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DESIGN AND PERFORMANCE EVALUATION OF IMAGE QUALITY ASSESMENT USING MODIFIED SPECTRAL RESIDUAL SIMILARITY

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Abstract: *Image Quality Assessment (IQA) has become a subject of intense research interest in the recent years. The demand for accurate, consistent, computationally simple and easy-to-use quality assessment tools that can be used to measure, control, and improve the perceptual quality of images and video is increasing day by day. Applications of IQA include machine vision, medical imaging, multimedia communication, entertainment and other image processing activities. Systems embedded with IQA algorithms can replace humans for evaluating image quality in real-time applications and hard-to-reach environments. In the past decades, dozens of IQA models have been proposed. Though some of them can predict subjective image quality accurately, their computational costs are usually very high. In this wok a modified method is proposed which is based on Spectral Residual Similarity method. This method is basically based on specific visual saliency model, spectral residual visual saliency because an image's visual saliency map is closely related to its perceived quality. The concept of LUMA coefficient is introduced in existing method. By converting the RGB image into LUMA coefficient, accuracy of brightness can be improved. Also, it suppresses the noise level in input image. We have also used an average filter in early stage to* smoothen the *image*, i.e. *to reduce the amount of intensity variation between one pixel and the next. So, the proposed method calculates the Image Quality Assessment (IQA) Index. Along with SR-Similarity, We have also calculated 7 more parameters, so as to accomplish IQA i.e. Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR), Normalized Cross-Correlation, Average Difference, Structural Content, Maximum difference and Absolute error. MATLAB R2013a is used as an implementation platform using Image processing tool box and General MATLAB tool box.*

Keywords: *Image quality, objective measures, peak signal-to-noise ratio (PSNR), singular value decomposition (SVD), subjective evaluation etc.*

1. INTRODUCTION

1.1 QUALITY

A general definition of quality, regardless of field, is that quality is the conformance to requirements. This definition is general, and has been adapted by many authors. Related definitions are given by the International Organization for Standardization (ISO), who defines quality as the totality of distinctiveness of an entity that bear on its ability to satisfy stated or implied needs [7] or as the ability of a set of inherent uniqueness of a product, system or process to fulfill necessities of customers and other interested parties. All of these definitions relate quality to some sort of requirements.

1.2 IMAGE QUALITY (IQ)

The concept of image quality can be approached by first defining good quality. Good quality has always two sides: subjective opinions and an image itself. Subjective opinions are affected by complex physical and psychological parameters, while image goodness is simpler to define. For a good quality image, properties like optimal photography, technical excellence, and natural color reproduction are required. Furthermore, when assessing many images at the same time, the balanced and equal output of the images is essential for good quality experience [8].

1.3 SUBJECTIVE AND OBJECTIVE QUALITY

Fundamentally, image quality is always an outcome from human sensation. Human observers make the final decisions about quality based on their own visual preferences that, naturally, are not only affected by the psychophysical aspects of the observer, but also by e.g. the fidelity of the image and the observation situation. For evaluating image quality, testing with human observers, i.e. subjective evaluation is often considered the most reliable way to estimate the quality of images. From subjective evaluation measures, the mean opinion score (MOS) is the most widely used. Another option for quality evaluation, objective assessment, relies on computational models that can predict the image quality observations of humans [4]. An accurate objective image quality model predicts the image quality sensation of an average human observer. In other words, strong correlations to subjective observations are essential when defining a good objective quality model. Since image quality is strongly based on subjective observations, traditional objective models such as the mean-squared-error (MSE) rarely work accurately on a quality context. A good objective model may, for instance, exploit the knowledge of human visual system (HVS) in calculations. Objective quality assessment usually takes one of three forms [6]: full reference (FR-QA), reduced reference (RR-QA), and no reference (NR-QA) [9]. An ideal image quality measure should be able to describe [1], [3]

(1) The amount of distortion
(2) The type of distortion
(3) The distribution of error.

1.4 APPLICATIONS

Measuring the image quality is of fundamental importance for numerous image processing applications, where the goal of image quality assessment (IQA) methods is to automatically evaluate the quality of images in agreement with human quality judgments. The goal of objective IQA is

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to design mathematical models that are able to predict the quality of an image accurately and also automatically. An ideal objective IQA method should be able to mimic the quality predictions of an average human observer. Objective IQA methods have a wide variety of applications:

1. They can be used to monitor image quality in quality control systems.
2. They can be used to benchmark image processing algorithms.
3. They can be used to optimize image processing and transmission systems.

