CHAPTER – 4
ERADICATING SEMANTIC GAP WITH THE HELP OF IMAGE QUALITY ASSESSMENT

Image quality measures are used to evaluate the performance of any given image. Human observers can be used to perform subjective evaluation in order to access quality of image. Mean Opinion Score (MOS) which is the mean value of scores obtained by human observers, is used as quality measure of image. Early retrieval systems are lacking in recognizing the existence of semantic gap. By using some better image quality measure, semantic gap can be reduced significantly. In this chapter, a different approach based on a simple model of Human Visual System (HVS) having one user defined parameter is used as quality measure. Value of user defined parameter can be adjusted according to reference image. The main limitation of MSE (Mean Squared Error) is that it cannot be used to measure structural similarity between original and distorted image. This limitation can be overcome using proposed quality measure which is based upon the concept of average value of locally computed correlation coefficients. Proposed measure will also make differentiation between signal dependent distortion and random distortion. Simulation results shows that the proposed strategy provides better quality of given image in case of distortion or noise i.e. semantic gap is significantly reduced.

4.1 INTRODUCTION
The semantic gap is the lack of coincidence between the information that one can extract from the visual data and the interpretation that the same data have for a user in a given situation [AWM2000]. Most of the early retrieval systems were lacking in recognizing the existence of the semantic gap and its consequences for system set-up.

Classification of image quality assessment methods: There exist two
categories of image quality assessment methods.

- **Subjective Methods:** Concept of MOS is used in these methods, where several human observers assigns a score value by judging the quality of given image. The mean value of their scores called MOS is used as the quality measure [ZWA2007].

- **Objective Methods:** Concept of Mean Squared Error (MSE) is used in these methods, where Peak Signal to Noise Ratio (PSNR) and Signal to Noise Ratio (SNR) can be used. The main goal of objective (quantitative) measures is to find value of image quality that correlates well with the value as perceived by HVS.

A lot of work has already been done for image quality assessment by taking into account the properties of HVS. Most of the presented algorithms tried to model the nonlinear relationship between image intensities and perceived brightness, frequency response of HVS (contrast sensitivity function) and texture masking. In [TNP1996], authors used a nonlinear function for modeling the brightness perception of the image. This function is then used to modify the input intensities of image. The modified images are then filtered using 2-D filter to model the frequency response of HVS. The main limitation of proposed method is that it can not produce a single value indicating image quality. In [RJS1989], authors developed Image quality measures as a part of image processing algorithms using properties of HVS. An overview of image quality measures is presented in [TNP1996]. In [ACB2002], authors analyzed the performance of several proposed quality measures in which distorted images are created using four different image coding algorithms producing different types of degradation.

In [ZWA2002], authors discussed some previously proposed quality measures and noted down that these measures frequently use some problematic assumptions. The work also highlighted that MSE or some modified MSE completely fail to measure structural similarity between
two given images. These quality measures only compute error between the corresponding pixels and do not provide correlation between that pixel and surrounding pixels in any of the two input images. Algorithms presented in [RJS1989] [SDA1993] also not able to measure structural similarity. A new image quality measure algorithm which is mainly based upon the concept of correlation coefficient is presented [ZWA2002]. Correlation coefficient measures the degree of linear relationship between the corresponding blocks of pixels.

4.2 SIMPLE HVS MODEL
The simple model of HVS shown in Fig. 4.1 models the brightness perception and frequency response of HVS. The output signal in this case depends on the viewing distance, width, height and the number of pixels of the input image.

\[ f(m,n) \rightarrow \text{Nonlinear Function} \rightarrow 2D \text{ Filter} \rightarrow x(m,n) y(m,n) \]

Fig. 4.1 Architecture of HVS Model

4.3 PROPOSED SYSTEM MODEL
The proposed model is based upon simple model of HVS as shown in Fig. 4.2. Initially, two images (original image and distorted image) are given as input to Module I of system. Module I consist of a nonlinear function used to model brightness perception of the images. After processing, the resulting intermediate outputs of original and distorted images from Module I are passed to Module II of system. Module II consists of a degradation filter used to model the frequency response of the system.
The degradation used in Module II is not fixed and depends upon one user-defined parameter (say $\alpha$). It can be adjusted depending on the context of the reference image. After processing of two input images, the correlation coefficients are computed on a block-by-block basis. Finally, quality measure is computed as the average correlation coefficient between the original image and distorted image, adjusted by average correlation coefficient between the original image and error image.

