Evauation of Image Quality Assessment by Decoupling Detail Losses and Regression Techniques

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***Abstract*— Image quality assessment plays a fundamental role in Image processing and communication applications. In my work, two types of spatial distortions, i.e., detail losses and additive impairments, are decoupled and evaluated separately for spatial quality assessment. The detail losses refer to the loss of useful visual information that will affect the content visibility caused by data compression and so on. To assess the performance of image quality metrics (IQMs), some regressions, such as logistic regression and polynomial regression, areused to correlate objective ratings with subjective scores. However, some defects in optimality are shown in these regressions. In this correspondence, monotonic regression (MR) is found to be an effective correlation method in the performance assessment of IQMs. The experimental results have proven that MR performs better than any other regression.**

***Index Terms*—Correlation, Image Quality Metrics(IQM), Monotonic Regression(MR),objective ratings.**

I. Introduction

Image processing is one of the emerging areas of science and technology. The two principal application areas that stems from digital image processing methods are improvement of pictorial information for human interpretation and processing of image for storage, transmission and representation for autonomous machine perception.

An image may be defined as a two dimensional function $f(x, y)$ where x and y are spatial coordinates, and the amplitude of f at any pair of coordinates (x, y) is called the intensity or gray level of the image at that point. When x, y, and the intensity values of f are all finite, discrete quantities, we call the image a digital image. The field of digital image processing refers to processing digital images by means of a digital computer. A digital image is composed of a finite number of elements, each of which has a particular location and value. These elements are called picture elements or pixels. Image processing is a discipline in which both the input and output of a process are images. A digital image is represented by a matrix of values, where each value is a function of the information surrounding the corresponding point in the image. A single element in an image matrix is a picture element or pixel. In a colour system, a pixel includes information for all colour components.

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Image digitization refers to the process whereby an apparently continuous analog image is recorded as discrete intensity values at equally spaced locations on an*xy*-grid over the image field. This grid is called a raster. Typically the image area is divided into an array of rows and columns in much the same way as a television image. In North and South America and Japan, the television image is composed of 483 lines covering a rectangular area having proportions that are 3 units high by 4 units wide. If each line in such an image is divided into about 640 equal picture elements or pixels, then each pixel will be square if you discard three lines and record a raster of 640 x 480 pixels.

Digital images are composed of pixels(short for picture elements). Each pixel represents the colour (or gray level for black and white photos) at a single point in the image, so a pixel is like a tiny dot of a particular colour. By measuring the colour of an image at a large number of points, we can create a digital approximation of the image from which a copy of the original can be reconstructed. Pixels are a little like grain particles in a conventional photographic image, but arranged in a regular pattern of rows and columns and store information somewhat differently. A digital image is a rectangular array of pixels sometimes called a bitmap.

The process of getting an image to look the same between two or more different media or devices is called colour management and there are many different colour management systems available today. Unfortunately, most are complex, expensive, and not available for a full range of devices. The hue of a colour identifies what is commonly called “colour”. For example, all redshave a similar hue value whether they are light, dark, intense, or pastel.

II. IMAGE QUALITY ASSESSMENT

The need to measure image quality arises in the development of image equipment and in the delivery and storage of image information. The principles presented can be applied to other types of motion video and even still images. The methods of image quality assessment can be divided into two main categories: subjective assessment (which uses human viewers) and objective assessment (which is accomplished by use of electrical measurements). While we believe that assessment of image quality is best accomplished by the human visual system, it is useful to have objective methods available which are repeatable, can be standardized, and can be performed quickly and easily with portable equipment. These objective methods should give results that correlate closely with results obtained through human perception.