With the rapid proliferation of digital imaging and communication technologies, image quality assessment (IQA) has been becoming an important issue in numerous applications such as image acquisition, transmission, compression, restoration and enhancement, etc. Since the subjective IQA methods cannot be readily and routinely used for many scenarios, e.g. real-time and automated systems, it is necessary to develop objective IQA metrics to automatically and robustly measure the image quality.

2. PROPOSED METHODOLOGY

2.1 SPECTRAL RESIDUAL VISUAL SALIENCY

In *Spectral residual visual saliency* (SRVS) the spectral residual is obtained at first from the log spectrum of the examined image. And then, the VS (Visual Saliency) map is obtained by transforming the spectral residual to the spatial domain. Spectral residual actually approximately represents the innovation part of an image by removing the statistical redundant components [5].

Suppose f is the examined image. SRVS can be computed as the following:

$$M(u, v) = abs(F\{ f(x, y)\}(u, v)) \quad (1)$$

$$A(u, v) = angle(F\{ f(x, y)\}(u, v)) \quad (2)$$

$$L(u, v) = \log(M(u, v)) \quad (3)$$

$$R(u, v) = L(u, v) - h(u, v) * L(u, v) \quad (4)$$

$$SRVS(x, y) = g(x, y) * (F^{-1}\{ \exp(R + jA)\}(x, y))^2 \quad (5)$$

In the above equations, $F(F^{-1})$ denotes the Fourier (inverse Fourier) transform, $abs(\cdot)$ returns the magnitude of a complex number, $angle(\cdot)$ returns the argument of a complex number, $hn(u, v)$ is an $n*n$ mean filter, $g(x, y)$ is a Gaussian function, and $*$ represents the convolution.

2.2 SR-SIM: Spectral residual based similarity

Since bottom-up VS models are basically based on image's low level features, VS values themselves actually vary with the change of the image quality. Therefore, in SR-SIM, we propose to use SRVS map as a feature to compute the local similarity map between the reference image and the distorted image. However, SRVS value at a pixel actually is a measure reflecting its relative distinctiveness to its surroundings. Thus, it is weak to characterize image's absolute local contrast. Hence, we need to use an additional feature to compensate for the lack of contrast sensitivity of SRVS. The simplest feature of this kind may be the gradient modulus (GM). With Scharr gradient operator, partial derivatives $Gx(\mathbf{x})$ and $Gy(\mathbf{x})$ of an image $f(\mathbf{x})$ are calculated as:

$$G_x(\mathbf{x}) = \frac{1}{16}\begin{bmatrix} 3 & 0 & -3 \\ 10 & 0 & -10 \\ 3 & 0 & -3 \end{bmatrix} * f(\mathbf{x})$$

$$G_y(\mathbf{x}) = \frac{1}{16}\begin{bmatrix} 3 & 10 & 3 \\ 0 & 0 & 0 \\ -3 & -10 & -3 \end{bmatrix} * f(\mathbf{x}) \quad (6)$$

The GM of $f(\mathbf{x})$ is then defined as G(x) = $G(\mathbf{x}) = \sqrt{G_x^2(\mathbf{x}) + G_y^2(\mathbf{x})}$.

VS and GM are complementary and they reflect different aspects of the HVS in assessing the local quality of the input image. Suppose that we are going to calculate the similarity between images $f1$ and $f2$. Denote by $R1$ and $R2$ the SRVS maps extracted from images $f1$ and $f2$ using the SRVS model, and by $G1$ and $G2$ the GM maps extracted from $f1$ and $f2$. Similar to other IQA indices, the computation of SR-SIM consists of two stages. In the first stage, the local similarity map is computed, and in the second stage, we pool the similarity map into a single quality score. We separate the SR-SIM measurement between $f1(\mathbf{x})$ and $f2(\mathbf{x})$ into two components, each for SRVS and GM.

First, the similarity between $R1(\mathbf{x})$ and $R2(\mathbf{x})$ is defined as:

$$S_V(\mathbf{x}) = \frac{2R_1(\mathbf{x}) \cdot R_2(\mathbf{x}) + C_1}{R_1^2(\mathbf{x}) + R_2^2(\mathbf{x}) + C_1} \quad (7)$$

where $C1$ is a positive constant to increase the stability of SV.

Similarly, the GM values $G1(\mathbf{x})$ and $G2(\mathbf{x})$ are compared as:

$$S_G(\mathbf{x}) = \frac{2G_1(\mathbf{x}) \cdot G_2(\mathbf{x}) + C_2}{G_1^2(\mathbf{x}) + G_2^2(\mathbf{x}) + C_2} \quad (8)$$

where $C2$ is another positive constant. Then, $SV(\mathbf{x})$ and $SG(\mathbf{x})$ are combined to get the local similarity $S(\mathbf{x})$ of $f1(\mathbf{x})$ and $f2(\mathbf{x})$.

