Combined Opportunity Cost and Image Classification for Non-Linear Image Enhancement

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Abstract— **In this paper, it is shown that nonlinear image enhancement can be used to improve the quality of a blurred image by using the concept of opportunity cost with image classification. However, one observes from computer simulation that the values of clipping and scaling parameters are quite different in image enhancement for various blurred images. Therefore, one aim of this paper is to develop an effective image classification technique to decide the best combination of clipping and scaling parameters by the opportunity cost method for image enhancement. Experimental results show that the proposed opportunity cost method with image classification for the nonlinear image enhancement achieves a better subjective and objective image quality performance than the method using the opportunity cost without image classification and other nonlinear image enhancement methods.**

Keywords- nonlinear image enhancement; clipping; scaling; opportunity cost; image classification

I. INTRODUCTION

Image enhancement is a commonly used method for the improvement of the quality of a blurred image. Among many image enhancement approaches, the nonlinear image enhancement (NIE) method has a simple structure and can obtain a good processing effect [1][2]. The conventional NIE method in [4][5], which uses a low-pass filter and non-linear operator to predict a high-frequency component, can be used to enhance the visual quality of a blurred image. In addition, this NIE method uses the Gaussian-Pyramid [4] or Filter Subtract and Decimate (FSD)-Pyramid [5] representation of an image to extract the high-frequency component of a blurred image. That is, a high-frequency component can be predicted by a nonlinear filter. The new enhanced (output) image is generated as the sum of the given blurred (input) image and the high-frequency component. Furthermore, it is also shown in [5] that a tradeoff exists between the perceived ringing side-effects and the sharpness of the edges in the NIE scheme. In other words, the exact relationship between clipping and scaling parameters to the blurring and ringing deviations is complex in the NIE approach.

For different blurred images, it is difficult to decide the most suitable clipping and scaling parameters for the NIE method. The authors in [8] developed a modified NIE method with cubic B-spline filter [3] and using the opportunity cost [6][7] to improve the conventional NIE method [4][5]. The concept of opportunity cost can be used to analyze the image enhancement parameters. However, one solution of enhancement parameters cannot fit all occasions of image enhancement, an effective image classification technique is proposed in this paper. In this technique, the wavelet transform and the three-fold cross validation with leave-one-out [12] are proposed for image classification. Then, using the opportunity cost with an optimal parameter combination algorithm, the best combination of clipping and scaling parameters can be obtained for the proposed NIE method.

There is no standard of image quality assessment that can serve as the objective criterion for the image enhancement. In this paper, some standard images are firstly blurred to low-resolution images, and then the proposed NIE method and other NIE methods are used to enhance these blurred images. Finally, their subjective and objective image quality of the corresponding enhanced images can be compared in this paper.

The rest of this paper is organized as follows. Section 2 describes the nonlinear image enhancement method. The opportunity cost in nonlinear image enhancement is proposed in Section 3. Section 4 describes the optimal parameter combination algorithm. Section 5 shows the image classification algorithm. The experimental results are illustrated in Section 6. The last section shows the conclusions of this paper.

II. NON-LINEAR IMAGE ENHANCEMENT METHOD

In the conventional NIE method [5], a low-pass filter, which is a 5-tap binomial approximation of a normalized Gaussian, was used of the form: [1, 4, 6, 4, 1]/16. In this paper using the same procedure, described in [8], the 2-D cubic B-spline filter [3] with the form: [1, 4, 1; 4, 16, 4; 1, 4, 1]/36 are used to improve the NIE method which is shown in Fig.1.