After some investigation of compressed image, it becomes clear that the perceived quality of the image after passing through a given digital compression system is often a function of the input scene. This is particularly true for low bit-rate systems. A scene with little motion and limited spatial detail (such as a head and shoulders shot of a newscaster) may be compressed to 384 Kbits/sec and decompressed with relatively little distortion. Another scene (such as a football game) which contains a large amount of motion as well as spatial detail will appear quite distorted at the same bit rate. Therefore, we directed our efforts toward developing perception-based objective measurements which are extracted from the actual sampled image. These objective measurements quantify the perceivedspatial and temporal distortions in a way that correlates as closely as possible with the response of a human visual system. Each scene was digitized (at 4 times sub-carrier frequency) to producea time sequence of images sampled at 30 frames per second (in time) and 756 x 486 pixels (in space).

Objective measurement of video quality was accomplished in the past through the use of static video test scenes such as resolution charts, colour bars, multi-burst patterns, etc., and by measuring the signal to noise ratio of the video signal These objective methods address the spatial and colour aspects of the video imagery as well as overall signal distortions present in traditional analog systems. With the development of digital compression technology, a large number of new video services have become available. The savings in transmission and/or storage bandwidth made possible with digital compression technology depends upon the amount of information present in the original (uncompressed) video signal, as well as how much quality the user is willing to sacrifice.

Compression is achieved through the use of a codec: a compression –decompression algorithm that looks for redundancy in data files. For example, XXXYYYY could be reduced to 3X4Y. In this example, the compression is considered “lossless” because the file can be decompressed and restored to the original format without any loss of data. Video compression, however, is considered “lossy” because it results in a loss of data. When compressing video, codec’s look for redundancy in areas where the human eye or ear cannot distinguish between differences. Since the human eye is less sensitive to colour differences than to brightness, the colour information (chrominance) is separated from the brightness information (luminance). The codec then averages the chrominance data for adjacent pixels, which reduces the volume of data. The luminance data is not changed. Normally, individuals cannot perceive the differences caused by the lossy compression. However, when the image is enlarged, the data loss is obvious, and it will look blocky.

III. PERFORMANCE OF IQA ALGORITHMS

The performance of several publicly available objective IQA models was evaluated on our database. Many popular IQA algorithms are licensed and sold for profit and are not freely available.

Peak Signal to Noise Ratio is a simple function of the Mean Squared Error between the reference and test videos and provides a baseline for objective IQA algorithm performance.

Structural Similarity is a popular method for quality assessment of still images that was extended to video. The SSIM index was applied frame-by-frame on the luminance component of the video and the overall SSIM index for the video was computed as the average of the frame level quality scores. Mat lab and Lab view implementations of SSIM are freely available for download.

Multi-Scale SSIMis an extension of the SSIM paradigm, also proposed for still images that have been shown to outperform the SSIM index and many other still image quality assessment algorithms. We extended the MS-SSIM index to video by applying it frame-by-frame on the luminance component of the video and the overall MS-SSIM index for the video was computed as the average of the frame level quality scores. A Mat lab implementation of MS-SSIM is freely available for download.

Speed SSIMis the name we give to the IQA that uses the SSIM index in conjunction with statistical models of visual speed perception. Using models of visual speed perception was shown to improve the performance of both PSNR and SSIM Weevaluated the performance of this framework with the SSIM index, which was shown to perform better than using the same framework with PSNR.A software implementation of this index was obtained from the authors.

Visual Signal to Noise Ratio *(VSNR)* is a quality assessment algorithm proposed for still image andis freely available for download. We applied VSNR frame-by-frame on the luminance component of the video and the overall VSNR index for the video was computed as the average of the frame level VSNR scores.

Image Quality Metric*(IQM)* is an IQA algorithm developed at the National Telecommunications and Information Administration (NTIA). Due to its excellent performance in the VQEG Phase 2 validation tests, and as the IQM methods were adopted by the American National Standards Institute (ANSI) as a national standard, International Telecommunications Union RecommendationsIQM are freely available for download for research purposes.

