Subtractive Impairment, Additive Impairment and Image Visual Quality

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Abstract— **In this paper, we propose an engineering-based image quality metric which distinguishes subtractive impairment from additive impairment. Since the amount of subtractive impairment is up-bounded by the total details within the reference image but the same limitation can't be applied to additive impairment, intuitively visual quality degradation due to the two types of impairments should be measured differently. In the proposed metric, subtractive and additive impairments are separated and represented in the wavelet domain, and their influences to image visual quality is measured by different equations. We tested the proposed metric on five subjectively-rated databases and proved its effectiveness in objective image quality assessment.**

I. Introduction

In image processing, MSE and PSNR are extensively adopted as objective quality metrics, mostly because of their simplicity. However, it has been well acknowledged that these pixel-based difference measures do not correlate well with the Human Visual System (HVS). A better objective image quality metric is in demand, and its success will provide guidance to a large number of image processing algorithms, e.g. image compression, watermarking, image fusion, feature enhancement and detection, restoration, retrieval, etc.

In decades, many advanced image quality metrics have been developed, and from the viewpoint of design approach, they can be categorized into two groups: HVS-model-based metrics and engineering-based metrics [1]. HVS-model-based metrics employ the HVS mode to simulate the HVS response to visual signals and gauge quality by comparing these responses. The HVS mode used is based on experimental data from psychophysical studies. Most of these studies used only a few simple visual stimuli like sine-wave gratings or Gabor patches and target at contrast threshold evaluation. This leads to two disadvantages of HVS-model-based metrics: first, a natural image usually is a superposition of a large number of simple stimuli, and their interactions cannot be fully described by a model which is based on experimental data of only one or two simple stimuli; second, there is no justification for the use of experimental data of contrast threshold evaluation in gauging visual quality, especially for images with supra-threshold distortions. On the other hand, engineering-based quality metrics are designed by using the engineering methodology. Instead of founding on accurate experimental data, engineering-based metrics are more based on assumption and prior knowledge (assumption about feature types that are closely related to visual quality, and prior knowledge on the types of distortions that contaminate the visual content). In most cases, engineering-based metrics are easy to calculate and their performance is guaranteed by training on subjective ratings.

Engineering-based quality metrics also have their disadvantages. For example, they are not good at measuring threshold distortions, and they intent to be specific for certain distortion types instead of serving general purpose. In this paper, a general-purpose engineering-based image quality metric is proposed. It decouples subtractive impairment and additive impairment which are considered to be two uncorrelated distortion factors. Quality degradations due to subtractive and additive impairments are separately calculated and weightedly summed as the final objective metric score. Two simple measures are proposed to gauge the quality degradation due to the two impairment types. Since all kinds of distortions can be decomposed into subtractive component and additive component, the proposed metric is supposed to be versatile.

The paper is organized as follow: Section II introduces our definitions of subtractive impairment and additive impairment; Section III describes the metric design in detail, including how to decouple subtractive/additive impairments and how to correlate impairments with visual quality; Section IV shows the experimental results on five subjectively-rated image databases and discusses the possible improvement on the current implementation; Section V gives the conclusion.

II. Subtractive and Additive Impairments

As in many full-reference[1] image quality metrics, differences between reference and distorted images are taken as the distortions, and usually the reference image will act as the masker to adjust the distortion strength. However, it is obvious that due to distortions not all the original information can be restored from the distorted image anymore, so using the reference image to mask the distortions is questionable. Actually, differences between reference and distorted images can be decomposed into two distinguishable components: subtractive impairment and additive impairment. Subtractive impairment refers to distortions that cause loss of information which originally exists in the reference image. On the other hand additive impairment refers to artifacts that cause increment of redundant visual information. Distortion type that only

[1] According to the availability of the reference information, objective visual quality metrics can be classified into full-reference, reduced-reference, and no-reference metrics.