We define $S(\mathbf{x})$ as follows:

$$S(\mathbf{x}) = S_V(\mathbf{x}) \cdot [S_G(\mathbf{x})]^\alpha \quad (9)$$

where α is a constant used to adjust the relative importance of VS and GM features.

Having obtained the local similarity $S(\mathbf{x})$ at each location $\mathbf{x}$, the overall similarity between $f1$ and $f2$ can be calculated. It has been widely accepted that a good quality score pooling strategy should correlate well with human visual fixation. In our case, it is natural to use SRVS map to characterize the visual importance of a local region. Intuitively, for a given position $\mathbf{x}$, if anyone of $f1(\mathbf{x})$ and $f2(\mathbf{x})$ has a high SRVS value, it implies that this position $\mathbf{x}$ will have a high impact on HVS when evaluating the similarity between $f1$ and $f2$. Therefore, we use $Rm(\mathbf{x}) = \max(R1(\mathbf{x}), R2(\mathbf{x}))$ to weight the importance of $S(\mathbf{x})$ in the overall similarity. Thus, the SR-SIM between $f1$ and $f2$ is defined as:

$$\text{SR-SIM} = \frac{\sum_{\mathbf{x}\in\Omega} S(\mathbf{x}) \cdot R_m(\mathbf{x})}{\sum_{\mathbf{x}\in\Omega} R_m(\mathbf{x})} \quad (10)$$

where Ω means the whole image spatial domain.

2.3 Implementation of proposed method

1. Inputting and reading of original clear image.
2. Inputting and reading of distorted image.
3. Calculation of size of original image.
4. Calculation of Luma of color RGB image.

5. Determination of minimum dimension of Luma component matrix.
6. Computation of a factor to reduce the size of Luma component matrix.
   Factor=max(1, round (min Dimension/256));
7. Designing of an averaging filter according to factor.
8. Application of averaging filter on both modified image by computing the two-dimensional convolution of modified image and average filter.
9. Re-division of matrix of both images according to factor.
10. Calculation of the visual saliency maps for both images using the Spectral Residue method.

- Declaration of some input constant parameters.

A. Factor for scaling of image.
B. Size of average filter.
C. Standard deviation for Gaussian filter
D. Size of Gaussian filter.
E. Resizing of image according to scaling factor.

- Application of Spectral Residual for original modified image
- Application of two-dimensional discrete Fourier transform (DFT) on input image.
- Calculation of magnitude of each element of transformed image.
- Calculation of phase angle of transformed image.
- Designing of an average filter according to given size and then application of average filter on magnitude matrix.
- Getting of residual spectral image by subtraction of filtered image from magnitude image.
- Mixing of residual image and phase angle so as to reconstruct original image.
- Getting of saliency map of original image by application of two-dimensional inverse Discrete Fourier Transform (DFT) on mixed matrix.
- Display of saliency map of original image.

11. Post Processing for original modified image

- Designing of Gaussian low-pass filter of given size with given standard deviation.
- Application of Gaussian filters on saliency map of original image.
- Conversion of saliency map of original image matrix to the intensity image.
- Resizing of intensity image according to size of original image.
- Resizing of image according to scaling factor.

12. Application of Spectral residual for distorted modified image

- Application of two-dimensional discrete Fourier transform (DFT) on input image.
- Calculation of magnitude of each element of transformed image.
- Calculation of phase angle of transformed image.
- Designing of an average filter according to given size and then application of average filter on magnitude matrix.
- Getting of residual spectral image by subtraction of filtered image from magnitude image.
- Mixing of residual image and phase angle so as to reconstruct original image.
- Getting of saliency map of original image by application of two-dimensional inverse discrete Fourier transform (DFT) on mixed matrix.

13. Post Processing for distorted modified image

- Designing of Gaussian low-pass filter of given size with given standard deviation.
- Application of Gaussian filters on saliency map of original image.
- Conversion of saliency map of original image matrix to the intensity image.
- Resizing of intensity image according to size of original image.

