A Novel Technique of Spectral Image Quality Assessment Based on Structural Similarity Measure

Diana Kalenova, Dobromir Dochev, Vladimir Bochko, Pekka Toivanen, Arto Kaarna; Department of Information Technology, Lappeenranta University of Technology; Lappeenranta, Finland; Digital Media Institute, Tampere University of Technology; Seinäjoki, Finland*

Abstract

In this work, a novel technique of objective spectral image quality evaluation is presented. The method is based on a Structural Similarity technique. The traditional approach, which deals primarily with gray-scale images, is extended to incorporate spectral data. The novel method has previously been tested against the conventional two-dimensional technique and proven to be more effective. The performance of the three-dimensional Structural Similarity Index presented in this paper is tested along with the previously proposed kernel similarity metrics and a subjective technique - Perceptual Image Distortion Map. The tests show that the proposed three-dimensional Structural Similarity Index performance is comparable to the rest of the measures in the task of spectral distortion evaluation.

Introduction

Digital imaging nowadays is undergoing dramatic changes. Appearance of capturing, recording and display systems that are capable of working with spectral data creates a whole set of problems that exist for conventional imaging, e.g. image quality assessment and adjustment [1,2]. By image quality, in this case, we mean the measure of the perceived difference from a reference image [3].

In this paper, a novel technique of spectral image quality estimation is proposed. The main objective for creation of such measures is primarily lossy compression applications. A quality measure should be established with a possibility of computing the distortion value dynamically as the information is discarded from the image. This kind of metric should also be able to account for the characteristics of the human visual system. Other areas of application include, among others, electronic museums, archiving and printing industry applications.

Several approaches to spectral image distortion measurement exist at the moment [4,5,6]. The choice of the method depends primarily on the end-user of the imaging chain. In case of applications that require high accuracy, the most appropriate method of image quality evaluation is subjective assessment. However, such methods require significant time and money consumption, which gives rise to the appearance of multiple objective measures. Most of these have emerged from gray-scale image metrics: mean-squared error, signal to noise ratio, percentage maximum absolute distortion etc. Nevertheless, none of these measures account for the characteristics of the human visual system [7]. One of the most popular solutions existing at the moment is the CIE recommended 1976 CIELAB and CIELUV color difference formulae [8]. However, these show significant discrepancies with the judgments obtained using the subjective technique. In an attempt to improve the perceptual uniformity of the measures several metrics have been developed [3]: CMC [9], BFD [10, 11], CIE94 [12] and CIEDE2000 [13]. A Blockwise Distortion Measure for Multispectral images (BDMM) has been suggested in [5]. The measure computes a quality estimate that corresponds to the human evaluation; however, it deals with the artifacts in the spatial direction and does not account for the specific spectral distortions.

The algorithm, described in this paper, is an extension of a Structural Similarity Index (SSIM) [7] that incorporates spectral data [14]. SSIM is based upon an assumption that human visual system is highly adapted to extracting structural information from the images. SSIM compares local patterns of pixel intensities, assuming that luminance and contrast are normalized [7]. As a result a gray-scale spectral distortion map is obtained, which shows the areas where the visible distortions are in the image, and how large the distortions are. The three-dimensional SSIM has already been tested against the two-dimensional conventional measure. The novel method has proven to be more efficient in the task of color and spectral image discrimination [14].

Color Similarity Measures

One of the most popular color similarity metrics so far has been the Euclidean distance [8] and measures based upon it. These have an advantage of simplicity in understanding and realization, however such metrics are not optimal. Euclidean distance calculates the difference between colors not taking into account the angle between color vectors, which produces a significant divergence for RGB image reproduction [15].

An alternative set of color similarity metrics was proposed in [15]. These consist of a set of kernel similarity measures that include polynomial, Gaussian radial basis (RBF), and sigmoid metrics. It was shown in [15] that the measures provide an excellent fit to the response of the human visual system in the task of image quality assessment.

