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A NO REFERENCE OBJECTIVE COLOR IMAGE SHARPNESS METRIC

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ABSTRACT

In this work, we propose a no reference color image quality assessment metric. The proposed metric makes use of a wavelet-based multiscale structure tensor [1] as an extension of the single-scale structure tensor proposed by Di Zenzo [15]. The multiscale structure tensor allows for accumulating multiscale gradient information of local regions of the color image. Thus, averaging properties are maintained while preserving edge structure. This structure tensor is capable of identifying edges in spite of the presence of noise. Once edges are identified, we define a sharpness metric based on the eigenvalues of the multiscale structure tensor. Particularly, we show that the difference of the eigenvalues of the multiscale structure tensor can be used to measure the sharpness of color edges. Based on this fact we formulate our no reference sharpness metric for color images. Experiments performed on LIVE database indicate that the objective scores obtained by the proposed metric agree well with the subjective assessment scores.

1. INTRODUCTION

Recently, there has been an increasing need to develop quality measurement techniques that can predict perceived image/video quality automatically. These methods are useful in various image/video processing applications, such as compression, communication, printing, display, analysis, registration, restoration, and enhancement. For example, a noise metric can be used to estimate the quantization error caused by compression without accessing the original pictures, while a sharpness metric can be used as a control parameter for sharpness enhancement algorithms applied to digital imagery; a sharpness metric can also be used to estimate the blur caused by image compression algorithms.

Subjectively, to have a look is probably the best way to evaluate image quality, because human beings, e.g., end users, should make ultimate assessment on the performance of algorithms on digital images. However, subjective methods normally take/cost much time/resources as end users have to be highly involved, i.e., these methods cannot be routinely performed as there could even be a difference in assessment between different (groups of) end users. So, effective and efficient subjective IQA metrics are desirable but too hard to develop in real time systems. Therefore, objective IQA is more demanding.

Depending on whether or not the original image is used or on how much information from the original image is used, objective IQA can be classified into three types: full-reference (FR), no-reference (NR), and reduced-reference (RR) metrics.

FR metrics need full information of the original images and demand ideal images as references which can be hardly achieved in practice for some applications (such as broadcasting...). The traditional methods of FR (such as peak signal-to-noise-ratio PSNR) are based on pixel-wise error and have not always been in agreement with perceived quality measurement.

On the other hand, RR metrics make use of a part of the information from the original images in order to evaluate the visual perception quality of the distorted ones. Particularly, the metric is not relative to a reference image, but rather an absolute value is computed based on some characteristics of the given image.

NR metrics aim to evaluate distorted images without any cue from their original ones. Quality assessment without a reference is a challenging task; distinction between image features and impairments is often ambiguous.

Of particular interest of this work is the noise resilient wavelet-based no reference (NR) objective sharpness metric for color and multispectral images. For that we used a wavelet-based multiscale multispectral tensor [1] to detect the edges of multispectral images. This structure tensor is capable of detecting edges in spite of the presence of noise. Then, based on the eigenvalues of this structure tensor, we propose a NR sharpness metric.

The rest of the paper is organized as follows: section 2 is a state-of-the-art of the previous work. In section 3 a review of the multiscale structure tensor is given. In section 4 we present our NR metric. The last two sections summarize the experimental results, the conclusions and directions for future work.

2. STATE OF THE ART

This section presents an overview of the NR sharpness metrics existing in the literature. The easiest way to assess the quality of an image from edge information is to use the variance [6]. This method is based on the fact that, when an image is blurred, the transitions between the graylevels decrease. As a result the variance decreases. The problem of this method is that fine textures and edges in between small varying regions are regarded as blurred or smoothed edges.

Another simple technique is to use the image histogram [8]. The histogram method consists of fixing a threshold which is usually the mean of the image, then, the metric is defined as a weighted sum of the histogram bins which are above the threshold. A sharp image contains a high number of bins above the threshold and thus, increases the metric. The problem of this metric is that the selection of a good threshold

