



Modified Gradient Similarity Vs Structural Similarity for Image Quality Assessment

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Abstract: In this paper, we have proposed a Image Quality assessment (IQA) using gradient information which considers the image with edges to assess quality through contrast and structure comparison along with Luminance comparison. The existing structural similarity (SSIM) method measures structure loss based on statistical moments, i.e., the mean and variance, represents mainly the luminance change of pixels rather than describing the spatial distribution. However, the human visual system (HVS) easily identifies the quality when there is comparison of two images. Of course HVS is very sensitive to gradient changes. In this paper, we use the modified gradient similarity concept comparing with existing Structural similarity based IQA. Also we have shown here a better result Using modified gradient similarity when compared to simple gradient based IQA. Furthermore, considering the viewing condition, we extend the SSIM metric to the multi-scale space. Experimental results demonstrate the proposed IQA method is more consistent with the human perception than the SSIM metric and normal Gradient metric as well.

Keywords: Image Quality Assessment (IQA); Peak Signal-To-Noise Ratio (PSNR); Mean Square Error (MSE).

I. INTRODUCTION

Image is simply defined as a group of Pixels. A pixel represents smallest information. Given a distorted image, objective image quality assessment (IQA) evaluates how much the image is degraded by comparing it with the original image, i.e., how much the image is different from the original image in terms of intensity or color. IQA algorithms have been mainly developed for testing the performance of the image or video coding systems. Currently, commercial multimedia services become common and high quality services become inevitable for commercial success. Thus, IQA algorithms could be a crucial component to improve user satisfaction for the multimedia and network services. Also we have UID (Unique Identification) Project like Aadhar by the previous and existing governments playing a powerful role in civil ration distribution and many services to the citizens. This project aimed to give UID to each & every citizen of India which involves Biometrics. So our method may help in identifying fake biometrics as well. The mean square error (MSE) and peak signal-to-noise ratio (PSNR) can be considered as representative IQA methods. Currently, these two methods are widely used for evaluating the quality of an image or video. Here we proposed Modified Gradient Similarity method comparing to Structural similarity method for IQA.

Review:

First, unlike the PSNR and MSE that considers the only

difference of intensity or color values for the assessment of the image quality, the structural information-based IQA methods structural information of the image [1–8]. That is, the assessment of the image quality is to measure how much the structures of the image are distorted. Wang et al. [1] presented the structural similarity (SSIM), which uses the structural information such as the mean, variance, and covariance of intensity values of the original and distorted images. The enhanced version of the SSIM, the gradient-based SSIM (GSSIM) [2], was presented, which makes use of the gradient features as the structural information. In a similar way, the edge-based SSIM (ESSIM) was proposed [3]. It uses a histogram with eight bins corresponding to eight edge directions. The IQA algorithm proposed by Wang and Simoncelli [4] is based on the fact that statistical properties of wavelet coefficients in LH, HL, and HH bands are changed when an image is distorted. For measuring the quality of a distorted image, Won adopted the edge histogram descriptor (EHD) of moving picture expert group (MPEG)-7 standard and compared the EHD of the original image with that of the distorted one [5]. Also, Shnayderman et al. utilized singular value decomposition (SVD) to assess the quality of an image [6], which is reasonable because SVD well represents texture information as structural features of an image.

To assess the image quality, several metrics presented in [7] measure coding artifacts caused by international coding standards such as joint photographic expert group (JPEG), JPEG2000, moving picture expert group (MPEG)-2, MPEG-4, H.263, and H.264/AVC. These IQA methods measure the blurriness, blockiness, jerkiness, and so on. Second, the of an image. The EPSNR was adopted as Annex B of ITU-T recommendation J.144. A perceptually-tuned metric based on the wavelet transform and a measure of the intra- and inter-channel visual masking effect was also developed by Charrier and Eude [9]. The perceptual quality significance map was presented in evaluating the visual quality of a distorted image [10], which uses the concept of visual attention in the human visual system (HVS). Kusuma and Zepernick proposed the hybrid image quality metric based on the human visual perception [11], combining various image artifact measures such as the blocking measure, blur measure, edge activity measure, gradient activity measure, and intensity masking detection. Winkler proposed the spatio-temporal contrast gain control model [12], which achieves a close fit to contrast sensitivity and contrast masking data from several experiments.

