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A survey on Directional Anisotropy Structural Measurement (DASM) for analysing the quality of an image

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Abstract - An Objective of an Image Quality Assessment is to measure the difference between distorted image and reference image (data set) using varieties of known properties of the Human Visual System(HVS). There are two ways for assessing the quality, subjective and objective. An objective method is more friendly than subjective because most of the time reference image is not available for comparison. It is also accurate due to its mathematical comparison. Human Visual Perception is sensitive in extracting structural information from an image, whose alternative complementary framework assessed is also based on degradation of structural information. Full reference objective method is taken for analysis of structural information. For quality assessment, Directional Anisotropy Structural Measurement is proposed. In DASM, the quantitative measurement of gradient, Anisotropy, Local Directionality is made and whose output performance is measured by comparing with undistorted Image. The performance metrics considered here are Peak Signal to Noise Ratio (PSNR), Structural Similarity Index (SSIM), Quality Score and it is simulated in MATLAB. The effectiveness is verified by conducting experiments on six benchmark data bases.

Index Terms - Image Quality Assessment (IQA), Human Visual System(HVS), Structural Similarity Index (SSIM), Structural Measurement.

I. INTRODUCTION

Image quality is the characteristic that measures image degradation. But Image quality assessment enables to approximate image quality. Different distortions occurred in Digital image due to various reasons like image acquisition, pre-processing, compression, reproduction. It can be removed by applying different methods like reducing noise, improving brightness, which also result in a degradation of visual quality. Therefore, assessing the quality of an image and finding the solution accordingly is a key factor in the image information. The interest in objective image quality assessment has been growing over the past decade.

The recent progress on automatic quality assessment (objective method) that can predict quality of visual signals is exhilarating. In subjective quality assessment, image is provided to compare original images with distorted images manually in order to evaluate the quality of an image. Based on their evaluation, Mean Opinion Score is calculated which is taken as the image quality index. In subjective method, there is no mathematical equation and it is costly, inconvenient and time consuming. Three factors: luminance, Contrast and Brightness are taken into account for quality analysis. For proper assessing the image, this method needs at least 25 qualified observers and some set of scenes to finalise.

[1] In objective quality assessment, image or video quality of an image can be evaluated by means of a machine. Without human involvement automatic algorithms or mathematical equations are used for quality assessment that could analyse images and report their quality. This method reduces the cost and gives fast quality assessment. Based on the availability of an original image, objective image quality metrics are classified as

- Full-reference: when complete reference image is assumed to be known.
- No-reference: when reference image is not available. This is also known as "blind quality assessment".
- Reduced-reference: when reference image is known partially in the form of a set of extracted features as side information that helps in evaluation methods.

Full Reference method require full access to the reference image, while NR methods assume completely no access to the reference. This paper focuses on full reference IQA metrics.

For FR-IQA based assessment, PSNR (Mean Square Error) are generally used to predict the visual quality by mathematically comparing distorted image with original reference image based on pixels. But these metrics do not correlate well with human perception. Traditional FR metrics, such as the mean squared error (MSE) or the peak signal-to-noise ratio (PSNR) are simple, since they are purely defined on a pixel-by-pixel difference between the distorted and the original image, but they are also known for their poor correlation with perceived quality [2]. A HVS-based model is the noise quality measure which quantifies the psycho visual effects of frequency distortions by using a low pass contrast sensitivity function and a discrete cosine transform. Due to the complexity of HVS, these methods become complex and do not achieve high performance. Multi-scale structural similarity index provides more flexibility to incorporate the variations of viewing conditions than previous single-scale method.

A philosophy for image quality measurement was proposed [3], based on the assumption that the Human Visual System is highly adapted to extract structural information from the viewing field. Accordingly, the Structural Similarity is introduced to measure the distorted image's quality, and simulation results show that it is more consistent with HVS than Peak

Signal Noise Ratio. Meanwhile, SSIM introduces an effective similarity function qualitatively consistent with the masking effect of the HVS, and it has been regarded as a suitable paradigm for calculating the similarity features towards image quality assessment.

[4] Gradient-based Structural Similarity compares the edge information between the distorted image block and the original one, and replace the contrast comparison c(x, y) and structure comparison s(x,y). Some structure-based models measure the image structural degradation by identifying different structural patterns.