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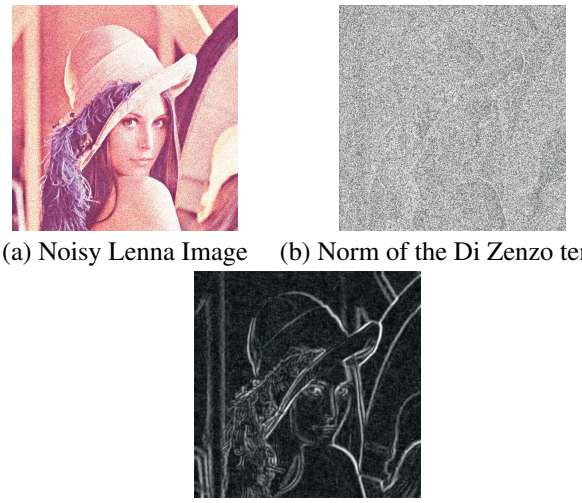
may not be obvious. Another histogram-based method has been proposed by Chern et al. in [5]. Chern et al. who defined their metric on the entropy computed from the histogram. The idea is that the entropy increases when the probability of occurrence of a gray level decreases and vice versa. Sharp images contain a larger number of gray levels, thus a lower probability and higher entropy.
An autocorrelation metric was proposed by Batten in [2]. Batten proposed to compute the difference between the autocorrelation values at two different distances along the horizontal and vertical directions. If the image is smoothed or blurred, the correlation between the neighboring pixels increases and the correlation increases. As a result, the sum of the difference metric decreases.
Other NR metrics use differential methods such as the gradient and the laplacian [3] to assess the sharpness of an image. While these methods have a high accuracy, they are very sensitive to noise.
Some other perceptual metrics such as the one proposed in [11] predict the sharpness of an image from the width of edges. In these metrics, an edge detection technique is first applied, then, the start and end positions of each edge are determined as well as the locations of the local maxima near the edges. Thereafter, sharpness measure is defined by the edge width.
Another statistic-based sharpness measure is the well known kurtosis measure [16] [4]. The kurtosis is a statistical measure of the peakness and flatness of a distribution and is inversely proportional to the sharpness.
Recently, Ferzli et al. [7] proposed a NR sharpness metric based on the notion of just noticeable blur (JNB). They showed that the human visual system will mask the blurriness around edges up to a certain threshold. They referred to this threshold as the JNB which is obtained by performing subjective tests. Then, they used a probability summation on the JNB to construct their metric.
The above mentioned metrics do not deal with color images, i.e. they do not take into account the multispectral aspect of the geometry of a color image. Furthermore, they do not take into account the noise factor. In fact, the presence of noise may affect the performance of the sharpness metric. A solution to this problem could be to denoise the image before applying the metric. However, this may cause the degradation of edges and, therefore, the failure to predict the edge sharpness.
In this work, we address the problem of evaluating the sharpness of a color image with and without noise. For that, we dused a multiscale multisctructure [1] tensor whose norm defines the edges of color images. Then, we define our sharpness metric based on the eigenvalues of this tensor.

3. REVIEW OF THE MULTISCALE WAVELET-BASED STRUCTURE TENSOR

The multiscale edge representation described in [12] and [13] is used to define the structure tensor. In this approach, x and $y-$directional wavelets are given by the partial derivatives of a separable, nonorthogonal scaling function $\theta(x,y)$ as follows:
$\left(\psi^1(x,y), \psi^2(x,y)\right) = \left(\frac{\partial\theta}{\partial x}(x,y), \frac{\partial\theta}{\partial y}(x,y)\right)$. The associated two-dimensional wavelet coefficients of an image $I \in$



(a) Noisy Lenna Image (b) Norm of the Di Zenzo tensor

(c) Norm of the multiscale structure tensor $(j=2)$

Figure 1: Norms of the Di Zenzo structure tensor and the multiscale structure tensor defined in (2)

$L^2\left(\mathbb{R}^2\right)$ at scale j are defined by:

$$\begin{pmatrix} W_j^1(x,y)I \\ W_j^2(x,y)I \end{pmatrix} = \begin{pmatrix} I * \psi_j^1(x,y) \\ I * \psi_j^2(x,y) \end{pmatrix} = \nabla\left(I * \theta_j\right) \quad (1)$$

Where $\psi_j^l\,(l=1,2)$ and θ_j represent the wavelet and the scaling function at scale j, respectively, defined by: $\psi_j^l(x,y) = \psi^l\left(x/2^j, y/2^j\right)\Big/\sqrt{2^j}$ and $\theta_j(x,y) = \theta\left(x/2^j, y/2^j\right)\Big/\sqrt{2^j}$. This stipulates that the wavelet transform of an image consists of the components of the gradient of the image, smoothed by the dilated smoothing function θ_j.
The direction of the gradient vector at a point (x_0, y_0) indicates the direction along which the image I has the steepest slope. Therefore, a point (x_0, y_0) is regarded as an edge point at scale j if the magnitude of the wavelet coefficient attains a local maximum along the gradient direction.
Based on this theory of singularity detection, a multiscale multistructure diffusion tensor can be constructed for an m-band image $I(\mathbf{x})$: $\mathbb{R}^2 \to \mathbb{R}^m$ with components for $I_i(\mathbf{x})$: $\mathbb{R}^2 \to \mathbb{R}$ for $i = 1,2,3,.....,m$ ($m=3$ for color images) as follows:

$$G_w^j = \begin{pmatrix} \sum_{i=1}^{m}\left(W_{n,j,i}^1\right)^2 & \sum_{i=1}^{m} W_{n,j,i}^1 W_{n,j,i}^2 \\ \sum_{i=1}^{m} W_{n,j,i}^1 W_{n,j,i}^2 & \sum_{i=1}^{m}\left(W_{n,j,i}^2\right)^2 \end{pmatrix} \quad (2)$$

