A Study on Opportunity Cost with Classification for Non-Linear Image Enhancement

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***Abstract*- Opportunity cost is a wide known theory in economics. The principle of opportunity cost and an effective image classification are utilized to decide the most suitable combination of clipping and scaling parameters in the nonlinear image enhancement method for various blurred images. It is also shown that this new image classification and opportunity cost for the nonlinear image enhancement method obtains a better subjective and objective performance than other nonlinear image enhancement methods for image quality.**

Keywords*- *Opportunity Cost; Image Classification; Nonlinear Image Enhancement

I. INTRODUCTION

When a digital image is blurred, the image enhancement is an indispensable post-processing approach [1, 2]. The purpose of image enhancement is to process a given blurred image so that the blurred image is more suitable for image analysis or visual quality [2, 8]. In [4] and [5], an efficient nonlinear image enhancement scheme with both low-pass filter and nonlinear operator is developed in order to predict a high-frequency image used for enhancing the visual quality of blurred image. Furthermore, the Gaussian Pyramid [4] or Filter Subtract and Decimate (FSD) Pyramid [5] structure is used in the nonlinear image enhancement scheme for extracting the high-frequency image as shown in Fig. 1. In this figure, a high-frequency component L_{-1} is predicted by a nonlinear filter. The new output (enhanced) image is generated by the sum of the input (blurred) image and the high-frequency image L_{-1} as

$$Output\ Image = Input\ Image\ + L_{-1} \tag{1}$$

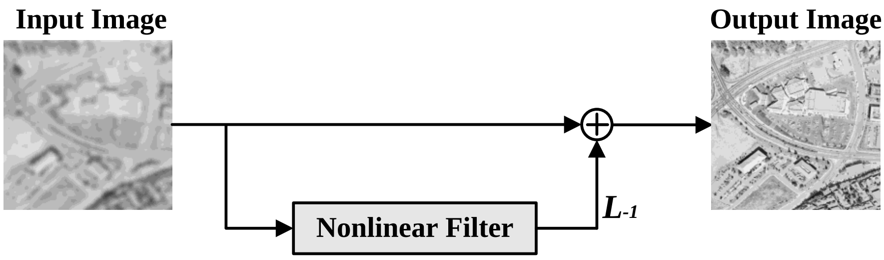

Fig. 1 Basic diagram of nonlinear image enhancement

In [5], a trade-off problem exists in the choice of clipping and scaling parameters to the blurring and ringing deviations is complex in the nonlinear image enhancement scheme. For different types of blurred images, it is difficult to decide the best combination of clipping and scaling parameters in nonlinear image enhancement. Opportunity cost is a well known theory in economics [6, 7]. The principle of opportunity cost can be used in the area of image enhancement for deciding the enhancement parameters [8]. Furthermore, the authors in [8] developed an improved nonlinear image enhancement scheme with cubic B-spline filter [3, 14] and the concept of opportunity cost to identify the most suitable combination of enhancement parameters. That is, the concept of opportunity cost can be used to analyse the combination of clipping and scaling parameters for the nonlinear image enhancement method. In addition, one more observes from [13] that the values of clipping and scaling parameters are very difficult to decide in the nonlinear image enhancement method. In this paper, an effective image classification algorithm is presented that the wavelet transform decomposition and the three-fold cross validation with leave-one-out [12] are used. In [13] part, the preliminary idea of opportunity cost combined with image classification is proposed for nonlinear image enhancement. The detailed scheme of using opportunity cost based on image classification to improve the nonlinear image enhancement method has not been presented. Therefore, this paper gives more detailed descriptions for the technique in [13]. Finally, an optimal parameter solution algorithm using the opportunity cost is used to obtain the most suitable combination of clipping and scaling parameters in the nonlinear image enhancement method. It is also shown by computer simulation that the proposed method and other nonlinear image enhancement methods are all compared in this paper for enhancing some standard blurred images. The proposed nonlinear image enhancement method achieves a better subjective

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and objective image quality performance than the method using the opportunity cost without image classification and other nonlinear image enhancement methods.

This paper is organized as follows. Section 2 describes the optimal parameter solution algorithm using opportunity cost for decide the best combination of clipping and scaling parameters in the nonlinear image enhancement. In Section 3, the effective image classification algorithm based on the wavelet transform decomposition is proposed. In Section 4, the proposed nonlinear image enhancement scheme with image classification is presented. Some experimental results are shown in Section 5. The last section discusses the conclusions of this paper.