In this paper the analysis of image quality by the use of gradient and two psych visual observations such as anisotropy and directionality is surveyed and also this method gives higher performance than existing.

II. ANALYSIS OF DIRECTIONAL ANISOTROPY STRUCTURAL MEASUREMENT

Human Visual System is highly adapted to extract structural information from images, so the image quality can be measured by the structural information loss. Accordingly, the effectiveness of structure based methods crucially relies on a discriminative structural feature used to perceive the structural distortion. So to identify the visually important structures, structural measurements are being used. Structural measurements work well on these two psycho visual observations called anisotropy and local directionality. The anisotropy N(p) and the local directionality D(p) are derived from the image gradient.

(1) Image gradient has been widely applied in image processing tasks to extract local structures. Gradient value is calculated as the maximum weighted average of difference or as maximal derivative along four directions as

$$g_x = \max_{k=1,2,3,4} \{ \text{mean2} (|x.M_k|) \} \qquad (1)$$

with M_k (k=1,2,3,4), where the weighting coefficient decreases as the distance from the central pixel increases, and mean2 (.) is the mean value for a matrix.

(2) Anisotropy. Structures that exhibit wider variation and directional change is a indication of visual perception. In case of structures with messed background there is a loss in the structural perception. In such ways measuring of structural information. The anisotropy measurement N(p) is computed as therelative discrepancy between the two eigenvalues $\lambda_{1,p}$ and $\lambda_{2,p}$. It is given by

$$N(p) = \frac{\lambda 1,p - \lambda 2,p}{\lambda 1,p + \lambda 2,p} \qquad (2)$$

Obviously, N(p) ranges from 0 to 1. For structures with predominant trend of intensity variation at the pixel, $\lambda_{1,p} >> \lambda_{2,p}$, thus N(p) is closed to 1. For isotropic pattern, whereas, $\lambda_{1,p} \approx \lambda_{1,p}$ and N(p) is closed to 0.

(3) Local directionality. It is more consistent for dominant structures and its intensity variation rather than textures. These dominant structures can also be obtained from measurement of local directionality. The image gradient merely reflects the directional change of the intensity in an image. The local directionality L(p) is calculated by the orthogonality distribution of eigenvectors $\eta_{1,p}$, $\eta_{2,p}$ corresponding to directions with minimum eigenvalues in a local neighbourhood.
Concretely, it is defined as:

$$L(p) = \sum_{q \in N(p)} \frac{A(p).(\eta 1,p\ .\eta 2,p\ )}{A(p)} \qquad (3)$$

The product of $(\eta 1, p\, .\eta 2, p\,)$ returns a value ranging from 0 to 1, which increases as the two vectors align closely, i.e., the included angle between them approaches 0 or π and equals to 0 as the two vectors get orthogonal. Also, pixels with high anisotropy are encouraged to contribute more, so N(p) is applied as a weight to better capture the primary direction.

4) DASM. The proposed structure measurement function is defined as:

$$DASM(p) = G(p).\ N(p).\ L(p) \qquad (4)$$

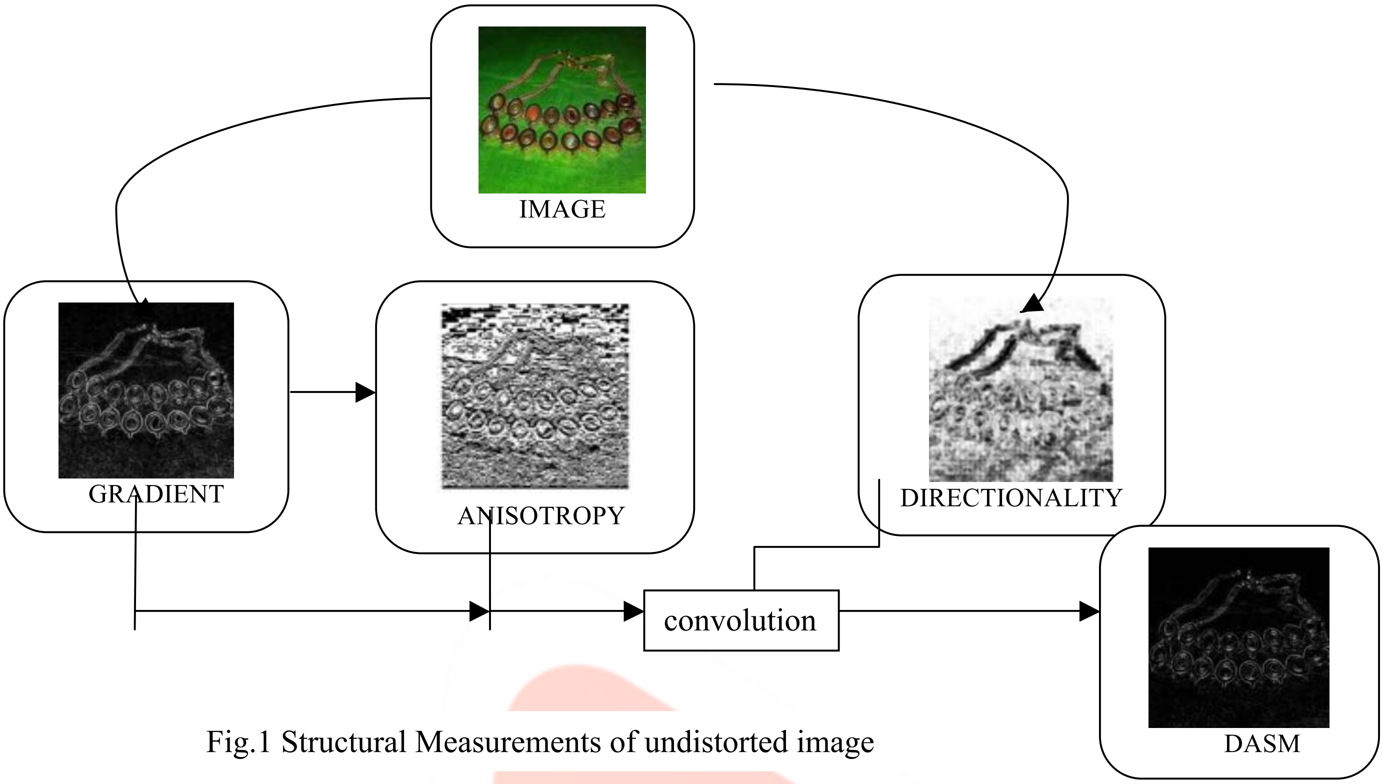

Fig.1 Structural Measurements of undistorted image

where DASM(p) evaluates the confidence strength of a pixel 'p' and G(p) is the gradient of an image, L(p) is local directionality in and N(p) is anisotropy measurement to estimate direction for structures that varies with direction.

Figure 1 shows the structural measurements of reference image with directionality and anisotropy and that DASM reduces the visual imperceptible texture details and well preserves the dominant structures compared to the previous measurements like gradient and phase congruency that are commonly used to extract structural information from images. Figure 2 gives all the parameters of DASM for blurred iamge.The DASM strengthens the object edges but suppresses the minor textures. For the complicated and noisy regions, the DASM only retains the dominant structural with fine anisotropy and local directionality.