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 K_0, called the residual image, is obtained by subtracting the low-frequency image I_1 from the input-blurred image I_0, i.e., $K_0 = I_0 - I_1$. By [5], the enhanced image I_{-1} is generated as the sum of the input-blurred image I_0 and the predicted high-frequency image K_{-1}; that is,

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DOI 10.1109/CISIS.2012.120

$$I_{-1} = I_0 + K_{-1} \quad (1)$$

where $K_{-1} = NL(K_0)$ is a non-linear operator of K_0, which includes both scaling and clipping steps, defined as follows:

$$NL(K_0) = s \times Clip(K_0) \quad (2)$$

where the scaling constant s is ranging between 1 and 10 and $Clip(x)$ is given by

$$Clip(x) = \begin{cases} T, & if\ x > T \\ x, & if\ -T \le x \le T \\ -T, & if\ x < -T \end{cases} \quad (3)$$

where x is the pixel of the high-frequency image K_0, $T = c \times K_0^{\max}$, $K_0^{\max}$ is the maximum pixel of the high-frequency image K_0 and the clipping constant c is ranging between 0 and 1. After a non-linear operator, the higher-frequency image K_{-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 NIE method with cubic B-spline filter.

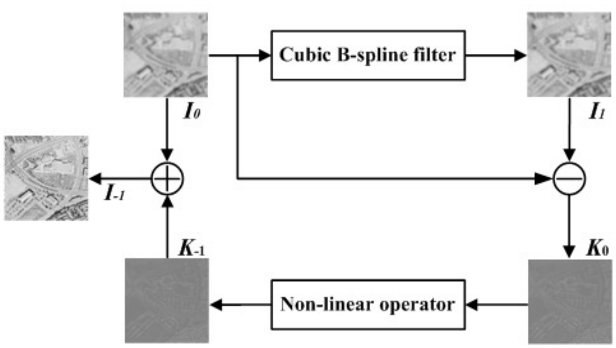

Figure 1. The proposed non-linear image enhancement method.

III. Opportunity Cost in Image Enhancement

When we make a decision, we are making our best choice and dropping the other alternatives. The opportunity cost of a decision [6][7] refers to the value of the maximum profit those discarded options can generate. For example, there is a farmer planning to breed poultry in his land. Due to the space limitation, he can keep only one kind of poultry in his fence, and has to make a decision between pig and chicken. If he chooses to keep pig he is not able to keep chicken. So the opportunity cost of keeping pig is the revenue generated from keeping chicken and vice versa. Assume that keeping pig and chicken can make a profit of 10 and 5 dollars, respectively. So the opportunity cost of keeping pig is 5 dollars, and the net revenue of keeping pig is 5 dollars more than that as keeping chicken. In other words, the opportunity cost of keeping chicken is 10 dollars, and if he chooses to keep chicken the net revenue will actually be 5 dollars less. There are, however, some other decisions which cannot be measured in monetary, such as the choice between studying in the library and watching television at home. Then the opportunity cost of studying in the library might be the relaxation when watching TV, and the opportunity cost of watching TV at home might be the knowledge you can get in the library.

In most NIE methods, it is complex to choose an optimal solution for clipping and scaling parameters [5][8]. The chosen solution is generally more effective to the certain type of image than others. That is, the optimal solution for one image is not necessarily the perfect one for another image. As mentioned above, when we make the decision among different solutions, there is an opportunity cost in each solution. Assume we have two images, X_1 and X_2. If we adopt the optimal solution for image X_2, instead of the optimal solution for image X_1, to enhance image X_1, we surely have the opportunity cost which might be quality or effect when adopting the optimal solution for image X_1. Likewise, the optimal solution for image X_1 have its own opportunity cost as well. So, for these two images, the solution having the less opportunity cost can be used to enhance the images. Our experiments focus on the blurred images. Through the optimal parameter combination algorithm, we simulate the clipping and scaling parameter values and identify the optimal combination of parameters to meet the different requirement of image enhancement methods. However, in image enhancement, while choosing the higher clipping parameter, the image becomes blurring; and while the higher scaling parameter is selected, the image appears ringing. Therefore, the choice of the clipping and scaling parameters involves trade-off and opportunity cost to determine the quality of image enhancement.