II. OPTIMAL PARAMETER SOLUTION USING OPPORTUNITY COST

Opportunity cost is a wide known theory in economics. When a decision is made, one best choice is making and the other alternatives are dropping [6-8]. For more details on this discussion, see [13]. In this paper, an optimal parameter solution algorithm using opportunity cost is proposed to obtain the best combination of clipping(*c*) and scaling(*s*) parameters for nonlinear image enhancement. In each group to identify the combination of *c* and *s* parameters, firstly, the *c* and *s* parameters are set to $c = \{0.1, \ldots, 1.0\}$ and $s = \{1, \ldots, 10\}$, respectively. The costs for different combinations of *c* and *s* parameters refer to their corresponding opportunity costs. That is, when the option of the parameters is chosen and the choice of the parameters is given up, the opportunity cost of this option with respect to the image is determined [8, 13]. Likewise, with the same parameters, the opportunity cost of each image can be determined. Then the sum of all these opportunity costs is had, called the total cost of the options. To obtain the optimal solution, the combination of *c* and *s* parameters having the minimum total cost is chosen. The peak signal-to-noise ratio (PSNR) is an objective measurement for image quality and can be used in the proposed optimal parameter solution algorithm described as follows. In order to analyze the selection of *c* and *s* parameters, firstly, we choose *n* original images and *n* blurred images of them. In addition, we use the blurred image as the input image. Then, the enhanced image can be obtained by using the nonlinear image enhancement method with *c* and *s* parameters. Let $I(x,y)$ and $I_{-1}(x,y)$ be the original and enhanced images, respectively, and let x, y for $0 \le x \le D_x - 1$ and $0 \le y \le D_y - 1$ be the index numbers that separate the vertical and horizontal directions of the image. The mean-square error (*MSE*) of an image is defined by

$$MSE = \frac{\left(\sum_{x=0}^{D_x-1}\sum_{y=0}^{D_y-1}\left|I(x,y)-I_{-1}(x,y)\right|^2\right)}{(D_x \times D_y)} \tag{2}$$

and the *PSNR* of an image is defined by

$$PSNR(dB) = 10 \times \log_{10}(255^2 / MSE) \tag{3}$$

In the case of *n* (*n* > 1) input images, each combination of *c* and *s* parameters can get a different PSNR value of the image. The optimal parameters of each image by these PSNR values are found, and there will be at most *n* sets of different optimal parameters. With these *n* different combinations of parameters, *n* opportunity costs for each image are had, and after the sum of opportunity costs with respect to each set of parameter, *n* total costs. The optimal combination of parameter values corresponding to the lowest total opportunity cost is obtained [8], as illustrated in Fig. 2. Let *i* be the index of distinct combinations of *c* and *s* parameters, *j* be the number of images, and *PSNR*(*i*, *j*) be the *PSNR* of an images with respect to the *c* and *s* parameters for $1 \le i \le m$ and $1 \le j \le n$, where *i, j, m* and *n* are integers.

Then, the optimal solution algorithm using opportunity cost of *c* and *s* parameters is summarized in the following steps:

Step 1: Compute the *PSNR*(*i*, *j*) of all images for all combinations of *c* and *s* parameters.

Step 2: Compute the optimal solution *OP_PSNR*(*j*) for all image by

$$OP\_PSNR(j) = \max(PSNR(1:m, j)) \ \text{for} \ 1 \le j \le n \tag{4}$$

Step 3: Compute the optimal *PSNR* of each image by

$$Optimal\_PSNR(j) = \max(OP\_PSNR(j)) \ \text{for} \ 1 \le j \le n \tag{5}$$

Step 4: Compute the opportunity cost of each image by

$$Cost(j) = \left| OP\_PSNR(j) - Optimal\_PSNR(j) \right| \ \text{for} \ 1 \le j \le n \tag{6}$$

Step 5: Compute the total opportunity cost of *n* images by

$$T\cos t = \sum_{j=1}^{n} Cost(j) \tag{7}$$

Step 6: Choose the minimum *Tcost* for optimal solution and the corresponding set of *c* and *s* parameters.