II. MODULE 1

A. SSIM

The structural similarity (SSIM) index is a method for measuring the similarity between two images. The SSIM 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. SSIM is designed to improve on traditional methods like peak signal-to-noise ratio (PSNR) and mean squared error (MSE), which have proved to be inconsistent with human eye perception. The difference with respect to other techniques mentioned previously such as MSE or PSNR, is that these approaches estimate perceived errors on the other hand SSIM considers image degradation as perceived change in structural information. Structural information is the idea that the pixels have strong inter-dependencies especially when they are spatially close. These dependencies carry important information about the structure of the objects in the visual scene.

B. VSNR

Signal-to-noise ratio (often abbreviated SNR or S/N) is a measure used in science and engineering that compares the level of a desired signal to the level of background noise. It is defined as the ratio of signal power to the noise power. A ratio higher than 1:1 indicates more signal than noise. While SNR is commonly quoted for electrical signals, it can be applied to any form of signal (such as isotope levels in an ice core or biochemical signaling between cells).

C. PSNR

The PSNR is most commonly used as a measure of quality of reconstruction of lossy compression codes (e.g., for image compression). The signal in this case is the original data, and the noise is the error introduced by compression. When comparing

perceptual information-based methods measure the distortion that the human vision system can perceive for assessing the image quality [8–12]. An edge PSNR (EPSNR) method was proposed [8], which is motivated by the observation that the human perceives sensitively intensity variation around edges

compression codes it is used as an approximation to human perception of reconstruction quality, therefore in some cases one reconstruction may appear to be closer to the original than another, even though it has a lower PSNR (a higher PSNR would normally indicate that the reconstruction is of higher quality). One has to be extremely careful with the range of validity of this metric; it is only conclusively valid when it is used to compare results from the same codec (or codec type) and same content.

MSE: Mean Squared Error is the average squared difference between a reference image and a distorted image. It is computed pixel-by-pixel by adding up the squared differences of all the pixels and dividing by the total pixel count.

For images $A = \{a_1 \dots a_M\}$ and $B = \{b_1 \dots b_M\}$, where M is the number of pixels:

$$MSE(A, B) = \frac{1}{M} \sum_{i=1}^M (a_i - b_i)^2 \quad (1)$$

The squaring of the differences dampens small differences between the 2 pixels but penalizes large ones.

D. PSNR

Peak Signal-to-Noise Ratio is the ratio between the reference signal and the distortion signal in an image, given in decibels. The higher the PSNR, the closer the distorted image is to the original. In general, a higher PSNR value should correlate to a higher quality image, but tests have shown that this isn't always the case. However, PSNR is a popular quality metric because it's easy and fast to calculate while still giving okay results. For images $A = \{a_1 \dots a_M\}$, $B = \{b_1 \dots b_M\}$, and MAX equal to the maximum possible pixel value ($2^8 - 1 = 255$ for 8-bit images):

$$PSNR(A, B) = 10 \log_{10} \left(\frac{MAX^2}{MSE(A, B)} \right) \quad (2)$$

E. MS-SSIM

Multi-Scale Structural Similarity is layered on SSIM. The algorithm calculates multiple SSIM values at multiple image scales (resolutions). By running the algorithm at different scales, the quality of the image is evaluated for different viewing distances. MS-SSIM also puts less emphasis on the luminance component compared to the contrast and structure components. In total, MS-SSIM has been shown to increase the correlation between the MS-SSIM index and subjective quality tests. However, the trade-off is that MS-SSIM takes a few times longer to run than the straight SSIM algorithm.

MS-SSIM*: MS-SSIM* is an extension to the original MS-SSIM algorithm proposed by Wang, et al. MS-SSIM* does away with the stabilization constants and defines concrete values for the edge cases. The signal authors-to-noise provide



ratio, the bandwidth that shows a modest increase in correlation between the MS-SSIM* index and subjective tests, as compared to MS-SSIM. MS-SSIM* is the default algorithm used by the `iqa_ms_ssim()` method.