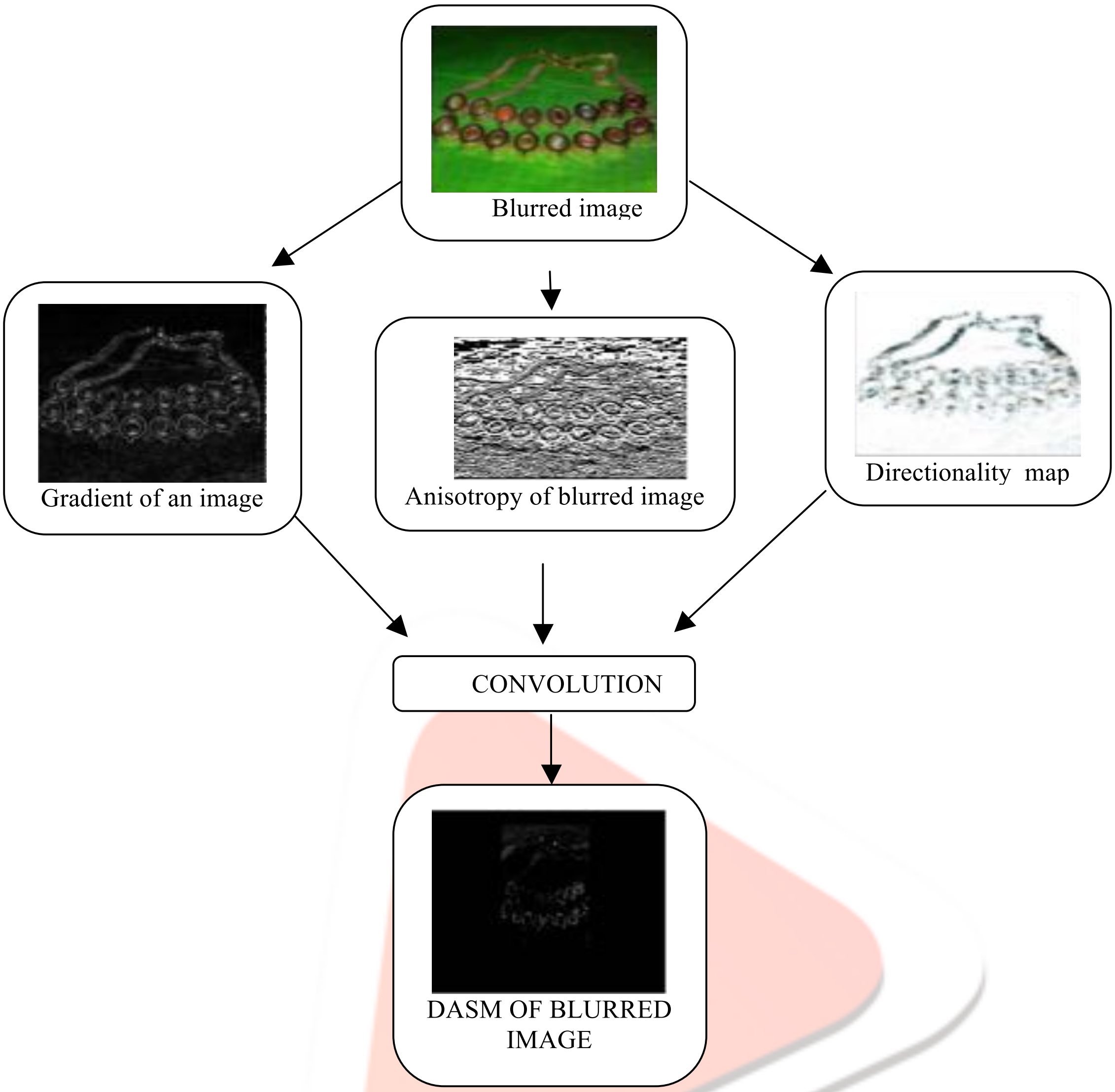

Fig.2 Structural Measurements of blurred image

III. Local Similarity Map

Local similarity Map is calculated by comparing Directional Anisotropy Structural measurement of both the distorted and reference image. An image quality metric that assesses the visual impact of three characteristics of an image: luminance, contrast and structure. For image quality assessment similarity map, a system is made which separates the task of similarity measurement into above three comparisons.

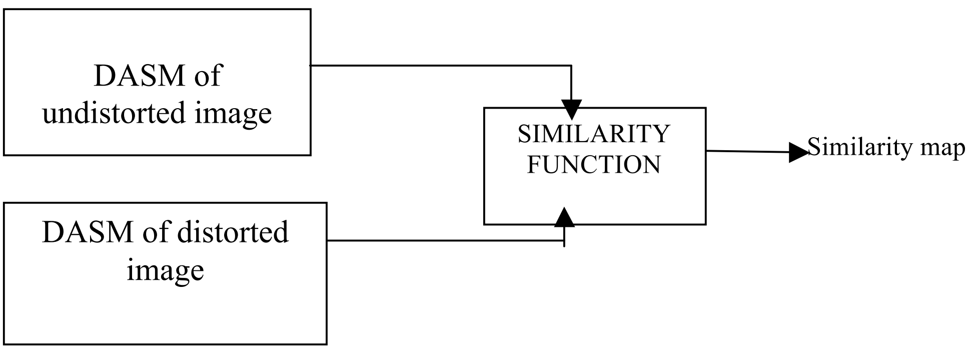

Fig.3 Block diagram for similarity map

For image quality assessment similarity map, a system is made which separates the task of similarity measurement into above three comparisons. Figure 3 is continuation to previous figure 2 in which output from figure 2 is taken and applied here to get similarity function. Structural Similarity Index gives an effective similarity function, satisfies masking effect and suits well for Image quality assessment.