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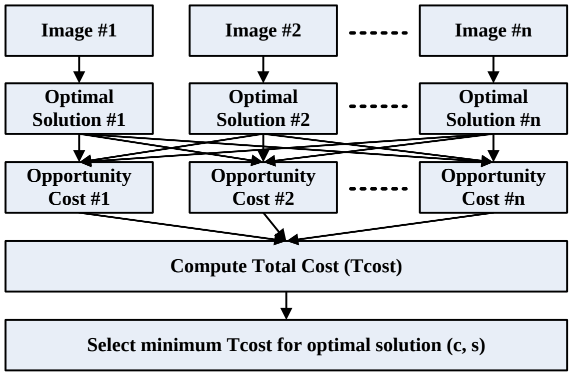

Fig. 2 The optimal parameter solution algorithm

III. PROPOSED IMAGE CLASSIFICATION ALGORITHM

In this paper, an effective image classification algorithm based on the wavelet transform decomposition is used with the opportunity cost for the nonlinear image enhancement method. The basic idea of the wavelet transform for an image is illustrated briefly as follows. An image can be transformed into the wavelet coefficients using the wavelet transform decomposition [9], in which a pair of wavelet filters including a low-pass filter and a high-pass filter is utilized to calculate wavelet coefficients. With the wavelet transform, an image can be first decomposed into four parts of low, middle, and high frequencies, i.e., low-low (LL_1), low-high (LH_1), high-low (HL_1), and high-high (HH_1) subbands, respectively. In addition, the decomposition can be repeatedly performed on the low-low subband to obtain the next four subbands. For example, the LL_1 subband is decomposed into four additional LL_2, LH_2, HL_2, and HH_2 subbands. An example of three-level wavelet transform decomposition [13] is shown in Fig. 3.

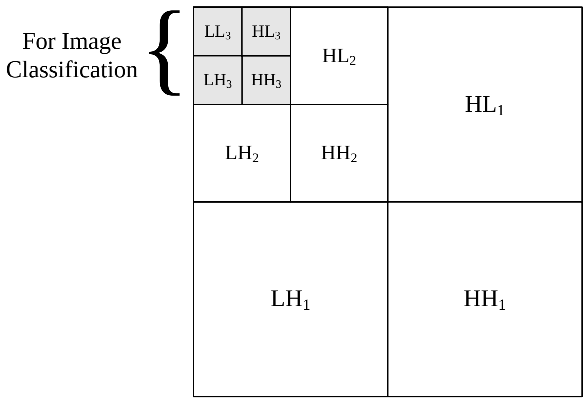

Fig. 3 Three-level wavelet transform decomposition

There are two processing stages in the proposed image classification algorithm. The first stage is the learning algorithm that uses in the theoretical analysis (training process). In the learning algorithm, the input images are all given images and the output classes are two classifications for all input images. The second stage is the image classification algorithm that uses in the proposed nonlinear image enhancement scheme. In the image classification algorithm, an unclassified image after this process will be obtained the corresponding image class. The detailed descriptions of the two algorithms are illustrated as follows:

A. The Learning Algorithm (Training Process) for Image Classification

[Input:] All given n input images ($n > 1$)

[Output:] Two image classifications for all input images

Step 1: Decompose a given input image with three-level wavelet transform decomposition to obtain four subbands in Level 3 (LL_3, LH_3, HL_3, and HH_3).

Step 2: Compute the energy values of four subbands in Level 3 (LL_3, LH_3, HL_3, and HH_3). If the subband is $x(s,t)$ with $1 \le s \le P$ and $1 \le t \le Q$, its energy [9] is

$$E = \frac{1}{PQ}\sum_{s=1}^{P}\sum_{t=1}^{Q}\left|x(s,t)\right| \tag{8}$$

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Step 3: Define the energy values of four subbands in Level 3 (LL_3, LH_3, HL_3, and HH_3) by $x = (x_1, x_2, x_3, x_4)$.

Step 4: For each image *i*, pick up its energy values and denote the energy value of image *i* by $y_i = (y_{i,1}, y_{i,2}, y_{i,3}, y_{i,4})$ for $1 \le i \le n$, and *n* is number of images.

Step 5: Compute the Mahalanobis distance [9] by

$$d_i = (x - y_i)^T C_i^{-1}(x - y_i) \text{ for } 1 \le i \le n \tag{9}$$

where C_i is the covariance matrix of image *i*.

Step 6: All input images are randomly partitioned into three subsets by using three-fold cross validation and leave-one-out algorithm [12].

Step 7: Generate two image classifications, i.e., *image-Class a* and *image-Class b*, for all input images.