![Fig. 4.2 Architecture of Proposed Model](image)

### 4.4 PROPOSED ALGORITHM

The main objective of proposed algorithm is to obtain image quality measure that will produce results which are in agreement with subjective assessment and ultimately reduces the semantic gap. The notations used in the description of proposed algorithm are illustrated in Table 4.1.

<table>
<thead>
<tr>
<th>Notation</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>$w$</td>
<td>Width of image</td>
</tr>
<tr>
<td>$h$</td>
<td>Height of image</td>
</tr>
<tr>
<td>$d$</td>
<td>Viewing distance of image</td>
</tr>
<tr>
<td>$p$</td>
<td>Number of pixels of image</td>
</tr>
<tr>
<td>$L$</td>
<td>Total no. of blocks in image</td>
</tr>
<tr>
<td>$I_{oi}(m, n)$</td>
<td>Input original or reference image having $m \times n$ pixels</td>
</tr>
</tbody>
</table>
The following steps are performed in proposed algorithm:

**Step1: Computation of value of** $FO_{oi} (m,n)$, $FO_{di} (m,n)$

The above model is used in order to obtain desired output as:

- Two images $I_{oi} (m,n)$, $I_{di} (m,n)$ are given to Module I which make use of standard mathematical formulas in order to compute brightness perception and to produce intermediate results accordingly.

  **Input Given to Module I:** $I_{oi} (m,n)$, $I_{di} (m,n)$

  **Output Produced by Module I:** $IO_{oi} (m,n)$, $IO_{di} (m,n)$

- The intermediate results obtained using Module I, value of $w$, $h$, $d$ and $p$ are then supplied to Module II which makes
use of standard mathematical formulas in order to compute contrast sensitivity function and produce final results accordingly.

Input Given to Module II: \( IO_{oi} (m,n) \) and \( IO_{di} (m,n) \)

Output Produced by Module II: \( FO_{oi} (m,n), FO_{di} (m,n) \)

**Step 2: Computation of \( err (m,n) \) between \( FO_{oi} (m,n) \) and \( FO_{di} (m,n) \)**

- Partition images \( FO_{oi} (m,n) \) and \( FO_{di} (m,n) \) into 8 * 8 pixel blocks.
- For each of these block \( j \), calculate the value of correlation coefficient \( \rho_{FO_{oi}FO_{di}}(j) \) using following equation:
  \[
  \rho_{FO_{oi}FO_{di}}(j) = \frac{\sigma_{FO_{oi}FO_{di}(j)} \ast \sigma_{FO_{oi}(j)}}{\sigma_{FO_{oi}(j)} \ast \sigma_{FO_{di}(j)}} \ldots \text{(1)}
  \]
- Calculate the average value of correlation coefficient using following equation:
  \[
  \rho_{FO_{oi}FO_{di}} \ast \text{avg} = \frac{1}{L} \sum_{j} \rho_{FO_{oi}FO_{di}(j)} \ldots \text{(2)}
  \]
- Calculate value of error image using following equation:
  \[
  err (m,n) = FO_{oi} (m,n) - \text{sign} \{ \rho_{FO_{oi}FO_{di}} \ast \text{avg} \} \ast FO_{di} (m,n) \ldots \text{(3)}
  \]

**Step 3: Computation of average correlation coefficient between images \( FO_{oi} (m,n) \) and \( err (m,n) \)**

- Compute local correlation coefficient on block by block basis between images \( FO_{oi} (m,n) \) and \( err (m,n) \) using equation 1.
- Obtain average correlation coefficient \( \rho_{FO_{oi}err \ast \text{avg}} \) between images \( FO_{oi} (m,n) \) and \( err (m,n) \) using equation 2.

**Step 4: Calculate the value \( Q \) using following equation:**

\[
Q = \text{sign} \{ \rho_{FO_{oi}FO_{di} \ast \text{avg}} \} \ast \rho_{FO_{oi}FO_{di} \ast \text{avg}} \ast f(\rho_{FO_{oi}err \ast \text{avg}}) \ldots \text{(4)}
\]
where

\[
    f(\rho F_O i_e r_{_a v g} -_{avg}) = a + b \frac{\exp\left(\frac{\rho F_O i_e r_{_a v g} -_{avg}}{c}ight)^{-d}}{\exp\left(\frac{\rho F_O i_e r_{_a v g} -_{avg}}{c}ight)} - \exp\left(\frac{\rho F_O i_e r_{_a v g} -_{avg}}{c}ight)^{-d}
\]

