CHAPTER 5

PERFORMANCE EVALUATION OF GLOBAL HISTOGRAM EQUALIZATION USING VARIOUS NEIGHBOURHOOD METRICS ON FACIAL DATABASES

This chapter gives an introduction to neighbourhood metrics. It discusses in detail the existing systems, namely Global Histogram Equalization using Voting Metric and Distinction Metric. In this chapter, a new method, namely Global Histogram Equalization using Fuzzy Approach on Neighbourhood metric is proposed. The implementation results and comparative analysis of GHE using Voting Metric, GHE using Distinction metric and the proposed methodology, namely GHE using Fuzzy Approach on neighbourhood metric are also presented in this chapter.

5.1 INTRODUCTION

GHE is extended to include the neighbourhood information or local information in order increase the dynamic range of the gray level value. The Neighbourhood metric is used to subdivide large histogram bins that would be indivisible using GHE. The inclusion of neighbourhood information or the local information in the global technique helped to improve the local contrast of the image. The usage of neighbourhood metric helps in dividing large bins into sub bins, where the pixels in the sub bins are of the same gray level and with same neighbourhood property. Some of the existing neighbourhood metrics are voting metric and distinction metric.

The Neighbourhood metrics decompose the large bins into sub bins which are then equalized independently. The results of equalizing the sub bins independently help to remap the gray levels in the same bin to different bins which results in obtaining a flat histogram. This helps to avoid large histogram bins and uses most of the available gray levels. The typical usage of neighbourhood metric is to divide large bins into sub bins and apply global histogram equalization. When applying GHE on the image without
considering the neighbourhood metrics, all the pixels in a particular bin get mapped to a single new value in the output image. While applying neighbourhood metric to divide large bins into sub bins and equalize them independently, there is a possibility of each sub bin of the large bins getting mapped to a different value. Hence, the choice of neighbourhood metric is crucial for dividing the large bins into sub bins. Hence, the neighbourhood metric selected must help to divide the large bins into more number of sub bins which are equalized independently to achieve more flat histograms.

The performance evaluation of the histogram equalization using two competing neighbourhood metrics, namely voting and distinction metric on the facial database has brought out the merits and demerits of aforementioned metrics with GHE on facial databases. The efficiency of the neighbourhood metric has consequently determined the number of different values to which each sub-bin can be mapped when equalizing independently.

5.2 VOTING METRIC

Voting metric for a pixel \((x,y)\) is defined as the number of pixels in the neighbourhood of order \(m \times m\) whose intensity values are strictly less than the centre pixel \((x,y)\). Voting metric represented as \(\beta_m(x,y)\) is computed using the equation (5.1).

\[
\beta_m(x,y) = \sum v(x, y, x', y')
\]  

(5.1)

where

\((x', y') \in R_m(x, y)\)

and the value of \(v(x,y,x',y')\) is computed using the formula given in equation (5.2)

\[
v(x, y, x', y') = \begin{cases} 
1, & c(x, y) > n(x', y') \\
0, & \text{otherwise}
\end{cases}
\]  

(5.2)

where

\(c(x,y)\) is the centre pixel and

\(n(x',y')\) are the neighbourhood pixels in the region \(m \times m\).
Figure 5.1 Voting metric for neighbourhood of size 3 x 3

Figure 5.1 illustrates the application of voting metric. The neighbourhood considered here is 3 x 3 where the centre pixel value is 50, but each 50 has different voting metric. Voting metric can divide histogram bin 50 up to 8 sub-bins where each sub-bin will comprise of intensity 50 with different voting metric.

5.3 GLOBAL HISTOGRAM EQUALIZATION WITH VOTING METRIC

The step by step procedure for Global Histogram Equalization using Voting metric is given below:

Step 1: Given an input image X, Evaluate the Voting metric for all occurrences of each intensity value in the input image.

Step 2: Calculate the probability of $X_k$ with neighbourhood metric i where $X_k$ is the pixel intensity

$$p(X_k \text{ with neighbourhood metric } i) = \frac{n_{ki}}{n}$$

where,

$n_{ki}$ stands for the number of times $X_k$ appears in the image with neighbourhood metric $i$,

$n$ is the total number of pixels in the image

$X_k$ ranges from 0 to $L-1$ and $i$ ranges from 0 to 8.