III. MODULE 2

In video, luma, sometimes called luminance, represents the brightness in an image (the "black-and-white" or achromatic portion of the image). Luma is typically paired with chrominance. Luma represents the achromatic image without any color, while the chroma components represent the color information. Converting R'G'B' sources (such as the output of a 3CCD camera) into luma and chroma allows for

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chroma subsampling: because human vision has finer spatial sensitivity to luminance ("black and white") differences than chromatic differences, video systems can store chromatic information at lower resolution, optimizing perceived detail at a particular bandwidth. Luminance changes can also cause the visible distortion although they are not as annoying as contrast/structure changes. However cannot account for the luminance change/distortion since it uses only the gradient information as the input and the gradient information is not affected by the noncontract/structure changes.

$$e(x_i, y_i) = 1 - \left(\frac{x_i - y_i}{L} \right)^2 \quad (3)$$

With a test image block and its reference block, the gradient (or contrast) of can be regarded as the gradient of being combined with an error signal; alternatively, the gradient of can be regarded as that of being combined with an error signal. When two visual signals combine, there is masking of one signal over the other, and a visibility threshold can be determined for the masked contrast against the masking contrast.

In general, the visibility threshold (below which the change is not noticeable to the HVS) for the masked signal increases with the masking contrast. Masked gradient change defined in (8) is a largely reasonable choice since, when the masking signal is higher (i.e., is higher), the perceptual effect of the masked signal is lower for a same amount of (resulting in a lower) due to higher. As discussed in Section III-A, the lower value of, the higher value for (therefore, the higher predicted quality of test block). The only problem for the formulation with and is the case with both the following conditions being met: (i) Causes distortion that is smaller than or close to; and (ii) is comparable to in value. With case (i), should be 0, and therefore, should be 1, because the difference between and is not visible; however, if this situation coincides with case (ii), (8) can give a value to that is significantly bigger than 0, and this overestimates the image distortion. As a general scheme, we need to make the necessary provision for overcoming the aforementioned overestimation. To this end, in (7) is modified to satisfy the following conditions: (A) does not cause too much change to when cases (i) and (ii) do not simultaneously happen; and (B) is close to 1 for the cases with both (i) and (ii). For (A), should be comparable with (several times of) and in (7); for (B) should be much larger than (e.g., more than 20 times of) and Note that both and lie in the range of [0, 2], and therefore, a reasonable value is for (A) and for (B)

$$g(x, y) = \frac{2(1-R)^{+K} / \max(g_x, g_y)}{1 + (1-R)^2 + K' / (g_x g_y)} \quad (4)$$

In this paper, we have chosen as, where is a positive constant and called as a masking parameter. Typically, is around 50 and 5 for (A) and (B),

respectively; hence, the choice of is between 200 and 1000 (we choose in the current stage of the work). Substituting the fine-tuned into, we get where in (9) is still in the range of [0, 1]. To illustrate the effect of fine tuning for, Fig. 5(a) and (b) shows two simple image blocks that have gradient values of 1 and 4, respectively; the visibility threshold for is 4.7 using the method in. In the figure, we can see that and are very similar, and this represents a case for condition (B). However, the quality score given by is 0.47 (which means that (a) and (b) are not similar). On the contrary, the score given by is 0.989, which is more reasonable. In video, luma, sometimes called luminance, represents the brightness in an image (the "black-and-white" or achromatic portion of the image). Luma is typically For paired example, with the chrominance gradient information. Luma represents is the same the ifa constant achromatic image without any color, while the chroma components represent the color information. Converting R'G'B' sources (such as the output of a 3CCD camera) into luma and chroma allows for chroma sub sampling: because human vision has finer spatial sensitivity to luminance ("black and white") differences than chromatic differences, video systems can store chromatic information at lower resolution, optimizing perceived detail at a particular bandwidth.