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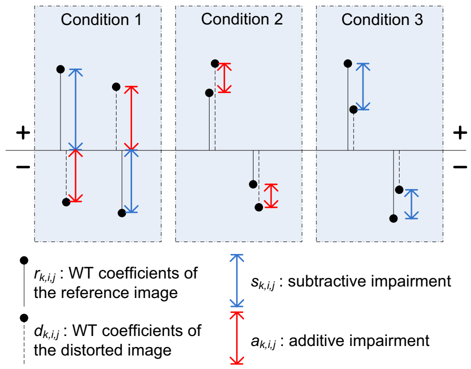


Fig. 1. Decouple subtractive and addtive impairments by comparing wavelet transform coefficients.

causes subtractive impairment is Gaussian Blur, while most other distortion types cause both of them, e.g., JPEG coding brings both blurry (subtractive) and blocky/ringing (additive) artifacts.

The necessity of decoupling subtractive and additive impairments comes from the assumption that the two types of impairments correlate with visual quality in different manners. Subtractive impairment causes information/details loss whose amount is limited by the total details within the reference image, while apparently this limitation can't be applied to additive impairment. In the proposed metric, the ratio between the details loss and the total details is used to predict visual quality degradation due to subtractive impairment; visual quality degradation due to additive impairment is measured in a way like MSE but in the wavelet domain. In [2], the authors also argued the need of separating subtractive and additive impairments. They claimed that quality degradation due to subtractive and additive impairments should be weighted differently which is also applied to our metric. Our metric is different from the one proposed in [2] because there are 7 subtractive or additive impairments measured by their metric while our metric only uses 2 to represent all, and moreover, their metric is for video quality measure but ours is for image.

III. Metric Design

The proposed metric consists of the following processing steps: firstly, reference and distorted image are wavelet transformed, and the subtractive and additive impairments are separated in the wavelet domain; secondly, the two types of impairments are measured generating two objective scores s_s and s_a; thirdly, by training on subjective ratings the s_s and s_a are non-linearly mapped to $pDMOS_s$ and $pDMOS_a$, respectively, which are in the subjective scale; finally $pDMOS_s$ and $pDMOS_a$ are weightedly summed together to generate the objective metric score. This section gives more detail on the proposed metric design. Two forward wavelet transforms need to be performed as briefly introduced above, and all the following processing will be based on the resultant wavelet coefficient maps and use simple calculation.

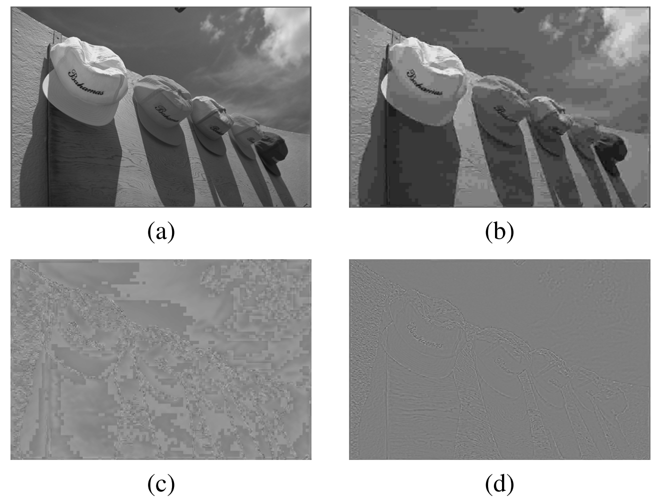


Fig. 2. Results for distortion type JPEG coding. (a) reference image, (b) distorted image, (c) reconstructed addtive impairment, (d) reconstructed subtractive impairment.

