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Improved Quality Measurement of Multicamera Image for Possible Distortions

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Abstract: *The quality of the image can be determined in two ways, subjective and objective. Here the objective evaluation of the multicamera image has been implemented. This paper details the techniques for implementing the quality measure of multicamera imagse. Here the quality of the image can determine by using PSNR, MSSIM, VIF and MIQM techniques. The PSNR, MSSIM and VIF are the commonly used image quality measurement techniques for single camera image but MIQM techniques is an alternative to the above mentioned techniques which do-not deal with the many issues found with multicamera image. Here while implementing these techniques, the multicamera images are simulated. Here the two distortions mainly considered called as photometric distortion and geometric distortion. The photometrically distorted images were created using the pepper and salt technique which is available in Matlab. To generate the geometrically distorted images, the two images were combining with each other with different overlap. Some images are also simulated which are a combination of both photometric distortion and geometric distortion. Then finally quality of all the simulated images is measured with the PSNR, MSSIM, VIF and MIQM techniques. The results of the mentioned quality measure techniques were compared with the implemented quality measure technique called MIQM.*

Keywords: *VIF, MSSIM, PSNR, MIQM, FTV, MSE*

I. Introduction

As per the consumers demand the electronics and computing technologies are taking the rapid growth but with this growth their cost are also rapidly decreasing. Day by day, the demand of the customers is also rapidly increasing. If the multimedia products are considered then for capturing the scenario high quality cameras are required. Furthermore to satisfy the demand, expected features of the cameras must increase in order to use them in various applications like video conferencing, sight-seeing, advertisement, security, medical etc. [1]-[2][3].Digital images undergo wide range of variety of distortions during its acquisition, processing, compression; storage; transmission and reproduction of image any of which results in degradation in a visual quality. [2][3]- [4]. The distortion is also created due to camera shake during expose creating motion blur which prevents from obtaining high quality images [2][5]. To determine the quality of the image is becoming an effective and efficient way to predict the visual quality of distorted image. Objective methods for assessing perceptual image quality traditionally attempted to quantify the deference’s between a distorted image and reference image using a variety of known properties of the human visual system. Determining the image excellence is becoming a vital task in multicamera image system. In the past most research has been made on single camera images but no such efforts given by the researchers on multicamera image system.

In concern about the image quality the quality of an image can be determined in two ways: Subjective and Objective [2], [6]-[7]. In recent years, there is large interest in generating objective image quality measurement methods which automatically predicts human behaviors in calculating image quality. Such measures have many applications in the evaluation, control, design and optimization of image acquisition, communication, and processing. According to availability of reference image, they can be classified as full reference, reduced reference and no reference algorithm. In full reference, the reference image is fully accessible while evaluating the distorted image. In reduced reference technique only fractional information about the reference image is available. In no reference no access to original image [8]. The target of the multicamera image method is to boost the consumers understanding further than the service given by single camera system. The multi-view video is a succession of images captured by different cameras at various locations [9]. The examples of multicamera images are not only panoramic videos or images but also in FTV (free view point), 3DTV and stereoscopic videos as well as pictures [10]. Multicamera images have certain distortions not found in single-view images that occur because of differences in the images captured and compressed by different cameras. The three common types of distortion are planar or rotational distortion, perspective or projective distortion, and blur. Planar distortion can occur from calibration problems related to camera position, either due to setup or environmental factors. Much like the human vision system sees slightly different views from each eye, perspective distortion occurs when cameras capture different views of the scene. Blur can occur due to focusing differences or lighting differences causing different dynamic ranges for the same image, either of which can be magnified by compression. Hence, defining a single quality measure that would capture the perceptible quality of all multicamera applications is impossible considering the difference in the means of presentation and the view compositing algorithms for each application[1][2][3].