Kernels, in general, can be assumed to be dot products of vectors in a certain feature space, meaning that if we have two vectors $\boldsymbol{x}_i$ and $\boldsymbol{x}_j$ in the input domain X, we can produce a mapping [16]:

$$\begin{aligned} &\Phi : X - F \\ &x \mapsto x := \Phi(x) \end{aligned} \tag{1}$$

Polynomial kernel similarity measure can be presented as follows [12]:

$$S_{polynomial} = (x_i, x_j)^d \tag{2}$$

where d is a parameter of the sensitivity of the measure, $\boldsymbol{x}_i$ and $\boldsymbol{x}_j$ are input color vectors.

The Gaussian RBF kernel has the following form [16]:

$$S_{Gaussian} = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right) \tag{3}$$

where $\sigma>0$, σ is the parameter of the sensitivity of the function.

And the sigmoid kernel based similarity can be presented as follows [16]:

$$S_{sigmoid} = \tanh(k * (x_i, x_j) + \vartheta) \quad (4)$$

where k and ϑ are variable sensitivity parameters.

In order to account for the characteristics of the human visual system the input data is multiplied by Spectral Luminous Efficiency Function for photopic vision [17] and illumination factor [18].

Structural Similarity Index

SSIM is based on an idea that the human visual system is highly adapted to extracting structural information from the images, which, in turn, can be defined as the attributes representing the structure of the objects in the scene, independent of the luminance and contrast [7]. SSIM is an objective measure of difference between a reference image (sometimes called original) and a modified image, and thus can be considered a quality metric of the second (processed) image.

Two-dimensional SSIM

Thus, given two spectral images, represented as vectors $\mathbf{x}_i$ and $\mathbf{x}_j$, as inputs, SSIM produces an output on a 0 to 1 scale, where 0 means that the images are "not similar at all" and 1 means "identical" [4]. The overall index is constituted of three parts: luminance, contrast and structure comparison, all three being relatively independent [7].

The overall measure is defined as follows [7]:

$$SSIM(x_i, x_j) = [l(x_i, x_j)]^{\alpha} \cdot [c(x_i, x_j)]^{\beta} \cdot [s(x_i, x_j)]^{\gamma} \quad (5)$$

where α, β, γ are non-negative parameters, used to adjust the importance of each of the components [6].

Luminance component $l(\mathbf{x}_i,\mathbf{x}_j)$ is estimated as [7]:

$$l(x_i, x_j) = \frac{2\mu_{x_i}\mu_{x_j} + C_1}{\mu_{x_i}^2 + \mu_{x_j}^2 + C_1} \quad (6)$$

where C_1 is a constant that is included to avoid instability when the sum of the squares of means is approximately zero and μ is the mean of the image [7].

Contrast component $c(\mathbf{x}_i,\mathbf{x}_j)$ is given as [7]:

$$c(x_i, x_j) = \frac{2c_{x_i}c_{x_j} + C_2}{\sigma_{x_i}^2 + \sigma_{x_j}^2 + C_2} \quad (7)$$

where C_2 is a constant and σ is the variance of the image [7].

The structure comparison component $s(\mathbf{x}_i,\mathbf{x}_j)$ is defined as follows [7]:

$$s(\mathbf{x_i}, \mathbf{x_j}) = \frac{c_{x_i x_j} + C_3}{\sigma_{x_i}\sigma_{x_j} + C_3} \quad (8)$$

where C_3 is a small constant given to avoid instability and σ_{xixj} is the covariance of $\mathbf{x}_i$ and $\mathbf{x}_j$.

Constants C_1, C_2 and C_3 can be computed as [7]:

$$C_1=(K_1L)^2;\ C_2=(K_2L)^2;\ C_3=C_2/2 \quad (9)$$

where L is the dynamic range of pixel values and $K_1<<1$, $K_2<<1$ are two scalar constants.

