illustrated in Figure 6.8, the proposed DTID framework performs relatively well when compared to existing GUMA by Guang Deng (2011). The filtering time taken on contrast images is drastically reduced by applying Rapid Bilateral Filtering process. This is because each pixel in multi-resolution high contrast images provided as input are observed with sharp localization that helps in reducing the filtering time taken on contrast images whereas in case of the existing methods, though the filtering time is reduced, the contrast images are compromised with the contrast while preserving the edges. Moreover, by evaluating weighted standard measure using the framework DTID that efficiently identifies the closeness between the edge pixels for filtering further minimizes the filtering time taken on contrast images by 56 % compared to GUMA and 36% and 14% as compared to proposed MICIA and IHE respectively.

6.2.9 Measurement of True positive rate

The true positive rate uses maximum likelihood function that performs redundancy reduction. The true positive rate is the total number of true
positive pixels points to the actual positive pixel points. The true positive rate of MICIA and comparison made with two existing methods. It measured in terms of percentage (%).

More accurately the influence of true positive rate with respect to the number of pixel points and comparison is made with proposed method and existing schemes. It can also be seen that the true positive rate increases with the increase in the number of pixel points.

![Graphic](image-url)

**Figure 6.9 Measure of true positive rate with respect to number of pixel points**

Figure 6.9 describes the true positive rate based on the number of pixel points in the range of 200 to 1400. From the Figure 6.9 it is illustrative that the true positive rate using the proposed MICIA is improved than the two other proposed and existing methods. Since the independent component used in MICIA method effectually reduces the dependency level and in turn improves the likelihood function.

Maximum likelihood function is used in MICIA method for richer segmentation attainment resulting in improved true positive rate by 38.5 % as compared to existing GUMA by Guang Deng (2011). In addition,
the MICIA method increased the true positive rate 22% and 10% when compared to proposed IHE and DTID respectively.

6.2.10 Measurement of Detection Accuracy Rate

The detection accuracy rate measures the ratio of difference between the image being sent and image being detected (i.e., in terms of pixels) to the image being sent (i.e., in terms of pixels). The detection accuracy rate is measured in terms of percentage (%). The comparison of detection accuracy is performed between proposed IHE, MICIA, DTID framework with the existing Generalized Unsharp Masking Algorithm (GUMA) by Guang Deng (2011).

The detection accuracy rate is measured with seven different image sizes. The detection accuracy rate returned over DTID framework increases gradually as compared to other methods shown in below Figure 6.10.

![Figure 6.10 Measure of detection accuracy rate](image)

From Figure 6.10, it is illustrative that the detection accuracy rate is improved using the proposed DTID framework. The detection accuracy rate using the DTID framework is improved with the application of Affine Planar
Transformation. By detecting continuous object in DTID framework using degeneration image threshold, which includes the summation of different probabilistic condition for high contrast image helps in improving the detection accuracy rate by 20% when compared to GUMA by Guang Deng (2011). Besides, the planar transformation with both longitude and latitude angle helps to easily detect the extracted edge filtered objects and thereby improving the detection accuracy rate by 12% and 8% as compared to proposed IHE and MICIA respectively.

### 6.3 SUMMARY

A perfect justification is discussed on analysis of IHE, MICIA and DTID technique. Theoretical analysis and experimental result shows, Degeneration Threshold Image Detection (DTID) framework employed for improving the contrast on edge filtered images. The detection accuracy of DTID is improved with the application of Affine Planar Transformation. The performance of the proposed Degeneration Threshold Image Detection (DTID) technique is implemented using Corel Image Features Dataset extracted from UCI repository. The MICIA method based on Watershed Cuts Principle and Independent Component Analysis based on InfoMax provides an efficient means of richer segmentation of color textures with Maximum Likelihood function Multi-Class Independent Component Analysis is performed using InfoMax method to assess multi-class normal distribution point with varying regions to maximize the true positive rate and also improves the sub pixel accuracy. Finally, the Intensity Histogram Equalization (IHE) method is developed for removing the noise defects and enhanced the image contrast and also improves the brightness quality. In addition, The IHE avoids the complex calculations and improve the max-flow computational operations are used for obtain real-time implementable algorithm.