II. Literature Survey

Hui Li, Zhengguo Li, Yih Han Tan et. al. [12] was describes the relationship between the Mean Square Error (MSE) and the Multistructure Similarity Index Measure (MSSIM) under an additive noise distortion model and derived a MSE-based image quality metric, Mean Square Error Structure Similarity Index Measure (MSE-SSIM). According to the Experimental results from evaluation on publically available databases they show that their theoretically derived metric compares favorably in terms of performance and complexity to several existing image quality metrics. Also due to simplicity of their proposed metric is amenable for optimization problems in a wide range of practical image and video processing task. Their implementation shows the improvement in objective MSE-SSIM scores and perceptual quality of images filtered with the MSE-SSIM –optimal Weiner filter as compared to the MSE–optimal Weiner filter.

Zhou Wang, Alan Conrad Bovik, Hamid Rahim Sheikh, Eero P. Simoncelli et. al [13] introduced an alternative complementary framework for quality assessment based on the degradation of structural information. They summarized the traditional approach to image quality assessment and enumerated its limitations. They proposed the use of structural similarity as an alternative motivating principal for the design of image quality measure. To demonstrate the concept they develop a structural Similarity index and demonstrate its promise through a set of intuitive examples with subjective and objective study on databases of images compressed with JPEG and JPEG 2000.

Jinjian Wu, Weisi Lin, Guangming Shi, and Anmin Liu et al. [14] were explained a novel reduced reference image quality assessment index based on visual information fidelity. They advocate that distortions on the primary visual information mainly disturb image understanding, and distortions on the residual uncertainty mainly change the comfort of perception. While implementation they separately compute the quantities of the primary visual information and the residual uncertainty of an image. Then the fidelities of the two types of information's are separately evaluated for quality assessment.

Chih-Wei Tang, Ching-Ho Chen, Ya-Hui Yu, and Chun-Jen Tsai et. al.[15] described a video bit allocation technique adopting a visual distortion sensitivity analysis for better rate-visual distortion coding control. This analysis directs the video coder to assign fewer bits to regions that tolerates larger distortions, and accordingly, the bit-rate saving is achieved. The key idea of this approach is to make use Instead of using complicated semantic understanding the analysis process analyzes both the motion and the texture structures in the video sequences in order to achieve better bit allocation for rate-constrained video coding. In this the techniques evaluates the perceptual distortion sensitivity on macro block basis, and allocates fewer bits to regions permitting large perceptual distortions for rate reduction. The designed algorithm can be incorporated into existing video coding rate control schemes to achieve same visual quality at reduced bit rate.

Zhou Wang,and Qiang Li et. al. [16] describe the multiscale information content weighing approach based upon a GSM model of natural images. They show that the novel weighting method leads to significant and consistence performance improvement of both PSNR and SSIM based image quality assessment algorithms. Hamid Rahim sheikh, and Alan c. bovik et. al. [17] described the image information measure that quantifies the information that is present in the reference image and how much of this reference information can be extracted from the distorted image. Combining these two quantities they propose the visual information fidelity measure for image quality assessment. Author explored the relationship between image information and visual quality, and presented a Visual Information Fidelity (VIF) criterion for full reference image quality assessment. The result of VIF was to be better than a HVS method which is explained in the state of art of the same paper, also the structural fidelity criteria and SSIM index.

Angela D' Angelo, Li Zhaoping, and Mauro Barni, et. al. [18] described a method to objectively assess the perceptual quality of geometrically distorted images, based on image features processed by human visions. The proposed metric is based on the use of Gabor filters to extract the structures of the image and on the evaluation of how such structures are distorted by the displacement field describing the geometric transformation between the original and the distorted image.

III. Types Of Distortions And Its Quality Measurement Techniques

3.1. Types of Distortions in Multicamera Image System.

Digital images undergo wide range of variety of distortions during its acquisition, processing, compression; storage; transmission and reproduction of image any of which results in degradation in a visual quality. [4]-[5]. The distortion is also created due to camera shake during expose creating motion blur which prevents from obtaining high quality images [6]. Distortions for multicamera image system can be classify as photometric and geometric distortion.