IV. Optimal Parameter Combination Algorithm

The choice and use of clipping(c) and scaling(s) parameters involves trade-off and opportunity cost [8]. In this paper, the optimal parameter combination algorithm is proposed to identify the c and s parameters in all the combinations as best as possible for a set of image enhancement to achieve the goal of optimization. For an input image, first it is blurred to low-resolution image, and then it is enhanced by the proposed NIE method. We use the optimal parameters in each group to identify the combination of c and s, and generate the corresponding opportunity costs. The c and s parameters in this paper are set to $c = \{0.1, 0.2, \ldots, 0.9, 1.0\}$ and $s = \{1, 2, \ldots, 9, 10\}$, respectively. The costs for different combinations of c and s parameters refer to their corresponding opportunity costs. That is, for one image, when we choose the option of the parameters and give up the choice of the parameters, we can determine the opportunity cost of this option with respect to the image. Likewise, with the same parameters, the opportunity cost of each image can be determined. Then we have the sum of all these opportunity costs, called the total cost of the options. To obtain the optimal solution, we can choose the combination of c and s parameters having the minimum total cost.

The peak signal to noise ratio (PSNR) is a simple objective measurement for image quality and can be used in the proposed optimal parameter combination algorithm stated as follows. In the case of n (n is more than one) input images, each different combination of c and s parameters can get a different PSNR value of the image. We can find the optimal parameters of each image by these PSNR values, and there will be at most n set of different optimal parameters. With these n different combinations of parameters, we will have n opportunity costs for each image, and then have, after the summation of opportunity costs with respect to each set of parameter, n total costs.

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. The proposed optimal combination algorithm is summarized in the following steps:

1) Calculate the values of $PSNR(i, j)$ of all images for all combinations of c and s parameters.
2) Compute the optimal solution $OP(j)$ for all images by

$$OP(j) = \max(PSNR(\cdot, j)) \tag{4}$$

3) Obtain the optimal PSNR of each image by

$$Optimal\_PSNR(j) = \max(OP(j)) \tag{5}$$

4) Compute the opportunity cost of each image by

$$Cost(j) = | OP(j) - Optimal\_PSNR(j) | \tag{6}$$

5) Compute the total opportunity cost of all images by

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

6) Select the minimum $Tcost$ for optimal solution and obtain the corresponding set of c and s parameters.

V. IMAGE CLASSIFICATION ALGORITHM

An effective image classification algorithm based on the wavelet transform is used to combine the opportunity cost for the proposed NIE method in this paper. The wavelet transform [9] can be implemented as filtering an image by a pair of lowpass filter and highpass filter and downsampling the filtered images by two, respectively. In addition, the multiresolution filter-bank decomposition of an image often performs recursively on the output of low-frequency subband, which leads to the idea of pyramid-structured wavelet transform (PSWT). That is, the PSWT decomposes an image only in the low-frequency subband. An image can be decomposed into four subbands by convolving the image with both lowpass and highpass filters. These four subbands characterize the frequency information of the image in the LL, LH, HL, and HH frequency subbands, respectively. An example of three-level PSWT can be constructed by the whole process of repeating decomposition in the LL subband, as shown in Fig. 2.

The proposed image classification algorithm is illustrated as follows:

A. The Learning Algorithm

[Input:] all given n images
[Output:] two classifications for input images

1) Decompose a given image with three-level PSWT scheme to obtain four subbands in level 3 (LL_3, LH_3, HL_3, and HH_3).
2) Calculate the energy values of four subbands. If the subband is $x(s,t)$ with $1 \le s \le P$ and $1 \le t \le Q$, its energy [9] is

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

3) Define the energy values of four subbands by $x = (x_1, x_2, x_3, x_4)$.
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.
5) Calculate the Mahalanobis distance [9] by

$$d_i = (x - y_i)^T C_i^{-1} (x - y_i) \tag{9}$$

where C_i is the covariance matrix of image i.
6) Using three-fold cross validation with leave-one-out algorithm [12], all images are randomly partitioned into three subsets. Each one is used in turn for testing while the remainder is used for training (i.e., 2/3 of images are used for training and 1/3 for testing).
7) Finally, generate the final classification from all of input images.