SSIM can be applied in a pointwise manner, but it is better to use the Gaussian weighting function $\mathbf{w} = \{\omega_i | i = 1,2,\ldots,N\}$, normalized to unit sum ($\sum\omega_i = 1$), as the windowing approach. The local statistics are then computed using the weights $\boldsymbol{w}$ [7]. And the overall SSIM image quality measure is computed by averaging all of the local windows in the image. This is done due to a number of reasons. For one thing image statistics are on the most part highly spatially non-stationary, the same can be assumed of the distortions introduced into the image. Moreover, localized measures provide more information about the quality degradation [7].

Three-dimensional SSIM

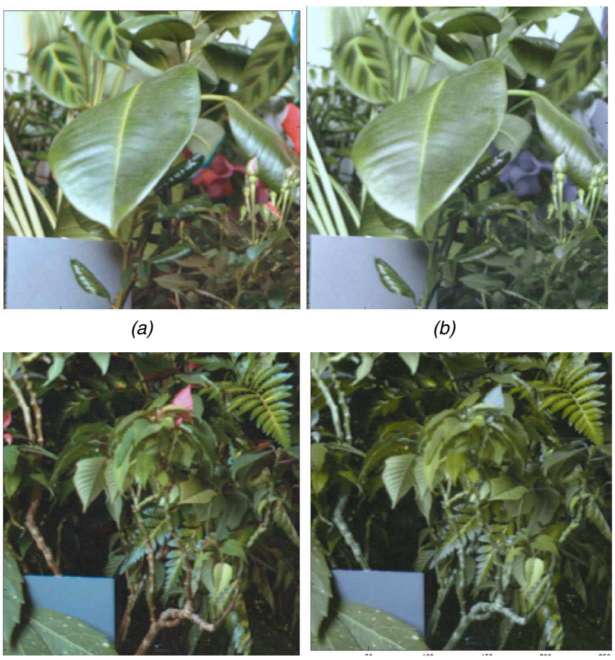
In the case of the three-dimensional SSIM measure the weighting function should be different, thus it is computed as follows [19]:

$$h(x, y, z) = \sqrt{2\pi}\sigma A e^{-2\pi^2\sigma^2(x^2+y^2+z^2)} \quad (10)$$

Experiments

Experiments were performed on spectral images of natural scenes from [20]. Two images – inlab2 and inlab5 were selected. Each image has the following dimensions: 256x256 in the spatial dimension and 31 components in the spectral dimension. Images were captured by a CCD (charge coupled device) camera in a 400-700 nm wavelength range at 10 nm intervals.

First, both of the images were compressed using PCA (principal component analysis) down to two principal components. The color reproductions of original images and reconstructed after compression are given in Fig.1.



(a) *(b)* *(c)* *(d)*

***Figure 1**. Color reproduction of spectral images inlab2 (a) original, (b) reconstruction after compression (PCA 2); inlab5 (c) original, (d) reconstruction after compression (PCA 2)*

Both of the images were multiplied afterwards by Spectral Luminous Efficiency function for photopic vision [17] and illumination factor [18]. The areas of color difference are clearly visible in the images, and concentrate primarily in red and brown regions.

Then difference maps were computed using the three-dimensional SSIM (Eq. 5, 10) proposed in this paper, and three previously proposed kernel similarity metrics [15]: polynomial kernel (Eq. 2), Gaussian radial basis kernel (Eq. 3) and sigmoidal kernel (Eq. 4). For the latter three, similarity between images was computed on a pixelwise basis. The resulting maps are shown in Fig. 2. The level of the intensity in the maps corresponds to the similarity scale: from black "not similar at all" to white "identical".