B. Image Classification Algorithm

[Input:] An unclassified input image

[Output:] An image class for the input image

Step 1: Decompose an unclassified image with three-level wavelet transform decomposition to obtain four subbands in Level 3 (LL_3, LH_3, HL_3, and HH_3).

Step 2: Compute the energy values by Equation (8) for these four subbands in Level 3 (LL_3, LH_3, HL_3, and HH_3) and denote this energy value by $x = (x_1, x_2, x_3, x_4)$.

Step 3: Compute the means of energy values as $m_a = (m_{a,1}, m_{a,2}, m_{a,3}, m_{a,4})$ and $m_b = (m_{b,1}, m_{b,2}, m_{b,3}, m_{b,4})$ by averaging the energy values over all images in *image-Class a* and *image-Class b*, respectively.

Step 4: Compute the Mahalanobis distance by

$$\bar{d}_a = (x - m_a)^T C_a^{-1}(x - m_a) \tag{10}$$

and

$$\bar{d}_b = (x - m_b)^T C_b^{-1}(x - m_b) \tag{11}$$

where C_a and C_b are the covariance matrices of image class *a* and *b*, respectively.

Step 5: If $\bar{d}_a < \bar{d}_b$, then the unclassified image is *image-Class a*. Otherwise the unclassified image is *image-Class b*.

IV. PROPOSED NONLINEAR IMAGE ENHANCEMENT

In the nonlinear image enhancement method [5], a low-pass filter with a 5-tap normalized Gaussian [1, 4, 6, 4, 1]/16 is used. Using the same procedure described in [8, 13], the cubic B-spline filter [3, 14-16] with the form: [1, 4, 1]/6 and opportunity cost with image classification are used to improve the nonlinear image enhancement scheme which is shown in Fig. 4. The low-frequency image I_1 is obtained from the input(blurred) image I_0 using the cubic B-spline filter, and the high-frequency image L_0, called the residual image, is obtained by subtracting the low-frequency image I_1 from the input(blurred) image I_0, i.e., $L_0 = I_0 - I_1$. The image classification algorithm described in Section III-B is used to decide the image class and identify the best combination of clipping and scaling parameters for the non-linear operator. Finally, by [5], the output (enhanced) image I_{-1} is generated as the sum of the input(blurred) image I_0 and the predicted high-frequency image L_{-1}, i.e.,

$$I_{-1} = I_0 + L_{-1} \tag{12}$$

where $L_{-1} = NL(L_0)$ is a nonlinear operator of L_0, which includes both scaling and clipping steps, defined as follows:

$$NL(L_0) = s \times Clip(L_0) \tag{13}$$

where the scaling constant *s* is ranging from 1 to 10 and *Clip*(*x*) is given by

$$Clip(x) = \begin{cases} T, & if\ x > T \\ x, & if\ -T \le x \le T \\ -T, & if\ x < -T \end{cases} \tag{14}$$

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where x is the pixel of the high-frequency image L_0, $T = c \times L_0^{\max}$, $L_0^{\max}$ is the maximum pixel of the high-frequency image L_0 and the clipping constant c is ranging from 0 to 1. After the non-linear operator, the higher-frequency image L_{-1} can be utilized to enhance the input-blurred image I_0. In [5], one parameter combination of $c = 0.45$, $s = 3$ from the theoretical evaluation and the other parameter combination of $c = 0.4$, $s = 5$ from the estimation analysis are proposed. In this paper, we use the concept of opportunity cost with image classification to find the most suitable combination of clipping and scaling parameters for the proposed nonlinear image enhancement scheme with cubic B-spline filter.