14. Calculation of the Gradient map

- Declaration of x-gradient matrix.
- Declaration of y-gradient matrix.
- Calculation of x direction partial Derivative of original modified by convolution of x-gradient matrix with contrast modified image.
- Calculation of y direction partial derivative of original modified by convolution of y-gradient matrix with contrast modified image.

$$G_x(\mathbf{x}) = \frac{1}{16}\begin{bmatrix} 3 & 0 & -3 \\ 10 & 0 & -10 \\ 3 & 0 & -3 \end{bmatrix} * f(\mathbf{x})$$

$$G_y(\mathbf{x}) = \frac{1}{16}\begin{bmatrix} 3 & 10 & 3 \\ 0 & 0 & 0 \\ -3 & -10 & -3 \end{bmatrix} * f(\mathbf{x})$$

- Getting of the gradient modulus or gradient map by mixing convoluted Gradient matrix.

$$G(\mathbf{x}) = \sqrt{G_x^2(\mathbf{x}) + G_y^2(\mathbf{x})}\ .$$

- Calculation of x direction partial derivative of distorted modified by convolution of x-gradient matrix with contrast modified distorted image.
- Calculation of y direction partial derivative of distorted modified by convolution of y-gradient matrix with contrast modified distorted image.
- Getting of the Gradient Modulus or gradient map by mixing convoluted gradient matrix.

$$G(\mathbf{x}) = \sqrt{G_x^2(\mathbf{x}) + G_y^2(\mathbf{x})}\ .$$

15. Calculate the Spectral Residual-Similarity index

- Declaration of a Positive constant to increase the stability.
- Declaration of a Positive constant to increase the stability.
- Constant used to adjust the relative importance.
- Calculation of similarity matrix between saliency Map of both images.

$$S_V(\mathbf{x}) = \frac{2R_1(\mathbf{x})\cdot R_2(\mathbf{x}) + C_1}{R_1^2(\mathbf{x}) + R_2^2(\mathbf{x}) + C_1}$$

16. Calculation of similarity matrix between gradient Maps of both images.

$$S_G(\mathbf{x}) = \frac{2G_1(\mathbf{x})\cdot G_2(\mathbf{x}) + C_2}{G_1^2(\mathbf{x}) + G_2^2(\mathbf{x}) + C_2}$$

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17. Computation of more importance weights by comparing both matrices.
18. Computation of local similarity by combining both matrices.

$$S(\mathbf{x}) = S_V(\mathbf{x}) \cdot [S_G(\mathbf{x})]^{\alpha}$$

19. Computation of final spectral residual similarity.

$$\text{SR-SIM} = \frac{\sum_{\mathbf{x}\in\Omega} S(\mathbf{x}) \cdot R_m(\mathbf{x})}{\sum_{\mathbf{x}\in\Omega} R_m(\mathbf{x})}$$

3. EXPERIMENTAL RESULTS

In this wok a modified method is proposed which is based on Spectral Residual Similarity method. This method is basically based on specific visual saliency model, spectral residual visual saliency because an image's visual saliency map is closely related to its perceived quality. The concept of LUMA coefficient is introduced in existing method. By converting the RGB image into Luma coefficient, accuracy of brightness can be improved. Also, it suppresses the noise level in input image. We have also used an average filter in early stage to *smoothen the* image, *i.e.* to reduce the amount of intensity variation between one pixel and the next. So, the proposed method calculates the Image Quality Assessment (IQA) Index. For implementation purpose, we have used image i.e. Tulip.jpg. Also, their distorted version are also taken for example Gaussian noise is added to the image i.e. Tulip.jpg. All of the above said images and their distorted version are shown in table1.

We have also calculated 7 more parameters, so as to accomplish IQA i.e. Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR), Normalized Cross-Correlation, Average Difference, Structural Content, Maximum difference and Absolute error. The value of each Index is given in Table 1 for Tulips.jpg image. MATLAB R2013a is used as an implementation platform using Image Processing Toolbox and General MATLAB Toolbox. Percentage improvement of SR Similarity (Proposed) for all the compressed version of all 3 test images has also been calculated and inserted in each table respectively. Also, comparison of 5 parameters i.e. SR Similarity (Proposed), SR Similarity, Normalized Correlation value, normalized absolute Error and Structural Content has been done using bar chart for all compressed version for Tulips.jpg images. These charts are given below from Figure 1 to Figure 5.