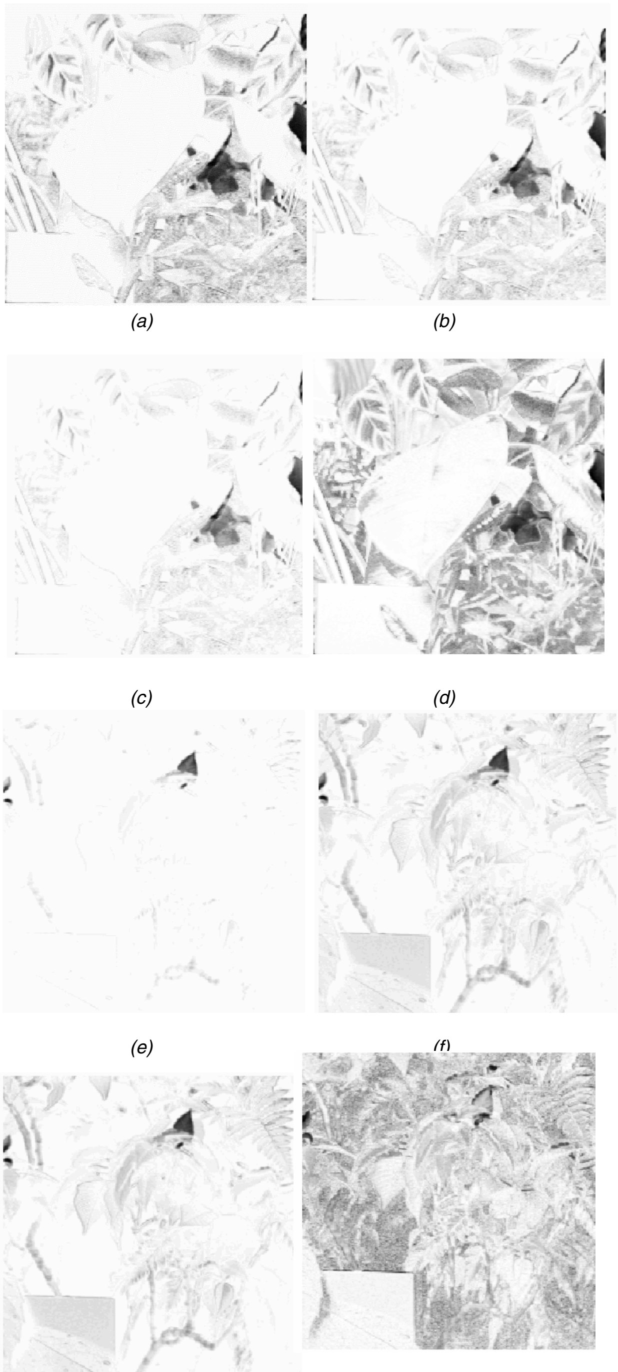


***Figure 2**. Difference maps. Inlab2 (a,b,c,d); inlab5 (e,f,g,h). (a,e) polynomial kernel; (b,f) Gaussian radial basis function; (c,g) sigmoidal kernel and (d,h) three-dimensional-SSIM*

Looking at Fig. 2, it can be stated that the difference maps produced using the kernel measures present a similar to a certain extent result, while the output of the three-dimensional SSIM gives a slightly different result specifically far more regions in the image are shown to be different.

Experimental Results

The accuracy of kernel similarity measures and the extended SSIM was tested using Perceptual Image Distortion Map (PIDM) [21]. PIDM is an empirical measure of the distribution of errors in the images [21]. PIDM can be obtained either on a pixelwise basis, or locally, with different marker sizes and shapes.

Five subjects were presented two sets of images, consisting of an original and a compressed image (Fig. 1). The users were asked to mark the regions that appeared different with a rectangular digital marker of size 4 by 4 pixels with different levels of gray-level intensity. Where black means "not similar at all" and white "identical". The subjects were instructed to mark the whole image area. Fig. 3 presents the mean of all subject maps [11,12].

***Figure 3**. Perceptual Image Distortion Map for images: (a) inlab2; (b) inlab5*

Fig. 3 clearly indicates that PIDM presents a practically excellent fit to the difference map calculated through the use of Gaussian RBF. Nevertheless, certain errors exist, which can be attributed to the fact that the marker size and shape caused several inaccuracies in stamping identical regions several times. Variance across the subjective judgments was equal to 0.0103, which is quite low and in turn means that subjects of the PIDM experiment were consistent in their estimations.