Step 3: Compute the cumulative density function which is defined as

$$c(X_{ki}) = \sum p(X_{ji})$$

where $j$ varies from 0 to $k$ and $i$ various from 0 to 8
Step 4: For remapping the intensity values the transformation function used is

\[ f(X_{ki}) = X_0 + (X_{L-1} - X_0) \cdot c(X_{ki}) \]

Step 5: The illumination pre-processed image \( Y \) is obtained from

\[ Y = f(X_{ki}) \]

where \( Y \) is histogram equalized image using voting metric

### 5.4 DISTINCTION METRIC

The Distinction metric is a metric which is defined as the summation of the difference between the centre pixel and its neighbour for which centre pixel value is greater than the neighbour pixel and it is denoted by \( d_m(x, y) \). The Distinction metric for a pixel \((x, y)\) is calculated using the formula given in equation (5.4) as,

\[ d_m(x, y) = \sum t(x, y, x', y') \]  

(5.4)

where \((x', y') \in R_m(x, y)\) and the value of \( t(x, y, x', y') \) is computed using the formula given in equation (5.5)

\[ t(x, y, x', y') = \begin{cases} 
\| x, y \| - \| x', y' \|, & \quad \| x, y \| > \| x', y' \| \\
0, & \quad \text{otherwise}
\end{cases} \]  

(5.5)

The distinction metric is used to subdivide the large bins into sub-bins. The distinction metric for a neighbourhood of size 3 x 3 is represented in Figure 5.2. Eight-neighbourhood is considered and each intensity value 50 has different distinction metric. In general, the intensity value 50 can have distinction metric ranging from 0 to \((50-0)\cdot8 = 400\). So, histogram bin for intensity value 50 can be subdivided into 400 sub-bins. For example, if the centre pixel is 255, then the histogram bin for intensity value 255 can be subdivided up to \((255-0)\cdot8 = 2040\) bins. After applying histogram equalization each intensity values of the original image gets mapped to single intensity value based on the transformation function \( T(X_k) = X_0 + (X_{L-1} - X_0) \cdot C(X_k) \) given in equation (4.3) mentioned in Chapter 4. When histogram equalizing the sub-bins independently, which are obtained using the neighbourhood
metric, the intensity value in the same bin gets mapped to different intensity values.

Figure 5.2 Distinction metric for a neighbourhood of size 3 x 3.

5.5 GLOBAL HISTOGRAM EQUALIZATION USING DISTINCTION METRIC

The step by step procedure for Global Histogram Equalization using Distinction metric is given below

Step 1: Given an input image X, evaluate the Distinction metric for all occurrences of each intensity value in the input image X.

Step 2: Calculate the probability of $X_k$ with neighbourhood metric $i$ as

$$p(X_k \text{ with neighbourhood metric } i) = \frac{n_{ki}}{n}$$

where

$X_k$ is the pixel intensity which ranges from 0-L-1.

$n_{ki}$ stands for number of times $X_k$ appears in the image with neighbourhood metric $i$.

$n$ is the total number of pixels in the input image $X$.

$i$ ranges from 0 to $X_k(8)$.

Step 3: Calculate the cumulative density function using the formula

$$c(X_k) = \sum p(X_{ij})$$

where $j$ varies from 0 to $k$ and $i$ varies from 0 to $X_k(8)$. 
Step 4: For remapping the intensity values the transformation function used is
\[ f(X_{ki}) = X_0 + (X_{L-1} - X_0) c(X_{ki}) \]

Step 5: The illumination pre-processed image \( Y \) is obtained from
\[ Y = f(X_{ki}) \]
where \( Y \) is histogram equalized image using distinction metric

5.6 REMAPPING CAPACITY OF GHE USING VOTING METRIC AND DISTINCTION METRIC

A sample dark lit image and its histogram representation are shown in Figure 5.3. Then are considered for analysing the remapping capacity of GHE with neighbourhood techniques, namely Voting Metric and Distinction Metric.

![Figure 5.3 Dark-Lit image and histogram representation](image)

Table 5.1 shows the intensity values, number of occurrences followed by the new range of values to which old intensity value is remapped after applying Global Histogram Equalization using voting metric. Here, the intensity values which have more number of occurrences in the image are taken for analysis. When using voting metric, each original intensity value in the image gets mapped to at most eight different intensity values. This is the maximum re-mapping capacity of Voting metric.
### Table 5.1 Remapping capacity of GHE-VM