IV. MODULE 3

A. Gradient

An image gradient is a directional change in the intensity or color in an image. Image gradients may be used to extract information from images. In graphics software for digital image editing, the term gradient is used for a gradual blend of color which can be considered as an even gradation from low to high values, as used from white to black in the images to the right. Another name for this is color progression. Mathematically, the gradient of a two-variable function (here the image intensity function) is at each image point a 2D vector with the components given by the derivatives in the horizontal and vertical directions. At each image point, the gradient vector points in the direction of largest possible intensity increase, and the length of the gradient vector corresponds to the rate of change in that direction. Since the intensity function of a digital image is only known at discrete points, derivatives of this function cannot be defined unless we assume that there is an underlying continuous intensity function which has been sampled at the image points. With some additional assumptions, the derivative of the continuous intensity function can be computed as a function on the sampled intensity function, i.e., the digital image. It turns out that the derivatives at any particular point are functions of the intensity values at virtually all image points. However, approximations of these derivative functions can be defined at lesser or larger degrees of accuracy.

The Sobel operator represents a rather inaccurate approximation of the image gradient, but is still of sufficient quality to be of practical use in many applications. More precisely, it uses intensity values only in a 3×3 region around each image point to approximate the corresponding image

gradient, and it uses only integer values for the coefficients which weight the image intensities to produce the gradient approximation. The gradient of the image is one of the fundamental building blocks in

and other visual representations of data in order to convey additional information. GIS tools use color progressions to indicate elevation and population density, among others. Six publicly available and subject-rated image databases in the IQA community are used, namely, LIVE, Tampere Image Database (TID), Toyama, A57, IVC, and CSIQ. The number of distorted images is 779 for LIVE, 1700 for TID2008, 168 for Toyama, 54 for A57, 185 for IVC, and 866 for CSIQ, and these images and their corresponding subjective ratings are used as the ground truths to be compared against the IQA scheme outputs as shown in Fig.1.



Fig.1. Input Image or Original Image.

To compare the efficiency (i.e., computational complexity) of different schemes, we measured the average execution time required for per image (512 * 512 in size) in A57 database on a PC with 2.40-GHz Intel Core 2 CPU and 2 GB of RAM. The required time in seconds per image, with all the codes being implemented with MATLAB. The codes for the SSIM, multiscale SSIM, VSNR, VIF, PSNR-HVS-M, MAD, and IW-SSIM respectively. The proposed scheme takes more time than the PSNR and the SSIM only, and it is faster than the multiscale SSIM since no multiscale image decomposition is involved in the proposed scheme. MAD and IW-SSIM also take much longer processing time than the proposed scheme. To be more precise, the proposed method takes only about 0.25% and 15.2% of the time taken by MAD and IW-SSIM, respectively.

B. SSIM

Consider Fig.2 in which the y-axis represents the predicted value from the scheme under consideration and the x-axis represents the subjective DMOS. We show the four-parameter logistic mapping curve between the objective outputs and the subjective DMOS as the middle curve. The

image processing. For example the Canny edge detector uses image gradient for edge detection. Image gradients are often utilized in maps

error is allowed; the DMOS value of the remaining images cannot be “correctly” predicted from the IQA scheme. The more the data points are between the bounding curves, the better the scheme is. If a data point lies below the lower bound, it means that the visual distortion is overestimated since the scheme predicts a higher score (i.e., lower image quality) than the actual DMOS value; the visual distortion is under estimated for the data points lying above the upper-bound curve. Fig. 4(a) shows the plot of DMOS versus SSIM for high distortion images (i.e., with DMOS values bigger than 50) from LIVE database, where blur, contrast, jpeg and fnoise represent the distortion types of JPEG 2000 compression, JPEG compression, white Gaussian noise, Gaussian blur, and fast fading, respectively.

upper curve denotes (here, as an example in the figure) the upper bound (i.e., with DMOS value being higher than the middle curve); the lower curve denotes the lower bound (i.e., with DMOS value being lower than the middle curve). In other words, the DMOS value of the images corresponding to the data points lying between the upper and lower curves can be “correctly” predicted by the IQA scheme if measurement

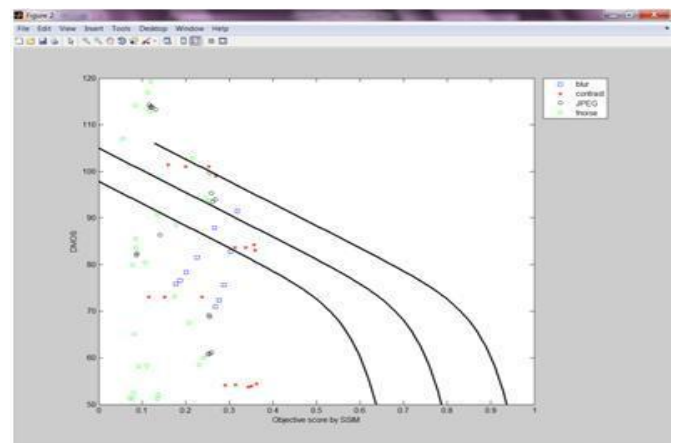


Fig.2. The Plot of The SSIM V/S DMOS.