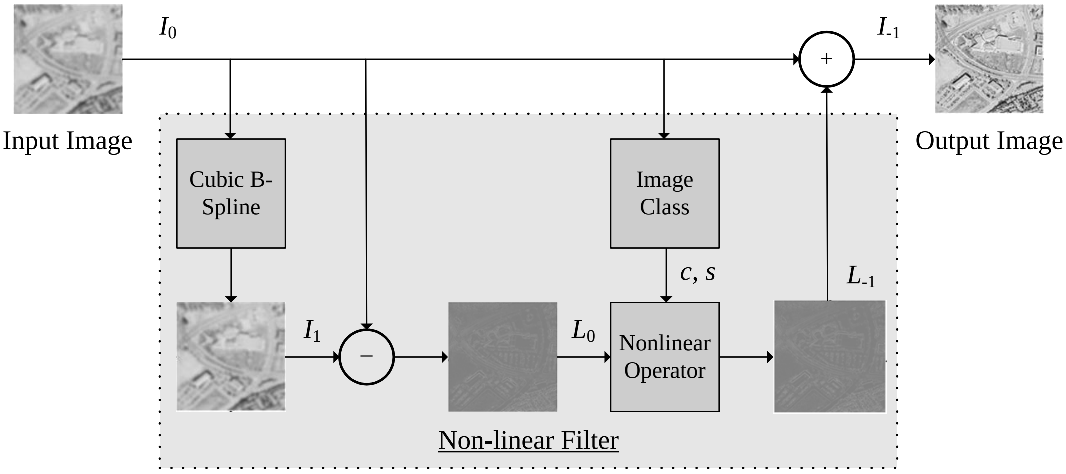

Fig. 4 The proposed non-linear image enhancement scheme

V. EXPERIMENTAL RESULTS

In this paper it is shown that the experimental results of some blurred images are presented using the proposed and other nonlinear image enhancement methods. Twenty standard gray images shown in Fig. 5, of size 512×512 are selected. In order to verify the objective PSNR performance of the proposed opportunity cost method, these twenty images are blurred into low resolution as input (blurred) images (I_0). Then, using the optimal parameter solution algorithm based on the opportunity cost method without image classification, the parameter solution of c = 0.7, s = 3 is found for these twenty images. In addition, the opportunity cost method without image classification and the methods in [4] and [5] are applied on these input (blurred) images, and a comparison on the PSNR generated in each method is shown in Table 1. These input images are originally blurred, and the Gaussian [4], FSD [5] and proposed opportunity cost methods are used for image enhancement. It follows from Table 1 that the PSNR values in (3) of the enhanced images using the proposed opportunity cost method without image classification are better than those of methods given in [4] and [5].

Aerial

Baboon

Barbara

Blackb

Boat

Couple

Crowd

Elaine

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Fig. 5 Twenty standard 512×512 gray images

TABLE 1 PSNR(DB) OF GRAY ENHANCED IMAGES FOR OPPORTUNITY COST WITHOUT IMAGE CLASSIFICATION

Image Name	**Blurred Image**	**FSD [5] c=0.45 , s=3**	**Gaussian [4]**	**Opportunity cost without classification c=0.7 , s=3**
Aerial	23.86	25.57	25.81	28.09
Baboon	18.66	18.99	19.25	19.97
Barbara	23.66	24.08	23.98	25.94
Blackb	28.99	30.26	30.13	33.68
Boat	26.53	27.95	27.86	30.50
Couple	25.78	26.76	26.86	29.52
Crowd	26.78	28.10	27.71	31.97
Elaine	30.30	31.09	29.73	32.19
F16	23.62	24.43	24.63	26.96
France	18.29	18.88	19.13	20.69
House	25.79	26.99	27.17	30.34
Lena	28.38	29.95	29.32	32.30
Peppers	28.97	30.72	29.80	32.85
Portofino	27.08	28.19	28.15	31.26
Sedona	24.38	25.15	25.51	27.53
Stagcoch	24.38	25.44	25.65	28.68
Stonehse	21.59	22.15	22.40	23.75
Tahoe	22.56	23.29	23.72	25.68
Utahmtn	20.19	20.76	21.13	22.64
Wood	25.25	26.18	26.22	28.78

Furthermore, the proposed image classification algorithm described in Section III is used to classify these twenty images. The results of these twenty images can be separated to two image classifications, called *image-Class a* and *image-Class b*. In other words, eight images, i.e., Baboon, Blackb, Couple, Portofino, Stagcoch, Stonehse, Tahoe, and Wood, are classified into *image-Class a*, and the remaining twelve images, i.e., Aerial, Barbara, Boat, Crowd, Elaine, F16, France, House, Lena, Peppers, Sedona, and Utahmtn, are classified into *image-Class b*. In addition, the optimal parameter solution algorithm using opportunity cost is again applied on these images of two classifications, respectively, one parameter solution of c = 0.1, s = 7 is proposed for *image-Class a*, and the other parameter solution of c = 0.3, s = 7 for *image-Class b*.