3.1.1. Photometric Distortion:

In Multicamera systems, photometric distortions are the visible changes in brightness levels and color gamut across the entire displayed image. The examples of photometric distortion are given below.

(a) Original Image

(b) Photometrically distorted Image

1.1.2. Geometric Distortion:

In Multicamera image system the geometric distortions can be defined as the visible misalignments, discontinuities, and blur in the handled image. These distortions can generate from perceptible calibration errors between adjacent cameras, affine/linear corrections, and error in scene geometry estimations. In manually built Multicamera images, these distortions may also occur due to the mismatch in the vertical and horizontal directions among images and irregular camera rotations.
The examples of geometric distortion are given below.

Fig. a) Geometrically Distorted image (Visible Misalignment)

Fig. b) geometrically distorted image (blur in the handled image)

3.2. Quality Measure Techniques in Multicamera Image System

3.2.1. Mean Square Error (MSE)

The MSE is the simplest and broadly used, full reference image quality measurement technique. Mathematically it is given by [1].

$$\text{MSE} = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(x(i,j)-y(i,j))^{2}$$

Here an error signal is obtained by subtracting the test signal from the reference signal and then by calculating the average energy of the error signal.

3.2.2. Peak Signal to Noise Ratio (PSNR)

PSNR is basically an objective technique because it measures the quality of the image by measuring the error in intensity between two dissimilar images [1]. In between reference image and test images peak signal to noise ratio is measured as a function of the mean squared error which gives a baseline for objective image analysis. It is defined as it is the ratio of maximum possible power to corrupting noise which affects illustration of image [1]. It is given by in db as:

$$\text{PSNR} = 10 \log_{10} \frac{(2^n - 1)^2}{\sqrt{MSE}}$$

3.2.3. Multistructure Similarity Index Measure:

The extension of the SSIM is nothing but the multistructure similarity index measure. It also proposed for the motionless images. It can be applied pixel by pixel or window by window or frame by frame on the luminance component of the image. Then the overall MS-SSIM index can be evaluated as average of the above quality score [1], [19]-[20].

The Multistructure similarity (MSSIM) index is a method for measuring the similarity between two images. The MSSIM index is a full reference metric; in other words, the measuring of image quality based on an initial uncompressed or distortion-free image as reference. MSSIM is designed to improve on traditional methods like peak signal-to-noise ratio (PSNR) and mean squared error (MSE), which have proven to be inconsistent with human eye perception. The difference of the multistructure similarity (MSSIM) index with respect to MSE or PSNR is that in mean square error and peak signal to noise ratio the perceived errors of the images are calculated; while in MSSIM the degradation in structural information of the image is considered.

3.3.4. Visual Information Fidelity (VIF)

A simple ratio of the two information measurements relates very well with visual quality. There is simple method to calculate VIF by extracting diagonal of correlation coefficient matrix between two images to be compared and it is given by the correlation coefficient matrix of n random variables $X_1... X_n$ is the n ×n matrix whose i, j entry is corr(X_i, X_j). If the measures of correlation used are product-moment coefficients, the correlation matrix is the same as the covariance matrix of the standardized random variables X_i / σ (X_i) for i = 1, ..., n. This applies to both the matrix of population correlations (in which case "σ" is the population standard deviation), and to the matrix of sample correlations (in which case "σ" denotes the sample standard deviation). Consequently, each is necessarily a positive-semi definite matrix.

The correlation coefficient matrix is symmetric because the correlation between X_i and X_j is the same as the correlation between X_j and X_i. Properties of VIF are:

1. VIF is bounded below by zero.
2. VIF is exactly unity if calculated between the reference image and its copy
3. A linear contrast enhancement of the reference image will result in a VIF value larger than unity, signifying a superior visual quality.