Hence Similarity index or function for structure as per figure 3 is defined as S(a,b) as follows

$$\frac{2(a+C)(b+C)}{(a+C)(a+C)(b+C)(b+C)} \qquad (5)$$

Where

'a' is DASM of reference image

'b' is DASM of distorted image

'C' is positive constant

C is added to avoid the instability when both a,b are very close to zero.The ultimate quality score is estimated by average pooing of local similarities .

$$\text{Quality score } = \frac{1}{N}\sum_{i=1}^{N} \text{LSM} \qquad (6)$$

using the above similarity method, the variation in 'C' in accordance with performance indicator by conducting experiments on six benchmark databases. In such a cases equation 5 gives better performance due to its insensitive nature to C and gives higher stability range.

IV. SIMULATION METRICS

The comparison is between proposed method and standard metrics to check the quality. The experiments are conducted in benchmark which is IQA databases. The ten full reference models are compared here.

V. IMAGE DATABASE

To assess the quality of an image with any of the metrics, it is necessary to test the performance. TID2013 (Tampere Image Database 2013) is easily available and largest database and comprises 25 reference images, 24 types of distortions with 3000 distorted images and 5 dissimilar levels for each type of distortion. Laboratory for Image & Video Engineering (LIVE) data base contains 29 reference images, 779 distorted images including five types of distortion as JPEG, JPEG2000, white noise, Gaussian blur, and Fast fading. MICT database contains 14 reference images and 196 distorted images degraded by JPEG2000 and JPEG. The A57 database consists of 3 reference images and 54 distorted images. The CSIQ database consists of 30 original images and a total of 886 distorted images, each of which is distorted using six different types of distortions at four to five different levels of distortion.

VI. PERFORMANCE METRICS

The following three popular performance measures are used to compare performance of various metrics: Pearson linear correlation coefficient (PLCC), Spearman rank order correlation coefficient (SROCC), Kendall rank order correlation coefficient(KROCC).

The calculation of the PLCC and RMSE should be nonlinear to reduce variation of score and also to provide mapping between predicted score and Mean Opinion Score. To have a higher SROCC, KROCC, PLCC and lower RMSE values, the result is said to have better quality.

VII. RESULTS

Image quality score can be obtained for image quality metrics. The results can be verified on six IQA databases as explained above. Here the performance of method is verified with LIVE databases and also reaches consistently well on A57 and TID2013 databases. The below table shows performance comparison:

Table 1 Performance comparison for full reference image assessment

Metric	SROCC	KROCC	PLCC	RMSE
PSNR	0.8723	0.6811	0.8713	13.301
SSIM	0.9431	0.7916	0.9432	8.9445
VIF	0.9611	0.8217	0.9589	7.6699
GSIM	0.9545	0.8121	0.9439	9.0376
FSIM	0.9643	0.8347	0.9598	7.6780
proposed	0.9501	0.8032	0.9399	7.7012

From the above table, image quality assessment using PSNR is low performance, but with FSIM gives higher performance. Among all metrics SROCC should be higher than other. When compared to RMSE of PSNR and proposed, the latter gives lower metric which is the required criteria. Other database also works on same criteria. All the above values are measured and tabulated as numerical values.

IV. CONCLUSION

Human Visual System is highly sensitive to change and degradation loss function in structures of an image. This paper gives a survey on two main psycho visual observations, anisotropy and local directionality in which the performance metrics for any image database is more precise than previously used full reference metrics. In addition to that, DASM technique gives more identification to dominant structures than textures according to human visual system. Similarity of DASM is an additional feature in Image Assessment Quality Metrics method. This technique gives higher performance metric when compared to existing techniques.

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