Volume 2, No. 5, Sept-Oct 2011

ISSN No. 0976-5697

International Journal of Advanced Research in Computer Science

RESEARCH PAPER

Available Online at www.ijarcs.info

Image Quality estimation of Images using Full Reference and No Reference Method

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Abstract: Image quality review is one of the challenging fields of digital image processing system. Measurement of visual quality is of elementary weight for abundant image and video processing applications, where the goal of quality assessment (QA) algorithms is to automatically judge the quality of images or videos in agreement with human quality judgments. The costing of image quality based on single strategy Human Vision System (HVS) may not very enough. We need some more dimensions. Full Reference method. Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR), and Structural Content (SC)) may contribute to calculate efficient result to image quality measurements. However, it is not always possible to get the reference images to assess image quality. Human observers can easily recognize the distortion and degradation of image without referring to the original image. Therefore, there is absolutely necessary to develop objective quality assessment that correlates well with human perception without the reference image (No-Reference).

Keywords: Full Reference, No Reference, Quality Assessment

I. INTRODUCTION

Image Quality Assessment (IQA) has always been an integral part of image processing. Many different approaches for IQA with different density have been developed in the last decade.

Digital images are subject to a variety of distortions during compression, transmission, processing, and reproduction. In order to maintain, control and possibly enhance the quality of the image and video data being delivered, it is important for data management system (network video servers) to be able to identify and quantify quality degradations on the fly. [1] Image QA methods can be classified as subjective and objective methods. The first approaches to image quality evaluation are subjective quality testing which is based on observers that evaluate image quality. These tests are time consuming, expensive and have a very strict definition of observational conditions. The second approaches are the objective image quality testing based on mathematical calculations. Over the years, a number of researchers have contributed significant research in the design of full reference image quality assessment algorithms, claiming to have made headway in their respective domains.

The QA research community realizes the importance of validating the performance of algorithms using extensive ground truth data, particularly against the backdrop of the fact that a recent validation study conducted by the video quality experts group (VQEG) discovered that the nine video QA methods that it tested, which contained some of the most sophisticated algorithms at that time, were “statistically indistinguishable” from the simple peak-signal-to-noise-ratio (PSNR) [2].

It is therefore imperative that QA algorithms be tested on extensive ground truth data if they are to become widely accepted. Furthermore, if this ground truth data, apart from being extensive in nature, is also publicly available, then other researchers can report their results on it for comparative analysis in the future.

In this paper we present our results of a wide subjective quality assessment study, and estimate the concert of six recognized QA algorithms. The psychometric study contained 200 images distorted using different distortion types and more than 500 human image quality evaluations. This study was miscellaneous in terms of image content, distortion types, distortion strength, as well as the number of human subjects ranking each image. We have also made the data set publicly available [3] to facilitate future research in image quality assessment.

In the current connected world, many users share and deliver multimedia data. The overall communication process includes manipulation, processing, storing, and transmission over (noisy) channels. Although there have been great improvements in compression and transmission techniques, each stage of processing may introduce perceivable distortions [4,5].

For example, blocking, ringing, and blurriness are only few of the artifacts that a lossy compression algorithm introduces in an image. For image quality assessment, Peak Signal to Noise Ratio (PSNR) is an objective quality measurement, based on the Mean Squared Error (MSE) between the original and received image.

Although it is known that PSNR can be unreliable especially for patterned noise, it is widely used. Indeed, PSNR has practical correlation with perceptual quality [6]. Two psychophysical experiments are conducted to collect perceived quality scores and perceived utility scores for a collection of test images corresponding to signal-based representations and visual-structure- preserving representations.

The results from these experiments provide evidence that any QA algorithm optimized to predict perceived quality scores cannot immediately predict perceived utility scores [7].

By contrast, designing objective No-Reference (NR) quality measurement algorithms is a very difficult task. This is mainly due to the limited understanding of the HVS, and it is believed that effective NR quality assessment is feasible only when the prior knowledge about the image distortion types is available [8].