IV. REGRESSION TECHNIQUES

To assess the performance of image quality metrics (IQMs), aScheme first proposed by Video Quality Expert

Group (VQEG) is widely adopted by researchers. The scheme is designed for theobjective measurement evaluation problem and can be applied for the assessment of image/video quality metric. It can be described by the following three steps:

Step 1. Metric computation

Rate a set of images by IQM, while mean opinion scores (MOSs)of these images are measured by human observers beforehand.

Step 2. Correlation (or regression)

Correlate the outputs of IQM with MOS via a predicting function(this process can be also called regression). Then, the predictedMOS is obtained by calculating the IQM ratings through the regressionfunction.

Step 3. Index computation

Compute the performance indexes between the MOS and the predicted

In this scheme, most of the research effort is devoted to step 1 inwhich the images are produced. The images are judged by human observersand rated to produce the MOS data. The IQMs are defined, implemented,and applied to the images. However, steps 2 and 3 havereceived less attention and could be improved. In particular, in step 2,a single standard optimal regression procedure has not been adopted and as a consequence, in step 3, the output index measure is not unique.This correspondence proposes a regression procedure that is optimaland produces a unique and maximum index measure.

As examples of the several regression procedures in use for the IQM research, VQEG recommended some nonlinear regressions for correlation, such as logistic regression (LR) and monotonic polynomial regression (MPR). Some other researchers also proposed their ownregression functions based on these. However, no matter which kind ofregression function is applied in step 2, they all face the same problems, i.e., regression is not optimal, whereas some regressions have a large computational burden. Moreover, the nonoptimal regression causes the problem that performance indexes may vary when only the regression function changes.

In this correspondence, we focus on step 2 (correlation or regression process) in the performance assessment of the IQM. As a result, we find monotonic regression (MR) to be an improvement for step 2, which is the correlation process. This correspondence is detailed as follows:

This section briefly discusses the principle of the correlation method with which VQEG is concerned and gives a detail introduction of the LR and the MPR. The experimental results and the advantages are discussed below, whereas the three commonly used correlation methods (LR, MPR, and MR) are tested on a certain database for comparison.In order to make ourpaper easier to understand, some additional materials are given in theappendixes.

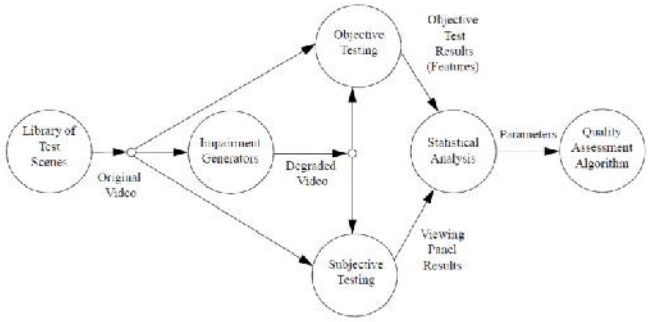

*Fig 1.*Development Process for Image Quality Assessment Algorithm

This stage of the development process utilized joint statistical analysis of the subjective and objective data sets. This step identifies a subset of the candidate objective measurements that provides useful and unique video quality information. The best measurement was selected by exhaustive search. Additional measurements were selected to reduce the remaining objective- subjective error by the largest amount. Selected measurements complement each other. For instance, a temporal distortion measure was selected to reduce the objective-subjective error remaining from a previous selection of a spatial distortion measure. When combined in a simple linear model, this subset of measurements provides predicted scores that correlate well with the true.

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Fig 2. Input image

The input image is shown above. We can add any type of noise parameters to the given input image and get various types of results. By adding some parameters like Blur, Gaussiannoise, jpeg we getting the result as distorted images is to be shown below. The results are

Fig 3. Jpeg compression

V. SIMULATION RESULTS

By demonstration the superiority of Monotonic Regression using actual data, the Correlation Coefficient of several representative Image Quality Metrics are computed on CSIQ Image Quality Assessment Database by Logistic Regression, Monotonic Polynomial Regression, and Monotonic Regression Usually, metric rating is directly regressed with MOS in correlation, but for some metric, such asSSIM. The predictive performance computed by Monotonic Regression is the highest.