<table>
<thead>
<tr>
<th>Intensity value</th>
<th>No of occurrences</th>
<th>Intensity values after applying Global histogram equalization using voting metric (GHE-VM)</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>1358</td>
<td>8 9 10 11 12 13 13 13 16</td>
</tr>
<tr>
<td>4</td>
<td>2573</td>
<td>15 18 20 22 23 23 23 23 29</td>
</tr>
<tr>
<td>5</td>
<td>3043</td>
<td>30 34 38 40 41 42 42 43 46</td>
</tr>
<tr>
<td>6</td>
<td>2487</td>
<td>42 44 46 48 49 50 50 50 56</td>
</tr>
<tr>
<td>7</td>
<td>4739</td>
<td>57 60 64 67 68 70 70 70 83</td>
</tr>
<tr>
<td>8</td>
<td>5250</td>
<td>84 88 91 94 96 97 99 99 111</td>
</tr>
<tr>
<td>9</td>
<td>3475</td>
<td>101 104 106 109 110 111 112 112 121</td>
</tr>
<tr>
<td>10</td>
<td>3610</td>
<td>111 115 118 120 122 123 123 123 132</td>
</tr>
<tr>
<td>11</td>
<td>2171</td>
<td>126 127 130 131 132 133 133 134 137</td>
</tr>
<tr>
<td>12</td>
<td>1005</td>
<td>130 131 132 133 134 134 134 134 135</td>
</tr>
</tbody>
</table>

The following Table 5.2 shows the range of values to which the intensity values in the dark lit shown in Figure 5.3 image gets mapped after applying Global Histogram Equalization using Distinction Metric.

### Table 5.2 Remapping capacity of GHE-DM

<table>
<thead>
<tr>
<th>Intensity value</th>
<th>No of occurrences</th>
<th>Intensity values after applying histogram equalization Global histogram equalization using distinction metric (GHE-DM)</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>1358</td>
<td>9 10 11</td>
</tr>
<tr>
<td>4</td>
<td>2573</td>
<td>14 15 16 17 18 19 20</td>
</tr>
<tr>
<td>5</td>
<td>3043</td>
<td>26 29 31 32 34 35 36 37</td>
</tr>
<tr>
<td>6</td>
<td>2487</td>
<td>40 44 47 50 52 53 54 55 56</td>
</tr>
<tr>
<td>7</td>
<td>4739</td>
<td>62 63 65 66 68 69 70 71 72</td>
</tr>
<tr>
<td>8</td>
<td>5250</td>
<td>84 88 91 94 96 98 99 100 101 102</td>
</tr>
<tr>
<td>9</td>
<td>3475</td>
<td>114 120 124 127 129 131 132 133 134 135 136</td>
</tr>
<tr>
<td>10</td>
<td>3610</td>
<td>144 147 149 151 153 155 156 157 158</td>
</tr>
<tr>
<td>11</td>
<td>2171</td>
<td>166 169 172 174 176 178 179 180 181</td>
</tr>
<tr>
<td>12</td>
<td>1005</td>
<td>185 187 188 190 192 193 194 195</td>
</tr>
</tbody>
</table>
5.7 LIMITATIONS OF GHE USING VOTING METRIC AND DISTINCTION METRIC

Images considered for application of Global Histogram Equalization using voting metric and distinction metric are shown in Figure 5.4. Initially a heavily shadowed image is considered, next a half-lit image is considered and finally, a dark image is considered.

![Images](a) (b) (c)

Figure 5.4 Illumination affected images considered for Illumination pre-processing (a) Heavily shadowed face image (b) Half-lit face image (c) Dark lit face image

For heavily shadowed face image and its histogram representation shown in Figure 5.5 (a), the resultant image after the application of Global Histogram equalization using voting metric (GHE-VM) is shown in Figure 5.5 (b) and the resultant image after the application of Global Histogram Equalization using distinction metric (GHE-DM) is shown in Figure 5.5 (c).

![Images](a) (b) (c)

Figure 5.5 Heavily shadowed face image and its histogram (a) without pre-processing (b) Pre-processed using GHE-VM (c) Pre-processed using GHE-DM
In Figure 5.6 (a) Half-lit face image and its histogram representation without any illumination pre-processing are shown. The resultant image after the application of Global Histogram Equalization using voting metric (GHE-VM) is shown in Figure 5.4 (b) and the resultant images after pre-processing using GHE-DM are shown in Figure 5.4 (c).

![Figure 5.6](image)

**Figure 5.6** Half-lit face image and its histogram (a) without pre-processing (b) Pre-processed using GHE-VM (c) Pre-processed using GHE-DM

In Figure 5.7 (a), dark-lit face image and its histogram representation without any illumination pre-processing are shown in Figure 5.7 (a). The resultant image after the application of Global Histogram Equalization using voting metric (GHE-VM) is shown in Figure 5.7 (b) and the resultant image after pre-processing using GHE-DM is shown in Figure 5.7(c).