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TABLE 2 PSNR(DB) OF GRAY ENHANCED IMAGES FOR OPPORTUNITY COST WITH IMAGE-CLASS A

Image Name	**Blurred Image**	**FSD [5] c=0.45, s=3**	**Gaussian [4]**	**Opportunity cost without classification c=0.7, s=3**	**Opportunity cost with class a c=0.1, s=7**
Baboon	18.66	18.99	19.25	19.97	19.97
Blackb	28.99	30.26	30.13	33.68	33.68
Couple	25.78	26.76	26.86	29.52	29.53
Portofino	27.08	28.19	28.15	31.26	31.26
Stagcoch	24.38	25.44	25.65	28.68	28.69
Stonehse	21.59	22.15	22.40	23.75	23.76
Tahoe	22.56	23.29	23.72	25.68	25.68
Wood	25.25	26.18	26.22	28.78	28.79

TABLE 3 PSNR(DB) OF GRAY ENHANCED IMAGES FOR OPPORTUNITY COST WITH IMAGE-CLASS B

Image Name	**Blurred Image**	**FSD [5] c=0.45,s=3**	**Gaussian [4]**	**Opportunity cost with class a** c=0.1,s=7	**Opportunity cost with class b c=0.3,s=7**
Aerial	23.86	25.57	25.81	27.73	28.80
Barbara	23.66	24.08	23.98	25.94	25.97
Boat	26.53	27.95	27.86	30.50	31.00
Crowd	26.78	28.10	27.71	31.96	31.97
Elaine	30.30	31.09	29.73	32.19	32.19
F16	23.62	24.43	24.63	26.96	27.01
France	18.29	18.88	19.13	20.69	20.69
House	25.79	26.99	27.17	30.33	30.34
Lena	28.38	29.95	29.32	32.30	32.30
Peppers	28.97	30.72	29.80	32.78	32.85
Sedona	24.38	25.15	25.51	27.53	27.53
Utahmtn	20.19	20.76	21.13	22.64	22.64

In addition, all of enhanced images (I_{-1}), obtained by the proposed and other nonlinear image enhancement methods, are evaluated their image quality using both objective and subjective quality assessments. The measurement of PSNR in (3) is used for the assessment of objective image quality between original image and enhanced image. It follows from Table 2 and Table 3 that the PSNR values of these enhanced images using the proposed opportunity cost method with image classification (c = 0.1, s = 7 for *image-Class a* and c = 0.3, s = 7 for *image-Class b*) are better than those of methods given in [4, 5] and the proposed method without image classification (c = 0.7, s = 3). Moreover, one observes in Table 2, the parameters of c = 0.1, s = 7 are used for eight images of *image-Class a*. One more observes from Table 3, the above *image-Class a* parameters of c = 0.1, s = 7 and the *image-Class b* parameters of c = 0.3, s = 7 are producing different results for the proposed nonlinear image enhancement method, that is, twelve blurred images of *image-Class b* which are enhanced with the parameters of c = 0.3, s = 7 are better than these images enhanced with the *image-Class a* parameters of c = 0.1, s = 7. That is, the proposed nonlinear image enhancement method using opportunity cost with image classification can achieve a better objective performance than the method using opportunity cost without image classification.

The MOS (Mean Opinion Score) is used for subjective quality assessment [10, 11]. The MOS method uses the 5-level impairment grades: 5 for excellent quality, 4 for good quality, 3 for acceptable quality, 2 for poor quality, and 1 for unacceptable quality, and is defined as

$$MOS = \sum_{x=1}^{5} xp(x) \tag{15}$$

where x is grade index and $p(x)$ is grade probability.

In the MOS experiments, twenty observers who are with some background in image processing, subjectively evaluate the enhanced image quality. Moreover, to find the correlation between subjective and objective image quality measurement, the correlation coefficient (r) is expressed as [10, 11]

$$r = \frac{\sum_x (s_x - \bar{s})(o_x - \bar{o})}{\sqrt{\sum_x (s_x - \bar{s})^2 (o_x - \bar{o})^2}} \quad \text{for} \, 1 \le x \le 5 \tag{16}$$

where s_x and o_x are the series of subjective and objective image quality measurement, and $\bar{s}$ and $\bar{o}$ are the average values of