IV. Mathematical Model

Image processing is a challenging topic aimed at solving many real-life problems by means of images. Applications range from intelligent road vehicles “looking” into the road for possible dangers, automatic fruit quality assessment, medical imaging non-invasively looking for tumors inside the body ,or the determination of the structure of a macromolecular complex . All these problems share the commonality of trying to solve the problem at hand by extracting features from the image such as borders, dimensions, distances, textures, shapes, etc. This is done with the help of a computer and an algorithm that effectively carries out the job.

In general, all these tasks are grouped under a single name, image processing, which is no more than a particular of a more general framework, signal processing. A signal is mathematically model as a function u (x, y).

A color image code is the RGB (Red-Green-Blue) in which each of the components represents the intensity of a red light beam, a green light beam, and blue light beam, all of them superposed at the same point to produce a color.

An ideal image is transformed into an observed image by linear and nonlinear transformations plus noise.

4.1.1. Luminance and Contrast Index

This index measures sudden local change in luminance and contrast around structured regions. Such changes are common in multicamera images. Multicamera images captured by cameras looking at different parts of the scene are subject to non-uniform levels of distortion due to the difference between different cameras or different levels of view processing. To capture such variation, a measure that is a combination of luminance LI,J and contrast CI,J comparison functions is used, and it is adjusted to give higher weights for structured regions. Let LI,J be the luminance comparison function, between the two images I and J , computed to each macroblock in the images. The matrix LI,J of all macro blocks is calculated as follows:

$$l_{I,J} = \frac{2\mu_I \mu_J + C_1}{\mu_I{}^2 + \mu_J{}^2 + C_1}$$

Similarly, the matrix Cij of all macroblocks is calculated as:

$$c_{I,J} = \frac{2\sigma_I \sigma_J + C_2}{\sigma_I{}^2 + \sigma_J{}^2 + C_2}$$

Where Cij is the contrast comparison function between I and J computed on each macroblock. where I is the original image and J is the distorted image; μi is the mean intensity of image I, and σi is the standard deviation of the intensity values of I. The mean and standard deviation are all calculated on the macroblock level. C1.and C2 are constants included to avoid instability when the denominator is close to zero [1] –[2].

4.1.2. Motion Index

In Multicamera image system the geometric distortions can be defined as the visible misalignments, discontinuities, and blur in the handled image. These distortions can generate from perceptible calibration errors between adjacent cameras, affine/linear corrections, and error in scene geometry estimations. So when geometric distortion were defined interms of blur which means the shiftinf of pixels or displacement of pixels in the test image(distorted image) with reference to original image. Therefore the motion index can be evaluated as

$$\text{Motion Index} = \sum \quad \sum \left(\frac{\frac{(Xi - Xj)^2}{255^2}}{100} \right)$$

Where Xi is the original image and Xj is the distorted image. The range of the motion index is from 1 to 0. Where value 1 for minimum distortion and 0 for maximum distortion.

4.1.3 Textural Index

To get a better correlation with subjective quality for MSSIM, structural similarity over edge maps should be evaluated instead of the actually images. When an image is blurred, the spatial edges won't change but the corresponding intensities are not preserved. The Multistructure similarity (MSSIM) index is a method for measuring the similarity between two images. The MSSIM index is a full reference image quality measurement technique.

The structural information might loss due to photometric & geometric distortions. Such loss includes degradation in texture quality or lost image components on intersection or overlapping areas. The locations of variations of intensity values and the relative intensity values at these locations are known as spatial edges.

When an image is blurred or quantized the locations of the spatial edges are conserved; however, the intensity values of these edges change. In geometric distortions, such as translations and rotations, the spatial edge locations change where there relative intensity is preserved. Hence, by comparing the local edge information, the loss of structural information due to both photometric and geometric distortions can be calculated. [1]- [2].