Where $W_{n,j,i}^k$ is the undecimated wavelet coefficient computed at scale j and position n for the image channel i.
The norm of G_w^j is defined in terms of its eigenvalues, $\left\|G_w^j\right\| = \sqrt{\lambda_+ - \lambda_-}$, and it describes the total local derivative energy. Figure 1 shows the norms of the multistructure tensor of Di Zenzo defined in [15] (Figure 1(b)) and the norm of the multiscale multistructure tensor defined in (2) (Figure 1(c)) of the noisy 'Lenna' image.

It is clear that the multiscale structure tensor provides a better characterization of the image edges. We formulate in the next section our NR sharpness metric for multispectral images based on the eigenvalues analysis of the multiscale structure tensor.

4. NO REFERENCE SHARPNESS METRIC

In this section, a noise-resilient sharpness metric for color images is presented. The proposed metric is based on the behavior of the eigenvalues of the wavelet-based structure tensor described in the previous section.

Let λ_+^j and λ_-^j be the largest and the smallest eigenvalues of G_w^j computed at a wavelet scale j.

λ_+^j is none other the derivative energy in the most prominent direction which is equal to the orientation in the image with maximum color change, while λ_-^j describes the amount of derivative energy perpendicular to the prominent local orientation. The difference $\lambda_+^j - \lambda_-^j$ describes the line energy, i.e., the derivative energy in the prominent orientation that is corrected for by the energy contributed by noise λ_-^j.

As the scale j increases, λ_+^j increases at the edge pixels while λ_-^j decreases at noise pixels. Thus, the difference $\lambda_+^j - \lambda_-^j$ can be used to predict image sharpness. Therefore, we define our sharpness metric as:

$$Score = \sum_{j=1}^{J} \sum_{m=1}^{M} \sum_{n=1}^{N} \lambda_+^j(m,n) - \lambda_-^j(m,n) \qquad (3)$$

where J is the largest wavelet scale (practically we set $J = 3$) and, M and N are the height and width of the image respectively.

5. EXPERIMENTAL RESULTS

A good sharpness metric is one which has a curve that declines slowly or does not decay abruptly when there is an increase in blurness. This ensures that the metric can perform robustly under a larger degree of blurness. To test the performance of our proposed metric we made use of the image set shown in figure 2.

The images of figure 2 are blurred with a Gaussian point spread function of different standard deviation σ values before separately introducing with two most common additive random noises, namely the zero-mean Gaussian white noise and salt-and-pepper noise. For each type of noise, two noise levels are introduced. For Gaussian white noise, its variance, v is set equal to 0.010 and 0.020 while for salt-and-pepper noise, the noise density, d is set equal to 0.10 and 0.20, respectively. Examples of the noisy blurred images are shown in figure 3 for the Lenna image.

The scores obtained for each image of figure 2 in the presence of salt-and-pepper and Gaussian noises are shown in figure 4. It is clear that the proposed metric is quasi robust to different noise levels and types.

We also evaluate our wavelet-based sharpness metric using the LIVE database generated by [9], which presents the most recent and comprehensive survey of the performance of various image quality metrics available in the literature.

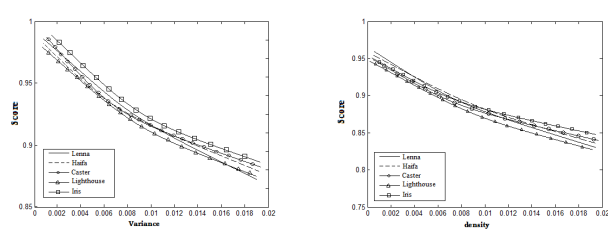
-a- -b- -c-

-d- -e-

Figure 2: Overview of the test material. a-Lena, b- Iris, c-Lighthouse, d-Caster and e-Haifa.