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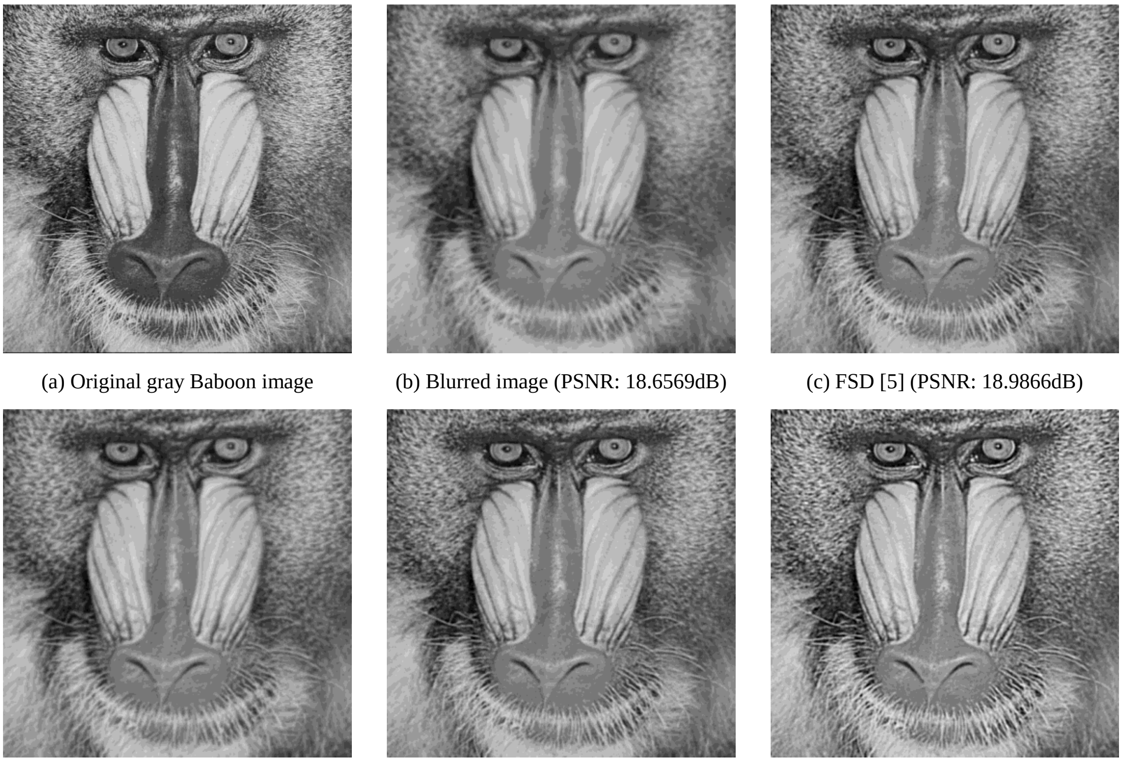
s_x and o_x, respectively. The possible values of r are between -1 and +1, the better correlation makes the closer r to -1 or +1. Our experimental results for PSNR, MOS, and r = 0.7863 are summarized in Table 4 for each enhanced image and the proposed method.

TABLE 4 ASSESSMENT RESULTS

Image	PSNR	MOS
Aerial	27.73	4.15
Baboon	19.97	3.85
Barbara	25.94	4.05
Blackb	33.68	4.6
Boat	30.50	4.1
Couple	29.53	4.1
Crowd	31.97	4.5
Elaine	32.19	4.3
F16	27.01	3.9
France	20.69	3.2
House	30.34	4.05
Lena	32.30	4.15
Peppers	32.85	4.05
Portofino	31.26	4.25
Sedona	27.53	3.75
Stagcoch	28.69	3.95
Stonehse	23.76	3.8
Tahoe	25.68	3.8
Utahmtn	22.64	3.75
Wood	28.79	3.75
Relability of Measurement (r)	0.7863	

Finally, in Figs. 6 and 7, one observes that the gray Baboon and France enhanced images, Fig. 6(f) and Fig. 7(f), processed by the proposed opportunity cost method with *image-Class a* (c = 0.1, s = 7) and *image-Class b* (c = 0.3, s = 7) obtains a better subjective quality and objective PSNR to the blurred images, respectively. These two images enhanced by the FSD, Gaussian and using opportunity cost without image classification are relatively worse in visual and PSNR quality.