In Fig.2, some (more than 60 in number) data points lie outside the bounding curves; note that these data points mainly correspond to the images with WN distortion, and therefore, we have statistically demonstrated that the SSIM shows higher sensitivity to white noise, i.e., it over estimates the visual distortion with WN. It can be also observed in Fig.2 that the SSIM tends to underestimate the visual distortion caused by JPEG compression.

C. Gradient Similarity

The similar plot with the data given by (5a) is shown in Fig.3, and only 29 data points lie outside the bounding



curves. The effect of WN is also overestimated but to a lesser extent; in addition, there is no underestimation for JPG error due to the proper emphasis on the edge information. Fig. 4 shows the scatter plots of the proposed IQA scheme on the six databases. We can see that the proposed scheme performs consistently well across all the databases. Although the performances of the proposed scheme and multiscale SSIM

and MAD are similar across databases, the proposed scheme has a clear advantage in terms of computational effort and time required (execution time will be compared in Section V-D); moreover, the proposed scheme can provide a quality map, whereas multiscale SSIM and MAD can only provide an overall quality score. With regard to IW-SSIM, it is a

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good IQA scheme because it basically weighs SSIM (which itself is a reasonably effective quality measure) values using weights derived via image information content.

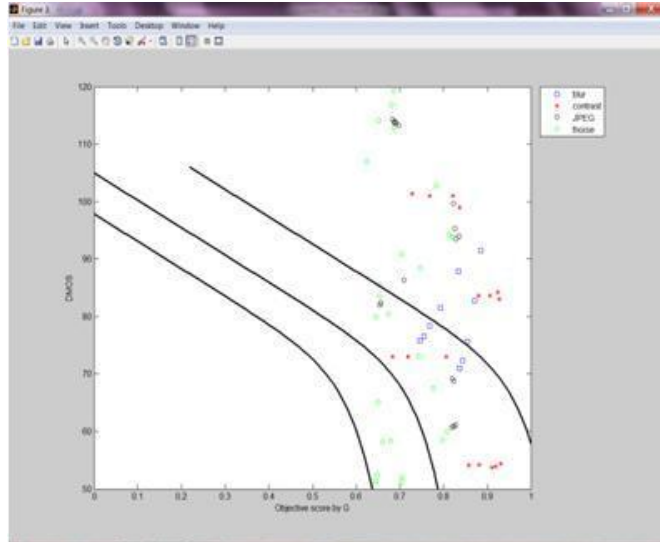


Fig.3. The Plot of The Gradient(G) V/S

DMOS. D. LOGISTIC MAP