II. METHODOLOGY

Step1:

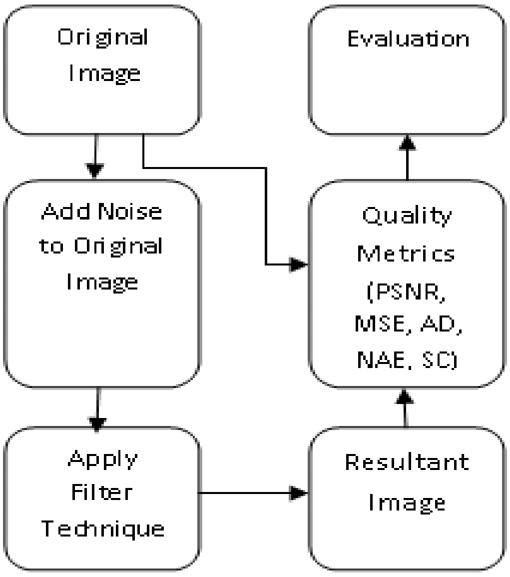

Figure 1: Process of efficiency verification for a given method of image filtering.

As a first step, a trial image (or a set of test images) presenting *good* value is selected. Then, according to the selected model of noise or distortion, a noisy version of the picture (images) is obtained and processed by a planned filter. The obtained output image is”compared” to the matching original image using measured quality metric. A value of the same metric is calculated for the noisy (distorted) image as well. By comparing the scores of these metrics it is possible to address the effectiveness of the designed filtering technique.

Step2:

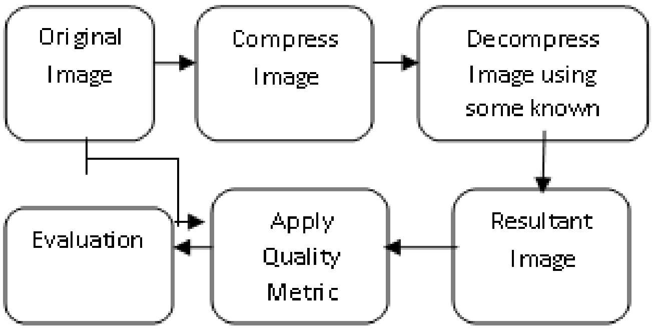

Figure 2: Process of efficiency verification for a given lossy compression technique.

In second step, a quality metric can be used both in the design of the compression block and in the overall performances evaluation. In the concluding case, a metric value calculated for a decoded image can be used in the tuning phase of the parameters in the coarse-to-fine compression schemes. Then if, for example, an obtained value of quality metric is unsuitable, an image can be compressed with better quality with smaller quantization step or, equivalently, with larger bit rate.

Step3:

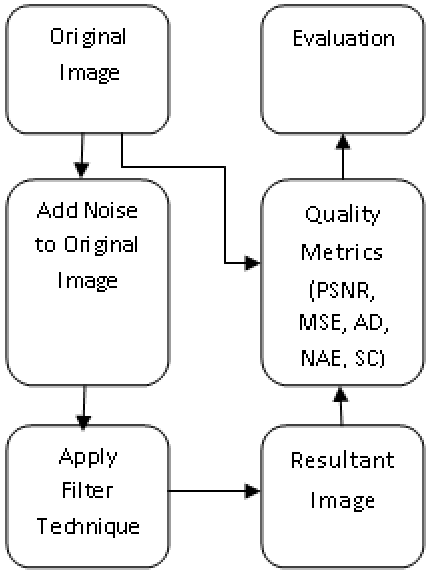

Figure 3: Process of calculating the sharp (blur) edge in original image, without referring the original image.

In third step, we identified and measured the sharpness found in image edges. Detection is achieved via mean and ratio of blurring present in the image edges. Sharpness of edges is estimated by difference between the intensity of current pixel and average of neighbor pixels. The difference is then normalized by the average. If the intensity of center pixel is closer to the average intensity of both side pixels, the center pixel is supposed to be on blurred edge.

Digital image processing techniques involves a variety of methods such as image filtering, reconstruction, inpainting, etc. For this class, image visual quality metrics are used only in the process of a method design and estimation of its efficiency.