Texture index includes mostly two algorithms SSIM and MSSIM the SSIM algorithm is considered a single-scale approach that achieves its best performance when applied at an appropriate scale. Moreover, choosing the right scale depends on the viewing conditions, e.g., viewing distance and the resolution of the display. Therefore, this algorithm lacks the ability to adapt to these conditions. This drawback of the SSIM algorithm motivated researchers to design a multi-scale structural similarity index (MS-SSIM) . The advantage of the multi-scale methods, like MS-SSIM, over single-scale methods, like SSIM, is that in multi-scale methods image details at different resolutions and viewing conditions are incorporated into the quality assessment algorithm. In MS-SSIM algorithm After taking the reference and test images as input, this algorithm performs low-pass filtering and downsampling (by factor of 2) in an iterative manner.

The final MSSSIM index is calculated using the following equation:

$$\text{MS-SSIM}(I_{ref}, I_{tst}) = [L_{Ms}(I_{ref}, I_{tst})]^{\alpha} \ \Pi \ [C_i(I_{ref}, I_{tst})]^{\beta i} \ [S_i(I_{ref}, I_{tst})]^{\gamma i}$$

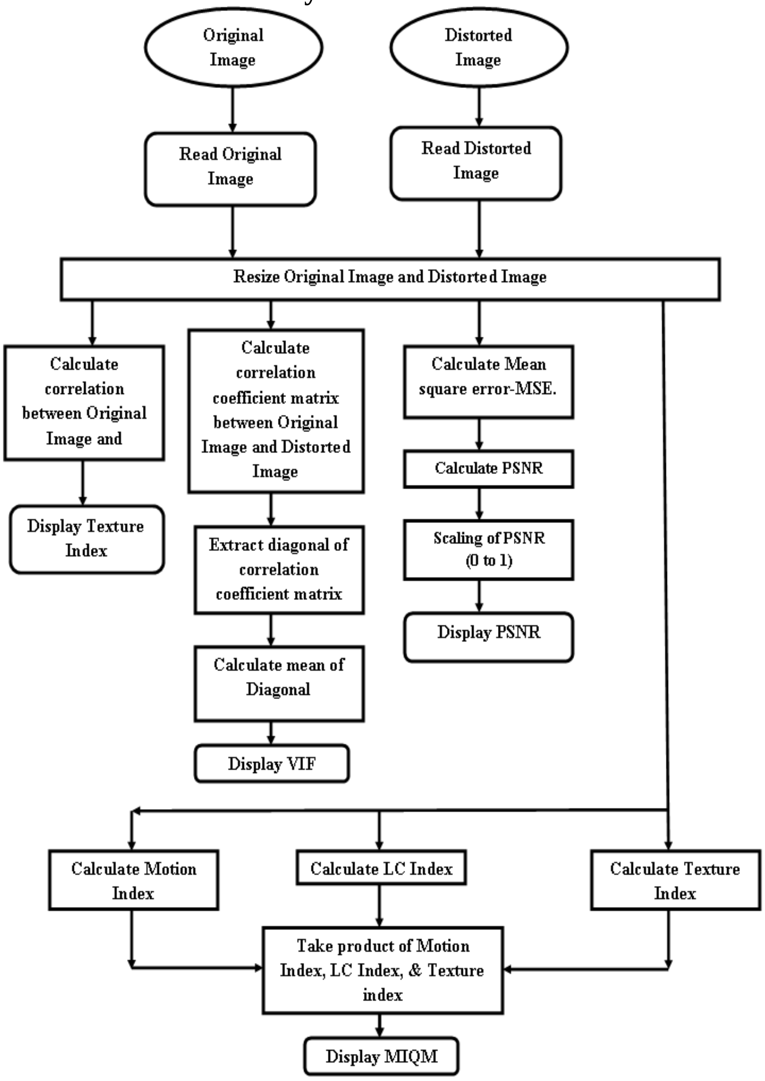
Where $C_i(I_{ref}, I_{tst})$ and $S_i(I_{ref}, I_{tst})$ are the contrast and the structure comparison function and $L_{Ms}(I_{ref}, I_{tst})$ is the Luminance comparison function. [21]