However, the results obtained using the [11] SSIM show significant difference with the results obtained using the PIDM technique.

Comparison of PIDM, SSIM and kernel metrics is given in Table 1, where each of the cells in first three columns present the mean deviation of the error maps, obtained through the use of polynomial, Gaussian RBF and sigmoidal kernels and the extended SSIM for each of the images, from the values of PIDM. Last column presents the value of the deviation of SSIM [7] error image from the PIDM.

Table 1. Comparison of SSIM, kernel metrics and PIDM

	Polynomial	Gaussian RBF	Sigmoidal	SSIM
Inlab 2	0.0499	0.0395	0.0551	0.1636
Inlab 5	0.0395	0.0291	0.0581	0.0986

PIDM presents a full map of empirical distortion data, which can be used in the task of evaluation of the accuracy of the metrics presented. Thus, looking at Table 1 it can be concluded that the most accurate evaluation of the human response in the quality estimation task is obtained through the use of Gaussian RBF kernel, while the worst one with SSIM, although the deviation between these is not large.

Taking into consideration all of the above it can be stated that the kernel similarity measures and SSIM are quality evaluation techniques that accurately predict the response of a human visual system in a distortion evaluation task. The values of these vary in the range from 0 to 1, representing the difference values from "not similar at all" to "identical". From the point of view of the probability theory it can be stated that these measures presents a probability of the subject identifying a certain pixel as similar, which allows avoiding time and money consuming procedure of expert survey, and gives the possibility of computing the distortion values dynamically as the information is discarded from the image, as for example in a lossy compression task.

Conclusions

In this paper a novel technique of spectral image quality evaluation using Structural Similarity Measure was proposed. The algorithm, described in this paper, is an extension of a Structural Similarity Index (SSIM) [7] that incorporates spectral data [14]. SSIM is based upon an assumption that human visual system is highly adapted to extracting structural information from the images. The algorithm, given in this paper, computes a localized difference between the original and the distorted images. A gray-scale image distortion map is obtained as a result, where the intensity of each of the pixels corresponds to the value of the similarity between them, which, in turn, shows the areas where the visible distortions are in the image, and how large the distortions are. The overall index is constituted of three parts: luminance, contrast and structure comparison, all three being relatively independent [7]. As a windowing approach a three-dimensional Gaussian windowing function was used. The overall measure is obtained via averaging.

SSIM [7] was tested against several images of natural scenes [20] (with spectral distortions introduced into the images) along with several previously proposed kernel similarity measures [15] and a Perceptual Image Distortion Map [21], where PIDM is an empirical measure of the distribution of errors in the images [21]. The choice of the kernel similarity measures for comparison is not incidental - these have previously proven to be effective in the task of spectral distortion evaluation [15]. It was shown in [15] that these mimic closely the response of the human visual system in a task of quality evaluation and can be considered among the best approaches to evaluation of spectral distortions introduced into the spectral images. The kernel similarity measures chosen are polynomial, Gaussian radial basis and sigmoidal kernels.

The three-dimensional SSIM has already been tested against the two-dimensional conventional measure. The novel method has proven to be more efficient in the task of color and spectral image discrimination [14].

Comparing the results obtained in this work, it can be stated that SSIM performs slightly worse than the rest of the measures whilst Gaussian RBF gives a practically excellent fit to the human observer evaluation. Thus it can be concluded that performance of the SSIM is comparable to the rest of the measures in the task of spectral distortion evaluation.

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Author Biography

Diana Kalenova received her MSc in Information Technology from Lappeenranta University of Technology (2003,) and is now working on her PhD at the same University. Her work has focused on spectral image analysis, color appearance models, statistical characteristics of images and image quality issues. She is a member of Pattern Recognition Society of Finland and IAPR.

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