A. Quality Assessment Parameters (QAP):

a. Mean Square Error (MSE):

MSE measures the average of the square of the "error." The error is the amount by which the estimator differs from the quantity to be estimated. The difference occurs because of randomness or because the estimator doesn't account for information that could produce a more accurate estimate.

$$MSE = \frac{1}{MN}\sum_{j=1}^{M}\sum_{k=1}^{N}\left(x_{j,k} - x'_{j,k}\right)^2$$

b. Peak Signal to Noise Ratio (PSNR):

The phrase **peak signal-to-noise ratio**, often abbreviated **PSNR**, is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation.

$$PSNR = 10\log\frac{(2^n-1)^2}{MSE} = 10\log\frac{255^2}{MSE}$$

c. Structural Content (SC):

The loss in perceived image quality is often determined by the nature and level of an artifact along with the context in which it appears. For example, in a highly structured image containing lines and edges, sharpness will likely be the most critical attribute in ranking image quality; where as, low-frequency uniformity may have little impact on the quality decision

$$SC = \sum_{j=1}^{M} \sum_{k=1}^{N} x_{j,k}{}^2 \Big/ \sum_{j=1}^{M} \sum_{k=1}^{N} x'_{j,k}{}^2$$

d. Sharpness:

Sharpness is calculated through mean and ratio of blurring present in the image edges.

$$Blur_{mean} = \frac{Sum_{blur}}{Blur_{cnt}}, \qquad Blur_{ratio} = \frac{Blur_{cnt}}{Edge_{cnt}}$$

And the proposed metric is then estimated via:

$$1 - (w_1 Blur_{mean} + w_2 Blur_{ratio})$$

III. RESULT ANALYSIS

(a) Original Image

(b) Distorted_1

(c) Distorted_2

(d) Distorted_3

(e) Distorted_4

Figure 4: Comparing with Motion Blurred Image

Table: 1

Parameters	MSE	PSNR	SC	Sharpness
Original	0	99	1	9.3456
Distorted_1	152.329	26.303	0.9912	3.5698
Distorted_2	126.621	27.105	0.9871	6.8765
Distorted_3	132.861	26.898	0.9613	2.0621
Distorted_4	105.861	27.883	0.9740	1.9508

(a) Original Image

(b) Distorted_1

(c) Distorted_2

(d) Distorted_3

(e) Distorted_4

Figure 5: Comparing with Distorted Image

Table: 2

Parameters	MSE	PSNR	SC	Sharpness
Original	0	99	1	8.3267
Distorted_1	1006.6	18.10	0.80	7.0986
Distorted_2	2221.5	24.67	0.97	6.6675
Distorted_3	1221.1	17.26	0.70	4.6732
Distorted_4	8998.1	8.58	369.8	1.8820

(a) Original Image

(b) Distorted_1 (c) Distorted_2

(d) Distorted_3 (e) Distorted_4

Figure 6: Comparing with Highly Distorted Image

Table: 3

Parameters	MSE	PSNR	SC	Sharpness
Original	0	99	1	8.8943
Distorted_1	212.5	83.675	0.65	8.0012
Distorted_2	816.5	54.987	0.87	7.0952
Distorted_3	4451.1	23.568	228.8	3.2341
Distorted_4	9328.1	7.652	418.6	1.0938

IV. CONCLUSION

The results show large sensitivity variations among the different methods. Most of the algorithms implemented here have been extended to evaluate the quality of images. The Peak Signal Noise Ratio (PSNR) is higher since in HSV color space there is normalization of pixel values so Mean Square Error (MSE) is very small, so little chance for comparison. It is clearly observed that the Structural Content (SC) is considerably enhanced, but still PSNR is beneficial for getting better quality when dealing with compressed images.

The main contribution of this thesis is the development of a NR objective quality assessment metric, which can be used not only for blind image quality assessment but also for real time disparity estimation. Two major artifacts in compressed images, blockiness and blur are addressed in this thesis and the test results of my proposed method illustrate the sufficient consistency with human visual perception.

V. FUTURE SCOPE OF THE WORK

In future, this approach can be applied for any other coded images irrespective of image artifacts or compression techniques. The improved approach may also include color information which may lead to better quality prediction accuracy.

In the next step, 3D video quality assessment is possible by incorporation of the temporal dependency between adjacent images (frames) of the video.

VI. REFERENCES

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