![Figure 5.7](image)

**Figure 5.7** Dark-lit face image and its histogram (a) without pre-processing (b) Pre-processed using GHE-VM (c) Pre-processed using GHE-DM
The subjective analysis of the image pre-processed using GHE-VM and GHE-DM remains unsatisfactory because the images have attained an unnatural enhancement in case of half-lit and dark-lit images. In the case of heavily shadowed, half-lit and dark lit images, inferences from the histograms reveal that many bins still remain large and some bins still remain empty.

The reason for the existence of large bins even after applying the voting or the distinction metric clearly reveals that in many cases the centre pixels do not have any neighbourhood pixel less in gray level value compared with the centre pixel gray level value.

In other words, the condition for applying voting metric or distinction metric does not hold good in many regions of the input face image considered. This deficiency disables the division of large bins into sub-bins and subsequently affects the mapping of each sub-bin to a different value when equalized independently.

5.8 GHE USING FUZZY APPROACH ON NEIGHBOURHOOD METRIC

In voting metric or the distinction metric, the rule states that only the intensity values that are less than the centre pixel are considered for subdividing the histogram bins. Hence, in some cases out of the eight neighbours of the centre pixel, only a few of them will be considered for deciding the neighbourhood metric. Other neighbours which do not satisfy the condition (less than the centre pixel) are discarded.

This idea is based on crisp or classical sets. A crisp set is defined to be a conventional set for which an element is either a member or not.

To overcome this drawback, fuzzy approach on the neighbourhood metric has been proposed. In fuzzy approach on the neighbourhood pixels, all the eight neighbours of the centre pixel have been taken into consideration to divide bins into sub-bins. The fuzzy membership function is applied on the eight neighbours to determine their relationship with the centre pixel. This process is repeated for entire input face image irrespective of whether their gray level values are less or greater than the centre pixel.
Figure 5.8 depicts the application of fuzzy approach on the neighbourhood metric.

![Figure 5.8 Fuzzy approach on neighbourhood metric of size 3 x 3](image)

Then fuzzy c-means clustering is performed to sub-divide the large bins. After the subdivision of large bins, histogram equalization is performed to map the intensity value in the same bin to different intensity values.

This reduces the size of the bins after histogram equalization and increases the spread. An increase of the spread results in contrast enhancement for given input face image. The flow diagram of Global Histogram equalization using fuzzy approach on the neighbourhood is depicted in Figure 5.9.

![Figure 5.9 Flow diagram for Global Histogram Equalization using fuzzy approach on the neighbourhood metric of size 3 x 3.](image)
This procedure would result in much flatter histogram and the equalization will make use of most of the gray level values. Larger bins will be divided into smaller sub-bins and would get distributed over many gray level values. Histograms will be stretched. This will result in a high contrast image.

Procedure for histogram equalization using fuzzy approach on neighbourhood metrics is given below:

Step 1: Consider all eight-neighbourhood pixels for a centre pixel

Step 2: Use any fuzzy membership function to obtain the membership value of all the eight neighbours to the centre pixel. All the eight membership values will range between [0, 1].

Step 3: Repeat step 2 for all the occurrences of the pixel intensity value considered in step 1 in the given image.

Step 4: Perform fuzzy c-mean clustering using eight membership values as eight attributes for a pixel intensity. This gives the number of groups and number of elements in each group.

Step 5: The same procedure is adopted for all the pixel intensity value ranging from 0-255, having them as the centre pixel.

Step 6: After grouping, perform histogram equalization.

5.9 EXPERIMENTAL RESULTS

The resultant images of equalizing the shadowed image, half-lit image and dark-lit images using Global Histogram Equalization using Voting Metric, Distinction Metric and Fuzzy approach on the neighbourhood metric are consolidated in Figure 5.10.