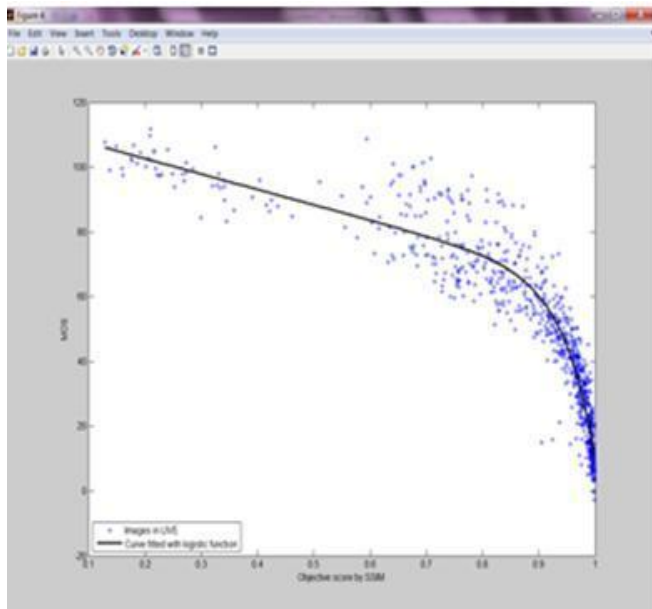
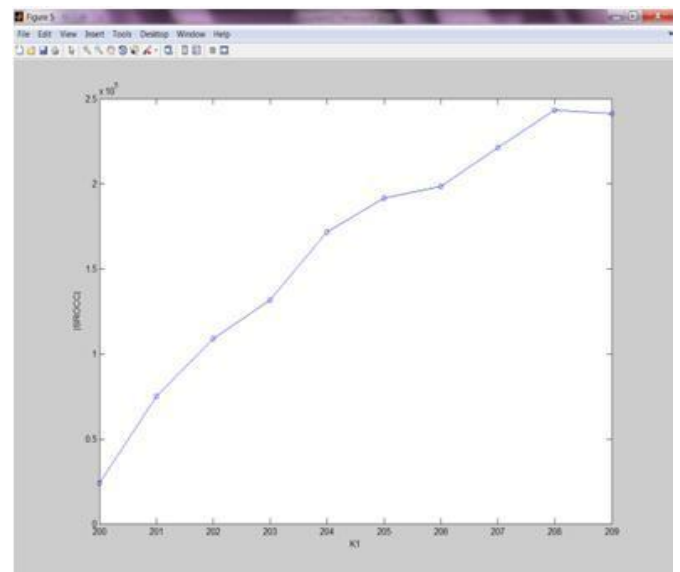


Fig.4. The Scatter Plots of The Proposed Iqa Scheme.

E. SROCC vs. K1

The impact of the parameter values is shown with the plots of SROCC as a function of the parameter values. In the proposed scheme, there are two parameters, i.e., k_1 and p , where k_1 is for the masking effect (its valuation has been determined in Section III-C) and p is used to integrate contrast–structure and luminance distortions. To confirm that

SROCC is nearly constant no matter what the value of p is used, the difference of SROCC values for different values of p is smaller than 0.01, and this is valid for every database. Although the optimal value of p to achieve the highest SROCC value is different for different databases (i.e., 15 for Toyama; 40 for LIVE, IVC, and CSIQ; and 1000 for TID and A57), there are two common trends for different databases, as shown in these plots: a) SROCC drops fast when the value of p is close to 0, and this is expected since, for a small p , the contrast masking effect for the case the masking signal is small, is not properly reflected; and when p is large, the SROCC is very close to 1 (i.e., no smaller than 97.7% of the highest possible value when the optimal value for p is used). Therefore, the choice of p is reasonable for our purpose.



the chosen p is a reasonable choice, Fig. 5 plots the SROCC as a function of K_1 for all the databases. As can be observed, when the value of K_1 is large (e.g., $K_1 \geq 200$), the value for the SROCC is high.

F. SROCC vs. P

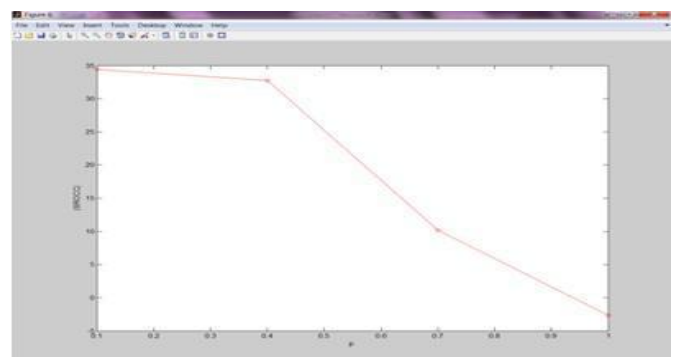


Fig.6. The Plot Of The SROCC vs. P.