After performing trial and error experiments using random and signal dependent distortion images, we set values of various constants as \(a=1.2, b=0.5, c=0.15, \) and \(d=0.3\)

### 4.5 SIMULATION RESULTS

#### 4.5.1 LENA IMAGE WITH VARIOUS TYPES OF DISTORTION

Performance of the proposed algorithm is tested on Lena image with height and width of 15 cm, viewing distance of 60 cm and image size of 512 x 512 pixels. Parameter \(\alpha\) which controls the rate at which CSF (Contrast Sensitivity Function) decreases after it reaches its maximum of 3.5 cycles/degree depends on the original image. The sequence of Lena images with various types of distortion is shown in Table 4.2. For this image, the value of user defined parameter \(\alpha = 0.75\). All images in the sequence has the same MSE value of 225 (except for JPEG coded image, which has MSE of 215), but their visual quality is very different. The results of proposed algorithm are shown in Table 4.3 and Fig. 4.3 respectively.

<table>
<thead>
<tr>
<th>Type of Distortion</th>
<th>MSE</th>
<th>Quality Measure (Q)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Impulsive salt-pepper noise</td>
<td>225</td>
<td>0.8543</td>
</tr>
<tr>
<td>Additive white Gaussian noise</td>
<td>225</td>
<td>0.7115</td>
</tr>
<tr>
<td>Multiplicative speckle noise</td>
<td>225</td>
<td>0.7224</td>
</tr>
<tr>
<td>Mean Shift</td>
<td>225</td>
<td>0.9954</td>
</tr>
<tr>
<td>Contrast stretching</td>
<td>225</td>
<td>0.9839</td>
</tr>
<tr>
<td>Blurring</td>
<td>225</td>
<td>0.2611</td>
</tr>
</tbody>
</table>
Table 4.3 Results of Lena Images under Various Types of Distortions using Proposed Algorithm

<table>
<thead>
<tr>
<th>Type of Distortion</th>
<th>MSE</th>
<th>Quality Measure (Q)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Impulsive salt-pepper noise</td>
<td>87.264</td>
<td>0.691</td>
</tr>
<tr>
<td>Additive white Gaussian noise</td>
<td>161.936</td>
<td>0.047</td>
</tr>
<tr>
<td>Multiplicative speckle noise</td>
<td>87.969</td>
<td>0.075</td>
</tr>
<tr>
<td>Blurring</td>
<td>170.459</td>
<td>0.017</td>
</tr>
<tr>
<td>Contrast stretching</td>
<td>269.263</td>
<td>0.554</td>
</tr>
</tbody>
</table>

Fig. 4.3 Lena Images with Various Types of Distortions
4.5.2 DENTURE IMAGES WITH VARIOUS TYPES OF DISTORTION

The same algorithm has been applied to medical images of denture dataset of 50 images collected from Department of Prosthodontics, M.M. College of Dental Sciences and Research, M.M. University, Mullana (Ambala). A view of images of patient teeth helps the doctors to analyze the pathology present but confirmation can be made through radiographs, so a good quality of images is required for analysis. The application of proposed algorithm on denture dataset generates results as shown in Table 4.4 and Fig. 4.4 respectively.

![Image of denture images with various types of distortions]

**Fig. 4.4 Denture Images with Various Types of Distortions**
Table 4.4 Results of Denture Images under Various Types of Distortions using Proposed Algorithm

<table>
<thead>
<tr>
<th>Type of Distortion</th>
<th>MSE</th>
<th>Quality Measure (Q)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Impulsive salt-pepper noise</td>
<td>26.854</td>
<td>0.498</td>
</tr>
<tr>
<td>Additive white Gaussian noise</td>
<td>144.592</td>
<td>0.009</td>
</tr>
<tr>
<td>Multiplicative speckle noise</td>
<td>26.900</td>
<td>0.060</td>
</tr>
<tr>
<td>Blurring</td>
<td>19.111</td>
<td>0.030</td>
</tr>
</tbody>
</table>

4.6 SUMMARY

An algorithm based on a simple HVS model for image quality assessment is presented. CSF used in this model is not fixed; it has one user-defined parameter to control attenuation at high frequencies. Finally, image quality measure is computed as the average correlation coefficient between two input images modified by the average correlation coefficient between original image and error image. It helps to differentiate between random and signal dependant distortion, which have different impact on a human observer.