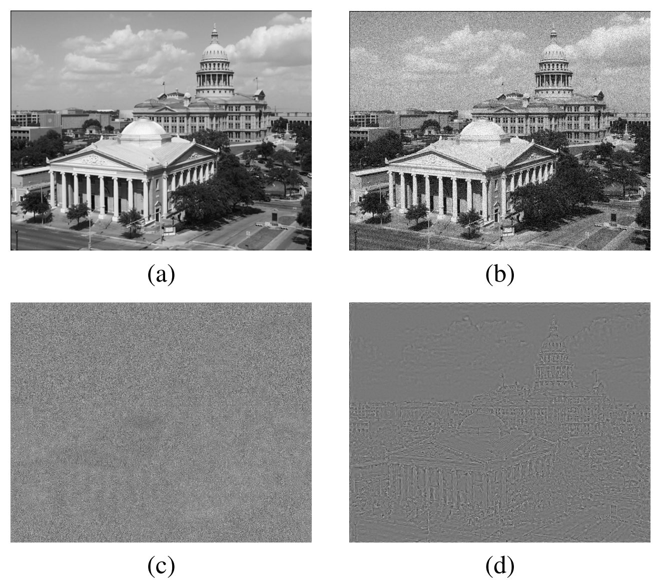
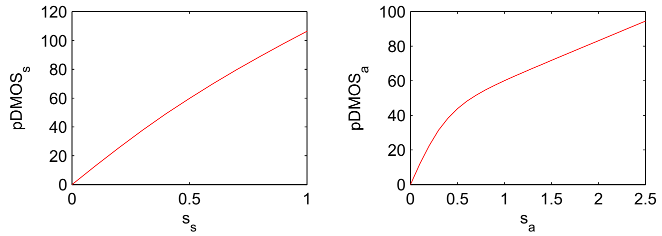


Fig. 3. Results for distortion type white noise. (a) reference image, (b) distorted image, (c) reconstructed addtive impairment, (d) reconstructed subtractive impairment.

A. Decouple Subtractive and Additive Impairments

We use non-decimated *db2* wavelet to transform the reference and the distorted image into 4 scales with 1 approximation subband plus 12 high frequency subbands. The $r_{k,i,j}$ and $d_{k,i,j}$ represent the wavelet transform (WT) coefficients of the reference and the distorted image, respectively, at subband k, spatial position (i,j). Then the subtractive impairment $s_{k,i,j}$ and additive impairment $a_{k,i,j}$ can be given by equation (1)



(a) (b)

Fig. 4. (a) Non-linearly mapping function from s_s to $pDMOS_s$ with $\beta_1 = 53.06$, $\beta_2 = 3.66$, and $\beta_4 = 81.17$; (b) Non-linearly mapping function from s_a to $pDMOS_a$ with $\beta_1 = 75.48$, $\beta_2 = 5.18$, and $\beta_4 = 22.71$.

and (2):

$$s_{k,i,j} = \begin{cases} 0 & k = 1 \\ r_{k,i,j} & k \neq 1\&\text{condition } 1 \\ 0 & k \neq 1\&\text{condition } 2 \\ r_{k,i,j} - d_{k,i,j} & k \neq 1\&\text{condition } 3 \end{cases} \tag{1}$$

$$a_{k,i,j} = \begin{cases} d_{k,i,j} - r_{k,i,j} & k = 1 \\ d_{k,i,j} & k \neq 1\&\text{condition } 1 \\ d_{k,i,j} - r_{k,i,j} & k \neq 1\&\text{condition } 2 \\ 0 & k \neq 1\&\text{condition } 3 \end{cases} \tag{2}$$

where $k = 1$ corresponds to the approximation subband, and condition 1 to 3 are:

- condition 1: $r_{k,i,j} \times d_{k,i,j} \leq 0$
- condition 2: $r_{k,i,j} \times d_{k,i,j} > 0$ & $|d_{k,i,j}| \geq |r_{k,i,j}|$
- condition 3: $r_{k,i,j} \times d_{k,i,j} > 0$ & $|d_{k,i,j}| < |r_{k,i,j}|$

Fig. 1 illustrates the function of equations (1) and (2) for $k \neq 1$. To evaluate the performance of the proposed algorithm, $s_{k,i,j}$ and $a_{k,i,j}$ are inverse-transformed to the spatial domain. Due to the limitation on the paper length, we only illustrate the performance of the proposed algorithm on distortion types JPEG coding and white noise in Figs. 2 and 3.