To assess the efficiency of the proposed technique Global Histogram Equalization using fuzzy approach on neighbourhood metric, Histogram Flatness Measure and Mean Squared Error are computed. Histogram Flatness Measure (HFM) and Mean Squared Error (MSE) are used to assess the quality of the images. If HFM value is minimal, then
<table>
<thead>
<tr>
<th>Face Image</th>
<th>Histogram Representation</th>
<th>GHE</th>
<th>GHE using VM</th>
<th>GHE using DM</th>
<th>GHE using Fuzzy Approach on NM</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1.png" alt="Image" /></td>
<td><img src="image2.png" alt="Image" /></td>
<td><img src="image3.png" alt="Image" /></td>
<td><img src="image4.png" alt="Image" /></td>
<td><img src="image5.png" alt="Image" /></td>
<td><img src="image6.png" alt="Image" /></td>
</tr>
<tr>
<td>Heavily shadowed Images</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><img src="image7.png" alt="Image" /></td>
<td><img src="image8.png" alt="Image" /></td>
<td><img src="image9.png" alt="Image" /></td>
<td><img src="image10.png" alt="Image" /></td>
<td><img src="image11.png" alt="Image" /></td>
<td><img src="image12.png" alt="Image" /></td>
</tr>
<tr>
<td>Half-lit Images</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><img src="image13.png" alt="Image" /></td>
<td><img src="image14.png" alt="Image" /></td>
<td><img src="image15.png" alt="Image" /></td>
<td><img src="image16.png" alt="Image" /></td>
<td><img src="image17.png" alt="Image" /></td>
<td><img src="image18.png" alt="Image" /></td>
</tr>
<tr>
<td>Dark-Lit Images</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 5.10 Subjective Comparison of Histogram Equalization using VM, DM, Fuzzy Approach over NM
A higher flatness ratio is higher. Higher flatness ratio indicates good contrast ratio in the image. Table 5.3 represents the histogram flatness measure after the application of global histogram equalization with various neighbourhood metrics on illumination affected images. It clearly reveals that for heavily shadowed images, HFM obtained after pre-processing with global histogram equalization using fuzzy approach on the neighbourhood metric shows the least value.

Table 5.3 Histogram Flatness Measure obtained after contrast enhancement with GHE using various neighborhood metrics

<table>
<thead>
<tr>
<th>Techniques</th>
<th>Standard Deviation (σ) for the frequency of occurrences of the pixels intensity values</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Heavily Shadow Image</td>
</tr>
<tr>
<td>GHE using Voting Metric (Existing Technique)</td>
<td>3846.7</td>
</tr>
<tr>
<td>GHE using Distinction Metric (Existing Technique)</td>
<td>2879.7</td>
</tr>
<tr>
<td>GHE using Fuzzy Approach over Neighborhood metric (Proposed Technique)</td>
<td>2488.9</td>
</tr>
</tbody>
</table>

The Mean Squared Error (MSE) rate is estimated between the face image acquired at proper illumination conditions and same face image after preprocessing using histogram equalization technique with various neighborhood metrics. MSE for illumination affected images is shown in Table 5.4.
Table 5.4 Mean Squared Error rate obtained after contrast enhancement with GHE using various neighborhood metrics

<table>
<thead>
<tr>
<th>Techniques</th>
<th>Mean Squared Error Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Heavily Shadow Image</td>
</tr>
<tr>
<td>GHE using Voting Metric (Existing Technique)</td>
<td>6915.3</td>
</tr>
<tr>
<td>GHE using Distinction Metric (Existing Technique)</td>
<td>7210.6</td>
</tr>
<tr>
<td>GHE using Fuzzy Approach over Neighborhood metric</td>
<td>6854.4</td>
</tr>
<tr>
<td>(Proposed Technique)</td>
<td></td>
</tr>
</tbody>
</table>

Experimental results clearly indicate that GHE using Fuzzy approach on neighborhood metric performs well on heavily shadowed and half-lit images which are shown in Table 5.4.

The experimental results mentioned in Table 5.3 and Table 5.4 reveal that histogram flatness measure and mean squared error obtained for face image pre-processed using Global Histogram Equalization using fuzzy approach on neighbourhood metric performs well on heavily shadowed images.

5.10 SUMMARY

In this chapter, heavily shadowed, half-lit and dark-lit face images have been pre-processed with GHE using voting metric, distinction metric. A new method namely Global Histogram Equalization using Fuzzy approach on the neighbourhood metric has been proposed and implemented. GHE-using Fuzzy Approach on neighbourhood metric increases the dynamic range of gray level values on heavily shadowed images. When the range of gray level values increases in the image, the contrast of the image also increases. An increase in contrast level makes brighter pixels more brighter and darker pixel darker. Hence, the inclusion of neighbourhood metrics results in a
highly contrast enhanced images. High contrast images reveal the features required for face recognition.

Comparing the performance of GHE using voting metric, distinction metric and fuzzy approach over the neighbourhood metric, the results reveal that fuzzy approach on neighbourhood metric performs well on heavily shadowed images and half-lit images compared with the dark lit images. The proposed method shows 13.57% decrease in Histogram Flatness measure on heavily shadowed images. As mentioned earlier, decrease in Histogram Flatness measure indicates that there is an increase in the contrast ratio of the face image.

Face recognition systems used for access control, and monitoring systems in ATMs and malls usually encounter face images that are heavily shadowed and half-lit. Hence, GHE using fuzzy metric on neighbourhood metrics can be used in such real-time environments to handle challenges caused by illumination variation. Dark lit images are a special case in criminology, and hence it can be taken up a special case.