(a) Original gray Baboon image (b) Blurred image (PSNR: 18.6569dB) (c) FSD [5] (PSNR: 18.9866dB)

(d) Gaussian [4] (PSNR: 19.2464dB) (e) Opportunity cost without classification c=0.7,s=3 (PSNR: 19.9674dB) (f) Opportunity cost with image-class a c=0.1,s=7 (PSNR: 19.9678dB)

Fig. 6 Comparison of subjective quality and objective PSNR of enhanced gray Baboon image

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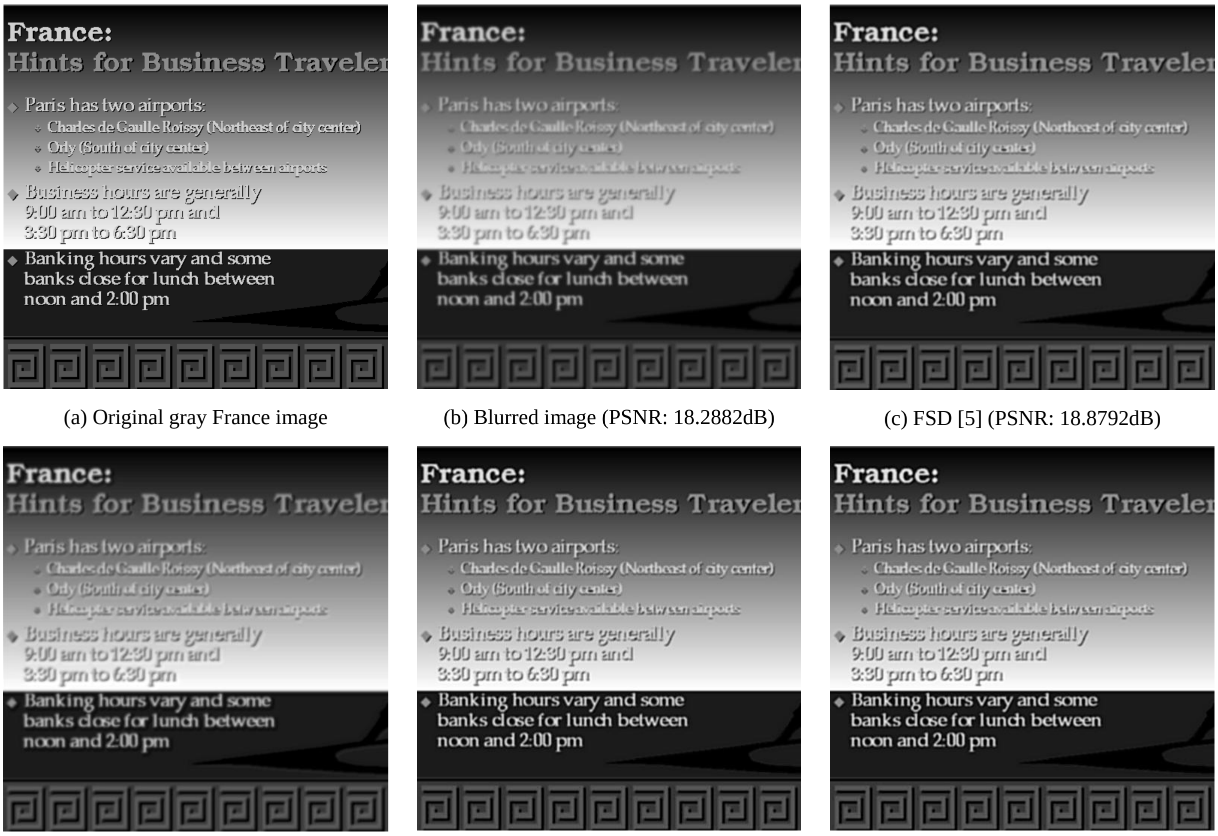

(a) Original gray France image (b) Blurred image (PSNR: 18.2882dB) (c) FSD [5] (PSNR: 18.8792dB)

(d) Gaussian [4] (PSNR: 19.1289dB) (e) Opportunity cost with image-class a c=0.1,s=7 (PSNR: 20.6876dB) (f) Opportunity cost with image-class b c=0.3,s=7 (PSNR: 20.6885dB)

Fig. 7 Comparison of subjective quality and objective PSNR of enhanced gray France image

VI. CONCLUSIONS

In this paper, the nonlinear image enhancement scheme using the principle of opportunity cost and an effective image classification algorithm is proposed to obtain the best combination of clipping and scaling parameters for various blurred images. Experimental results show that using the principle of opportunity cost with the optimal parameter solution algorithm, the *image-Class a* parameters of c = 0.1, s = 7 and the *image-Class b* parameters of c = 0.3, s = 7 are obtained for the proposed nonlinear image enhancement scheme. For improving the quality of blurred images, the proposed opportunity cost method with image classification yields a better subjective and objective performance than other nonlinear image enhancement methods and the opportunity cost method without image classification.

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