4.1.4 Multicamera Image Quality Measure (MIQM)

The multiplication of the previous mentioned three index measures turns into Multi-view Image Quality Measure, which is the main idea of the paper, using a single measurement to capture the quality of a multi-view image, where the values range from 1 for minimum distortion to 0 for maximum distortion.

$$MIQM_{I,J} = LC_{I,J}\, S_{I,J}\, T_{I,J}$$

V. System Architecture



I. Results & Analysis

6.1. MIQM Approach

As the multicamera images are suffers from mainly two types of distortion Geometric distortion and Photometric Distortion. So the results are obtained by considering the individual distortions. Here the single camera images are simulated for both the types of distortion in case of multiview.

6.1.1. Photometric Distortion - To simulate the Photometrically Distorted image, the noise were added to the original image by pepper and salt technique. The different amounts of noise were added to the original image ranging from 0.01 to 0.9. Here the 20 readings were taken and plot the graph for photometrically distorted image. Table 6.1 shows the comparative analysis of Multicamera image quality measure parameters. Also some input and output images before and after the applying the noise are shown in the following figures with their results.

Sr. No	Noise Level	MSSIM	PSNR	VIF	MIQM
1	0	1	1	1	1
2	0.01	0.928	0.4	0.9973	0.8697
3	0.02	0.8768	0.3716	0.9947	0.7670
4	0.03	0.8299	0.3549	0.9917	0.6773
5	0.04	0.7926	0.3443	0.9889	0.6064
6	0.05	0.7602	0.3358	0.9860	0.5429
7	0.06	0.7350	0.3307	0.9834	0.4989
8	0.07	0.7039	0.3246	0.9795	0.4434
9	0.08	0.6814	0.3197	0.9764	0.3991
10	0.09	0.6587	0.3165	0.9728	0.3648
11	0.1	0.6434	0.3126	0.9701	0.3297
12	0.2	0.4968	0.2940	0.9292	0.1246
13	0.3	0.4039	0.2863	0.8788	0.0426
14	0.4	0.3223	0.2824	0.8082	0.0075
15	0.5	0.2598	0.2796	0.7196	0.0095
16	0.6	0.1973	0.2778	0.6094	0.01
17	0.7	0.1511	0.2768	0.4742	0.015
18	0.8	0.1070	0.2757	0.3195	0.0130
19	0.9	0.0668	0.2750	0.1658	0.0092
20	1	0.0273	0.2746	-5.42	0.0041

Table 6.1. Shows Comparative analysis of Multicamera image quality measure techniques for Photometric Distortion.

Figure 6.1 shows graph for Comparative analysis of photometrically distorted Multicamera Image. From the graph it is observed that Compare to MSSIM, PSNR and VIF, the MIQM shows the better sensitivity to the distortion applied.

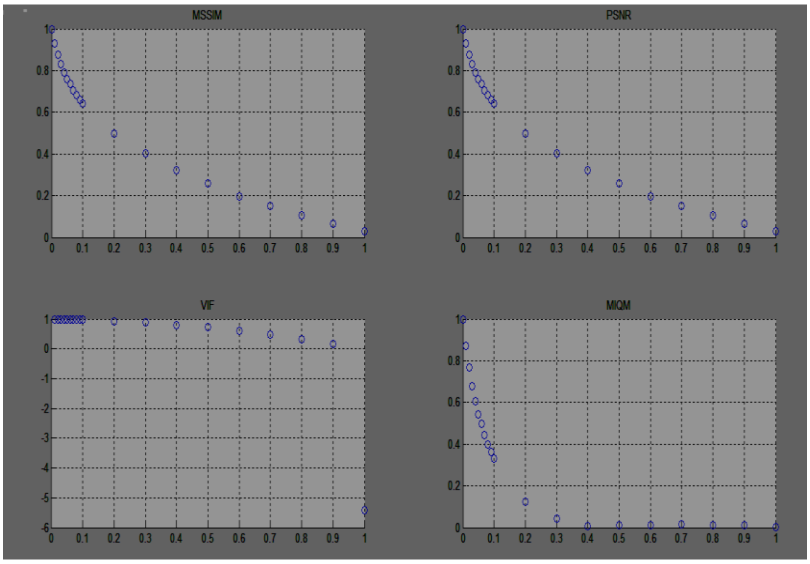


Figure 6.1 Graph for Comparative analysis of Multicamera image quality measure techniques for Photometric Distortion.