B. Measure Subtractive and Additive Impairments

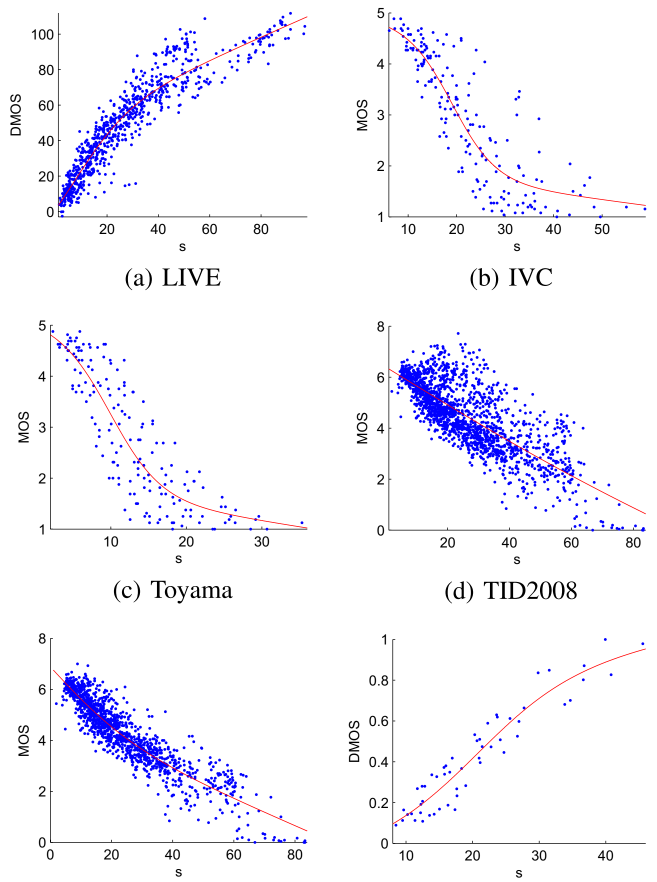
In the proposed metric, equations (3) and (4) are used to measure the subtractive impairment and the additive impairment, respectively:

$$s_s = \frac{\sum_k (\sum_{i,j} s_{k,i,j}^2)^{\frac{1}{2}}}{\sum_k (\sum_{i,j} r_{k,i,j}^2)^{\frac{1}{2}}} \tag{3}$$

$$s_a = \frac{\sum_k (\sum_{i,j} a_{k,i,j}^2)^{\frac{1}{2}}}{N} \tag{4}$$

where N in equation (4) is the total pixel number of the image. As introduced in Section II, in our metric subtractive and additive impairments are measured differently. The numerator of equation (3) approximates the details loss due to subtractive impairment and it is normalized by the total details within the reference image approximated by the denominator. On the other hand, in equation (4) for additive impairment, the total pixel number is used as the denominator.

As you can see, in both equations *Minkowski pooling* shown by equation (5) is employed and spatial pooling is performed



(a) LIVE (b) IVC

(c) Toyama (d) TID2008

(e) TID2008 (part) (f) A57

Fig. 5. Objective score versus subjective score for subjectively-rated image databases (a) LIVE, (b) IVC, (c) Toyama, (d) TID2008, (e) partial TID2008, and (f) A57.

before subband pooling. The typical value for β used by quality metrics is from 1 to 5. We choose β as 2 for spatial pooling and as 1 for subband pooling so as to make a balance between performance and computational complexity.

$$E = (\sum_i e_i^{\beta})^{\frac{1}{\beta}} \tag{5}$$

C. Correlate Impairments with Visual Quality

In this step, the obtained s_s and s_a is non-linearly mapped to the subjective quality scale. The mapped values $pDMOS_s$ and $pDMOS_a$ can be regarded as *in the same unit*, which makes their summation in equation (8) make sense. In our metric, these non-linearly mapping functions are modeled by equation (6) and (7) with β_3 and β_5 set to 0. $\{\beta_1, \beta_2, \beta_4\}$ are derived by training on 80 (out of 779) distorted images from the subjectively-rated image database *LIVE* [5] using MATLAB function *fminunc*. 40 images distorted by Gaussian blur are used to train the non-linearly relationship between s_s and $pDMOS_s$. 40 images distorted by white noise are used to train the non-linearly relationship between s_a and $pDMOS_a$.

TABLE I

PERFORMANCE OF THE PROPOSED METRIC TOGETHER WITH OTHER 3 IMAGE QUALITY METRICS: PSNR, SSIM, AND VIF.