G. RMSE vs. P

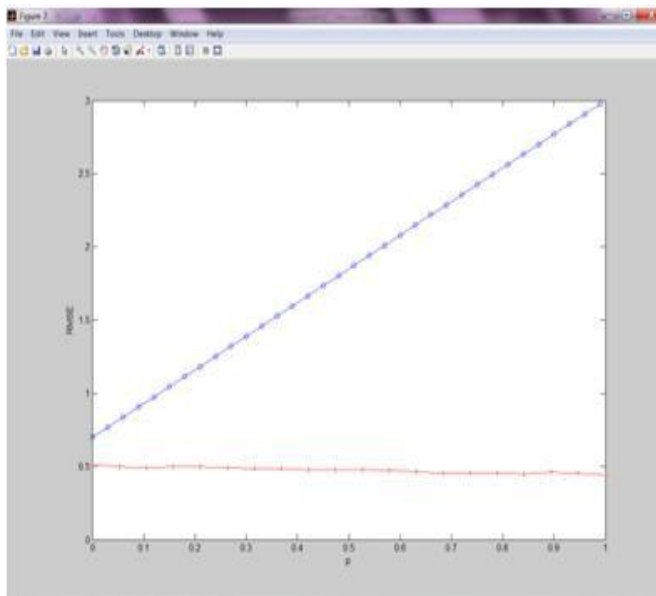


Fig.7. The Plot Of The RMSE vs. P.

H. CC vs.P

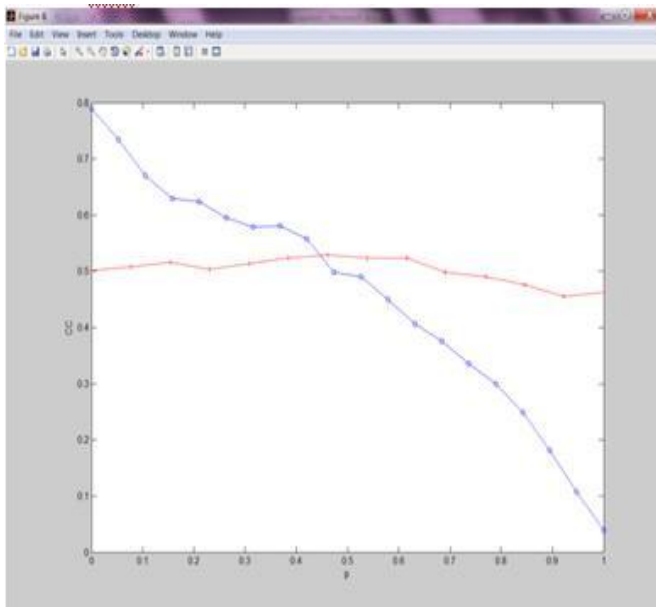


Fig.8. The Plot Of The CC vs. P.

To show the impact p of for, we simulated various values of on TID database first since it includes luminance distortion (mean shift distortion, with 25 reference images and 4 distortion levels for each reference image). In Fig. 6, 7 and 8, we show the absolute values of the SROCC, CC, and RMSE plotted as a function of for the overall performance (i.e., the images with all the 17 distortion types) and the performance on luminance distortion (i.e., the images with mean shift distortion). We found that to yield good tradeoff between performance on luminance distortion and for the overall cases (i.e., the SROCC value for is over 99% of the highest SROCC

value, among all the possible SROCC values when different values of are used). In the figure, we can see that the overall performance decreases with the increase in (i.e., increase in the contribution of in) since is less capable of measuring the contrast and structural distortions compared to . On the other hand, cannot be zero since that will mean the luminance distortion is completely ignored. Therefore, we use since it gives good performance both for luminance distortion and for the overall case.

V. CONCLUSION

The HVS is more sensitive to the edge regions than the non-edge ones, edge information should be carefully and explicitly incorporated in designing of an IQA scheme. We have proposed a new IQA scheme based on the concept of gradient similarity to alleviate the shortcoming of the existing relevant schemes in this regard. We have demonstrated that the proposed gradient similarity measure can be used to gauge contrast and structural changes. In addition, we have made our scheme match better with the masking effect and visibility threshold. Finally, luminance similarity is devised and incorporated to form a complete quality evaluation scheme. The effectiveness of the proposed IQA scheme has been demonstrated. In addition to its robustness and high accuracy, the proposed scheme also provides the pixel error map and is relatively simple with its mathematical formulation and computational complexity, making it more practical to be used and embedded in various optimization processes in image processing tasks. Finally we can say Modified Gradient Similarity based IQA is better than Structural based IQA. This scheme is the foundation for Video Quality assessment as well.

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