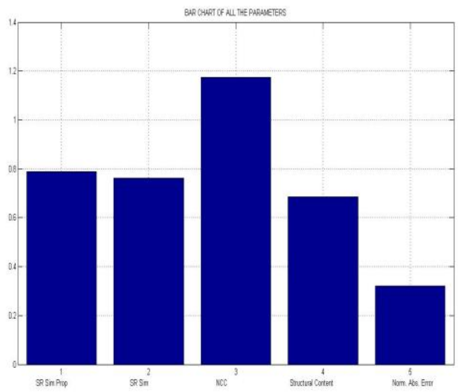

Figure 1: Comparison between various parameters for compressed image Tulip.jpg

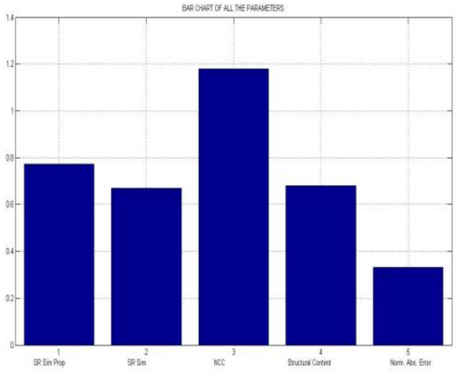

Figure 2: Comparisons between various parameters for compressed image Tulip.png

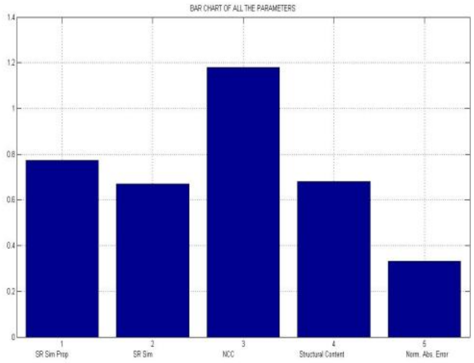

Figure 3: Comparisons between various parameters for compressed image Tulip.tif

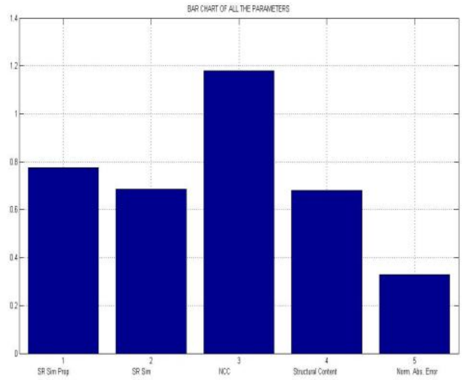

Figure 4: comparisons between various parameters for compressed image Tulip.jp2

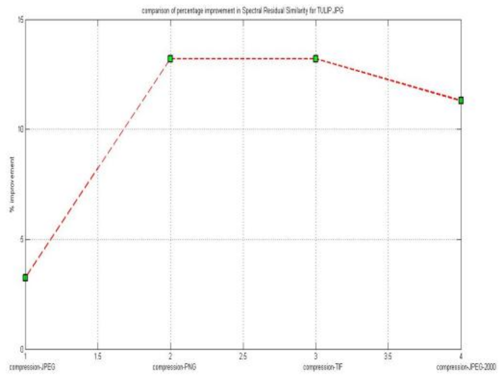

Figure 5: comparison of percentage improvement in Spectral Residual Similarity for Tulips.jpg

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Table 1: Different Index for Image Quality Assessment

Parameter	Tulip.jpg	Tulip.png	Tulip.tif	Tulip.jp2 (JPEG-2000)
	 	 	 	 
Spectral Residual Similarity (proposed)	0.7881	0.7728	0.7728	0.7740
Spectral Residual Similarity	0.7626	0.6707	0.6707	0.6865
% improvement in Spectral Residual Similarity	3.2356	13.2117	13.2117	11.3049
Mean Square Error	2.5213e+03	2.6389e+03	2.6389e+03	2.6344e+03
Peak Signal to Noise Ratio	14.1145	13.9166	13.9166	13.9240
Normalized Cross-Correlation	1.1750	1.1785	1.1785	1.1785
Average Difference	-15.0674	-15.2805	-15.2805	-15.2882
Structural Content	0.6855	0.6798	0.6798	0.6800
Maximum Difference	99.9510	101.6740	101.6740	101.4186
Normalized Absolute Error	0.3221	0.3303	0.3303	0.3300

4. CONCLUSION AND FUTURE SCOPE

With the study of previous chapters, it can be concluded that proposed method is efficient and effective method for IQA. Proposed method is based on a specific visual saliency model, spectral residual visual saliency. For deigning of proposed method it is assumed that visual saliency map of an image has a close relationship with its perceptual quality. Proposed method is very good substitute of Structural Similarity Index as it has very low complexity as compared to that of SSIM. Experimental results indicate that proposed method could yield statistically better prediction performance than all the other competing methods evaluated i.e. Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR), Normalized Cross-Correlation, Average Difference, Structural Content, Maximum difference and Absolute error. Thus, Modified Spectral Residual Similarity method can be the best candidate of IQA indices for real time applications. Also, the whole research work surveys the previous techniques for IQA in detail.

For further research, the proposed method could be more modified to find the similarity index for other type of multimedia files such as video, Audio and Text.

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