6.1.2. Geometric Distortion: - The second type of image distortions in Multicamera systems is geometric distortions. It is the visible misalignment between the images. Here the images was simulated which consist of both types of distortions i.e. Photometric Distortion and Geometric Distortion. Below the simulated images and results are shown.

Here the linear displacement is varied as 5 %, 20 % and 40% .The photometric distortion were varied as 0.01, 0.1 and 0.4 in correspondence to linear displacement and three different images were simulated. Figure 6.2 shows the Low Noise Low Overlap Multicamera Image (5 % linear displacement and 0.01 photometric distortion by pepper and salt technique), Figure 6.3 shows the Medium noise medium overlap Multicamera Image.

(20% linear displacement and 0.1 photometric distortion by pepper and salt technique) and Figure 6.4 shows the High noise High overlaps Multicamera Image (40% linear displacement and 0.4 photometric distortion by pepper and salt technique)

Figure 6.2 Low Noise Low Overlap Multicamera Image.

Figure 6.3 Medium noise medium overlap Multicamera Image.

Figure 6.4 High noise High overlaps Multicamera Image.

Quality Methods	Original Image	Low Noise Low Overlap	Medium Noise Medium Overlap	High Noise High Overlap
PSNR	1	0.3308	0.3167	0.3030
VIF	1	0.9675	0.8696	0.6240
MSSIM	1	0.6992	0.4592	0.2065
MIQM	1	0.4753	0.2547	0.0796

Table 6.2 Comparative analysis of Multicamera Image Quality Measurement Techniques for both photometrically and geometrically distorted Images.

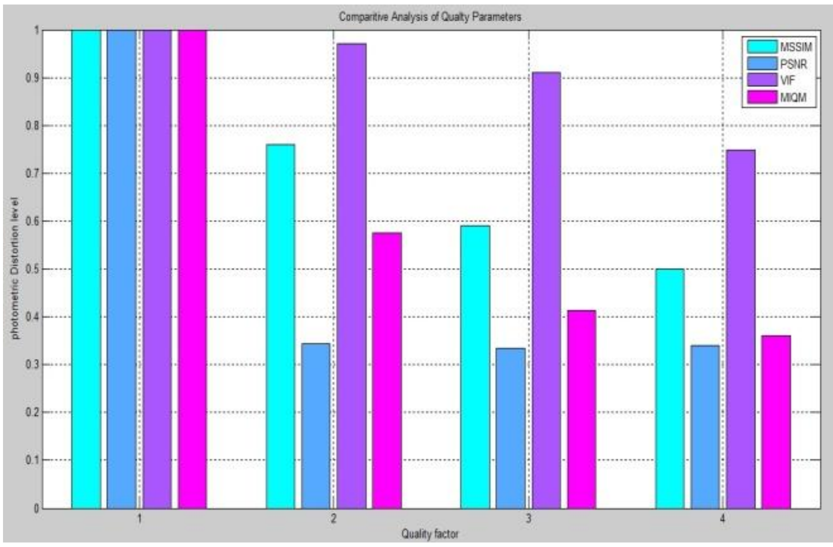


Figure 6.5 Comparative analysis of Multicamera Image Quality Measurement Techniques results in the form of Bar graph for both photometrically and geometrically distorted Images.