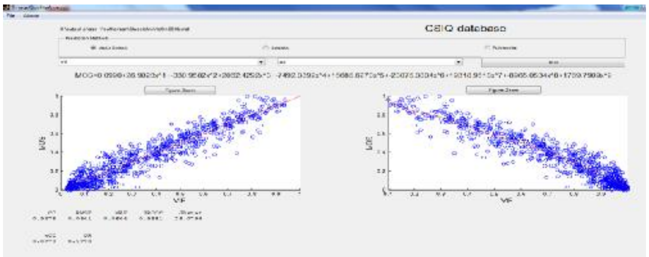

Fig 4. Output for Visual Information fidelity

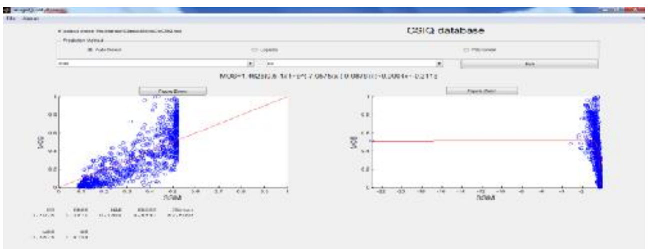

Fig 5. Output for Structural Similarity

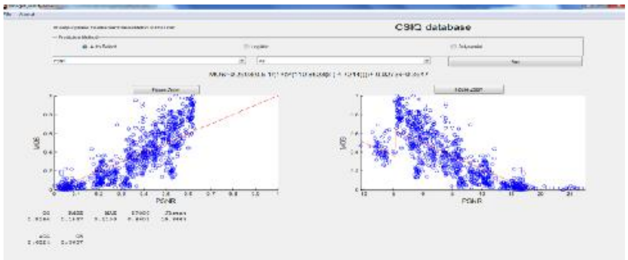

Fig 6. Output for Peak Signal Noise Ratio

Table 1 comparison of IQM parameters for Monotonic Regression

parameters	CC	RMSE	MAE	WCC
PSNR	0.816	0.154	0.119	0.682
SSIM	0.807	0.167	0.134	0.687
VSNR	0.806	0.163	0.124	0.697
VIF	0.947	0.084	0.064	0.877

VI. RESULTS AND DISCUSSION

To demonstrate the theoretical superiority of MR using actual data, the CC of several representative IQMs are computed on LIVE Image Quality Assessment Database (LIVE) by LR, MPR, and MR. Usually, metric rating is directly regressed with MOS in correlation, but for some metric, such as SSIM , VIF , the rating has to be transformed before correlation. The transform helps find a “better regression” by mapping ratings to a suitable space, as some metrics cannot exhibit real predictive performance under the common coordinate system. Here, better regression means that the metric will show higher predictive performance comparedwith others.

VIICONCLUSION

The quality metrics for image was successfully found out for different parameters like peak signal to noise ratio, correlation coefficient for various conditions like adding noise likeBlur, Gaussians noises. Thus the experimental superiority of Monotonic Regression using actual data, the Correlation Coefficient of several representative Image Quality Metrics are computed on Image Quality Assessment Database by Logistic Regression, Monotonic Polynomial Regression and Monotonic Regression. Usually, metric rating is directly regressed with Mean Opinion Scores in correlation, but for some metric, such as Structural Similarity. The predictive performance computed by Monotonic Regression is the highest.

In this correspondence, I have studied correlation methods in the Image Quality Metrics performance assessment and proved Monotonic Regression as an effective way of Mean Opinion Scores correlation. The experimental results have confirmed that Monotonic Regression is more appropriate and suitable than conventional methods. I believe Monotonic Regression might substitute other correlation methods in the Image Quality Metrics performance assessment in the future.

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