	LIVE		IVC		Toyama		TID		TID (Part)		A57	
	LCC	SROCC	LCC	SROCC	LCC	SROCC	LCC	SROCC	LCC	SROCC	LCC	SROCC
Proposed	0.945	0.949	0.877	0.871	0.877	0.873	0.777	0.761	0.912	0.914	0.949	0.927
VIF	0.960	0.964	0.903	0.896	0.913	0.908	0.809	0.749	0.894	0.873	0.618	0.622
SSIM	0.904	0.910	0.792	0.779	0.799	0.787	0.641	0.627	0.713	0.731	0.415	0.407
PSNR	0.871	0.876	0.720	0.688	0.636	0.613	0.570	0.579	0.762	0.772	0.696	0.619

The two non-linear functions are shown in Fig. 4.

$$y = \beta_1 logistic(\beta_2, (x - \beta_3)) + \beta_4 x + \beta_5 \quad (6)$$

$$logistic(\tau, x) = \frac{1}{2} - \frac{1}{1 + e^{\tau x}} \quad (7)$$

The weighted summation of $pDMOS_s$ and $pDMOS_a$ is the final metric score as given in equation (8). The weighting value w equals to 0.65 which is derived by training on 215 distorted images of the database *LIVE*.

$$s = w \times pDMOS_s + (1 - w) \times pDMOS_a \quad (8)$$

IV. EXPERIMENTS AND FUTURE WORK

The proposed image quality metric is testified on five subjectively-rated image databases: *LIVE* [5], *IVC* [6], *Toyama* [7], *TID2008* [8], *A57* [9]. Fig. 5 shows the scatter plot of the metric score versus subjective score for each of the databases. Since 4 (out of 17) distortion types (non eccentricity pattern noise, local block-wise distortion, mean shift, contrast change) in *TID2008* cannot be handled by our metrics currently, we also use part of the *TID2008* database which excludes these distortion types to test our metric. Table 1 shows the performance of the proposed metric together with other 3 image quality metrics VIF [3], SSIM [4], and PSNR. All tested metrics use luminance information only. The criteria used to evaluate metric performance are Linear Correlation Coefficient (LCC) and Spearman Rank Order Correlation Coefficient (SROCC). Higher value of LCC and SROCC indicates better performance with maximum value being 1 for both criteria. Before calculating the LCC and SROCC, objective scores from each metric are non-linearly mapped to the subjective scale by using equation (6).

From the experimental results, we can see that the proposed metric performs quite well on most image databases. Its prediction accuracy is consistently better than PSNR and one of the classic engineering-based image quality metric SSIM.

However, its shortcoming is also obvious. Firstly compared with the state of art metric VIF, there is still a performance gap on 4 out of the 5 tested image databases. Secondly, its performance on database *TID2008* needs to be improved greatly. As mentioned above, there are several distortion types in *TID2008* that the proposed metric cannot deal with. This fault will jeopardize its usage as a universal quality metric. Thirdly, the metric score s is supposed to be linearly related to the subjective scores, but as shown in Fig. 5, the proposed metric failed to achieve this.

These shortcomings can be overcome by better algorithms for decoupling subtractive and additive impairments together with better impairment measures. For simplicity the proposed metric decouples subtractive and additive impairments by simply comparing values of wavelet coefficients at the same frequency and spatial location. Better performance should be achieved by considering the intra- and inter-scale relationships of the wavelet coefficients, since for subtractive impairment these relationships should be similar with those for reference image while on the other hand will be different for additive impairment. Moreover, in the proposed metric when measuring the impairments only magnitude is considered. To handle local distortions the distribution of the impairments also needs to be taken into account. Our future work will focus on these directions.

V. CONCLUSION

We proposed an image quality metric which separated subtractive impairment from additive impairment. We argued the differences between the two types of impairments and used different measures to correlate them with visual quality. The proposed metric was found to perform quite well on 4 out of the 5 tested subjectively-rated image databases. Meanwhile we also pointed out the weak points of the current implementation, and discussed our future works on the metric's improvement.

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