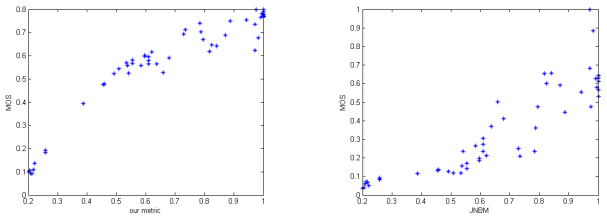
-a- -b-

Figure 3: Blurred noisy Lenna image, a- Gaussian noise $v = 0.02$, b- Salt and Peppers $d = 0.2$



-a- -b-

Figure 4: a- scores for the gaussian noise vs variance v, b- scores for the Salt and Peppers noise vs the density d



-a- -b-

Figure 5: a- MOS vs scores obtained by our metric, b- MOS vs scores obtained by the metric proposed in [7]

Table 1: Objective assessment scores

Model	PCC	SCC	MAE	OR
Ferzli et al. [7]	0.9477	0.9301	0.3428	0.3400
Our Metric	0.960	0.951	0.3	0.201

Particularly, we used the dataset from the LIVE database selected by the authors of [7] for evaluation. This dataset contains fifty images that were extracted from LIVE database. These images were subjectively evaluated for sharpness assessment. The sharpness mean opinion scores (MOS) as well as the source code for the objective metric proposed in [7] are downloaded from [10]. Figure 5 shows the MOS vs the scores obtained by our metric as well as the scores obtained by the metric proposed in [7].

Finally, we calculate the three measurements recommended by VQEG [14] to test the consistency of our sharpness metric and the subjective perception, namely, the Pearson correlation coefficients (PCC), the Spearman coefficient correlation (SCC), the mean absolute prediction error (MAE) and the outlier ratio (OR). The results are shown in table 1 for our metric and the metric proposed in [7]. From these results, we can see that the PCC and the SCC coefficients are high indicating that we can achieve a high accuracy with our metric.

6. CONCLUSION

This paper presented a wavelet-based noise-resilient sharpness metric for color images. First, a wavelet-based structure tensor is defined whose eigenvalues are used to define the metric. Experiment results showed that the proposed metric is resilient to noise and has a strong correlation with human judgment. The proposed metric can therefore eliminate the need to denoise the image before assessing the quality. For future work, we propose to conduct more extensive human experiment on high dynamic range HDR images and compare the consistency of our sharpness metric in evaluating the quality of this type of images.

REFERENCES

[1] A. Maalouf, P. Carré, B. Augereau, and C. Fernandez-Maloigne, *Regularization of Multivalued Images by Means of a Wavelet-Based Partial Differential Equation*, EUSIPCO2007, 15th European Signal Processing Conference, Poznan, Poland, 2007.

[2] C. F. Batten, *Autofocusing and astigmatism correction in the scanning electron microscope*, M.Phil. thesis, Univ. Cambridge, Cambridge, UK (2000).

[3] Al Bovik, *Handbook of image and video processing*, Academic Press, 2000.

[4] J. Caviedes and F. Oberti, *A new sharpness metric based on local kurtosis, edge and energy information*, Signal Processing **19** (2004), no. 2, 147–161.

[5] N. K. Chern, N. P. A. Neow, and M. H. Ang, *Practical issues in pixel-based autofocusing for machine vision*, Proc. IEEE Int. Conf. Robotics and Automation **3** (2001), 2791–2796.

[6] S. Erasmus and K. Smith, *An automatic focusing and astigmatism correction system for the sem and ctem*, J. Microscopy **127** (1982), 185–199.

[7] Rony Ferzli and Lina J. Karam, *A no-reference objective image sharpness metric based on the notion of just noticeable blur (jnb)*, IEEE transactions on image processing **18** (2009), no. 4, 717–728.

[8] L. Firestone, K. Cook, N. Talsania, and K. Preston, *Comparison of autofocus methods for automated microscopy*, Cytometry **12** (1991), 195–206.

[9] M. R. Sabir H. R. Sheikh and A. C. Bovik, *A statistical evaluation of recent full reference image quality assessment algorithms*, IEEE Transactions on Image Processing **15** (2006).

[10] http://www.ivulab.com/metadot/index.pl?iid=2487&isa=Category.

[11] P. Marziliano, F. Dufaux, S. Winkler, and T. Ebrahimi, *Perceptual blur and ringing metrics: Applications to jpeg2000*, Signal Processing: Image Communication **19** (2004), no. 2, 163–172.

[12] Mallat S. and Hwang W. L., *Singularity detection and processing with wavelets*, IEEE Trans. Information Theory **38** (1992), 617–643.

[13] Mallat S. and Zhong S., *Characterization of signals from multiscale edges*, IEEE Trans. Pattern Anal. Machine Intell. **14** (1992), no. 7, 710–732.

[14] VQEG, *Final report from the video quality experts group on the validation of objective models of video quality assessment*, http://www.vqeg.org (2000).

[15] S. Di Zenzo, *A note on the gradient of multi-images*, Computer Vision Graphics and Image processing **33** (1986), 116–125.

[16] N. Zhang, A. Vladar, M. Postek, and B. Larrabee, *A kurtosis-based statistitcal measure for two-dimensional processes and its application to image sharpness*, in Proc. Section of Physical and Engineering Sciences of American Statistical Society (2003), 4730–4736.