Now to show the system compatibility different images were used which are a combination of both types of geometric distortions i.e. linear and angular (Planar and Perspective). By changing the values of linear pixel displacement and angle the following results was obtained. These results again show the effectiveness of the approach. Fig.6.2 shows the Original Image. Fig.6.3 shows the distorted image with linear displacement 9 and angle 30 and Fig.6.4 shows the distorted image with linear displacement 30 and angle 100. Table 6.3 shows the comparative analysis of Image Quality Measure Methods for both linear and angular geometrically distorted Images.

Figure 6.5 Original Image

Figure 6.6 Distorted image with
with

Figure 6.7 Distor1ted image

linear displacement 9 and angular 30 linear displacement 30 and angle 100.

Linear Displacement	Angular Displacement	MSSIM	PSNR	VIF	MIQM
3	10	0.9635	0.3704	0.9906	0.8391
6	20	0.8749	0.3366	0.9676	0.6279
9	30	0.8045	0.3244	0.9462	0.5029
12	40	0.7520	0.3178	0.9290	0.4230
15	50	0.6990	0.3123	0.9087	0.3513
18	60	0.6559	0.3092	0.8907	0.3057
21	70	0.6466	0.3085	0.8830	0.2955
24	80	0.6504	0.3087	0.8773	0.2988
27	90	0.6582	0.3091	0.8698	0.3054
30	10	0.6156	0.3050	0.8482	0.2518

Table 6.3 Shows Comparative analysis of Image Quality Measure Methods for both linear and angular geometrically distorted Images.

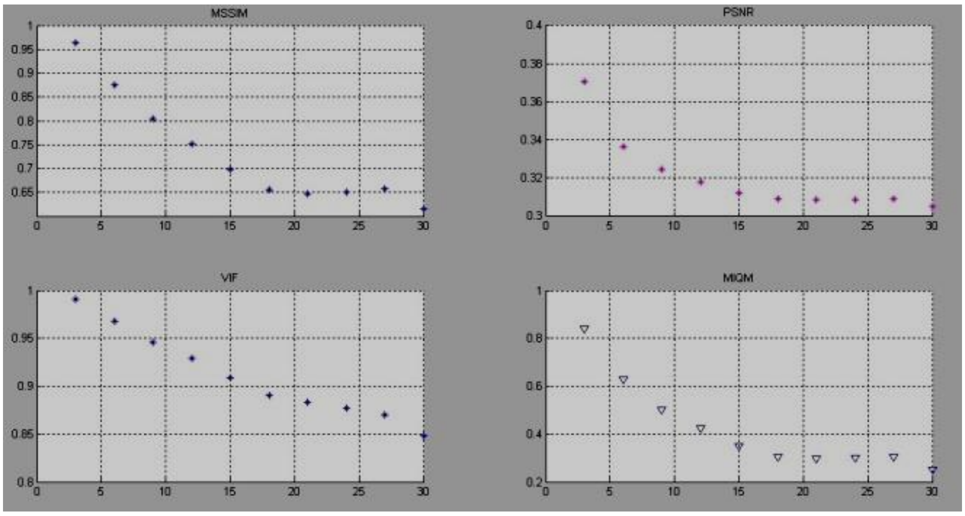


Fig.6.8 shows the Multicamera Image Quality Measure results in the form of Scatter graph for both linear and angular geometrically distorted Images. From this graph it is conclude that the MIQM has better sensitivity to all types of distortions compare to others.

VI. Conclusion

In this paper, to measure the quality of multicamera images, the objective methods such as PSNR, VIF, MSSIM and MIQM were implemented. As multicamera images suffer mainly due to two distortions which are photometric distortion and geometric distortion, so here both the types of distortions were studied and introduced (simulated). From results and analysis it is observed that for photometrically distorted multicamera images, geometrically distorted images as well as for blurred(pixel shifting) images the multicamera quality measure technique (MIQM) gives the better results compared to others like PSNR, VIF and MSSIM. Also the MIQM was tested to the images which are combination of both the types of distortions (Photometric distortion and geometric distortion). Here also MIQM gives the better result compare to others.

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