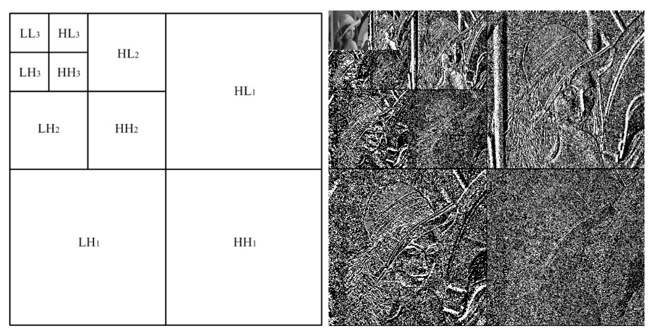

Figure 2. Three-level PSWT decomposition

B. Image Classification Algorithm

[Input:] an unclassified image
[Output:] the classification for unclassified image

1) Decompose an unclassified image with three- level PSWT scheme to obtain four subbands in level 3 (LL_3, LH_3, HL_3, and HH_3).
2) Calculate the energy values by equation (8) for these four subbands and denote this energy value by $x = (x_1, x_2, x_3, x_4)$.
3) For each classification i, calculate the mean of energy value as $m_i = (m_{i,1}, m_{i,2}, m_{i,3}, m_{i,4})$ by averaging the energy value over all images in the classification.
4) Calculate the Mahalanobis distance by

$$\bar{d}_i = (x - m_i)^T C_i^{-1} (x - m_i) \tag{10}$$

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

5) Assign the unclassified image to classification *i* if $\bar{d}_i < \bar{d}_j$ for all $j \neq i$.

VI. Experimental Results

Firstly, twenty standard gray images (Aerial, Baboon, Barbara, Blackb, Boat, Couple, Crowd, Elaine, F16, France, House, Lena, Peppers, Portofino, Sedona, Stagcoch, Stonehse, Tahoe, Utahmtn, and Wood) of size 512×512 are selected in our experiment. In addition, the three-fold cross validation with leave-one-out algorithm [12] is used to classify these twenty images. The results of these images can be separated to two classifications, called image *Class a* and image *Class b*. That is, eleven images of Aerial, Baboon, Barbara, Blackb, Boat, Couple, Portofino, Stagcoch, Stonehse, Tahoe, and Wood are classified into image *Class a*, and the remaining nine images of Crowd, Elaine, F16, France, House, Lena, Peppers, Sedona, and Utahmtn are classified into image *Class b*. In order to verify the performance of the proposed NIE method, twenty above original images are blurred into low-resolution ones. Furthermore, using the opportunity cost concept with the optimal parameter combination algorithm, one parameter combination of c = 0.1, s = 7 is proposed for image *Class a*, and the other parameter combination of c = 0.3, s = 7 for image *Class b*.

TABLE I. PSNR (dB) of Gray Enhanced Images for Gaussian, FSD, and Proposed Method by Opportunity Cost with Image Class A

Image Name	Blurred	FSD [5] c=0.45,s=3	Gaussian [4]	Proposed Method c=0.1,s=7
Aerial	23.8566	25.5691	25.8064	27.7287
Baboon	18.6569	18.9866	19.2464	19.9678
Barbara	23.6614	24.0844	23.9832	25.9393
Blackb	28.9937	30.2603	30.1298	33.6757
Boat	26.5271	27.9452	27.8608	30.5027
Couple	25.7814	26.7554	26.8610	29.5293
Portofino	27.0754	28.1894	28.1506	31.2647
Stagcoch	24.3761	25.4351	25.6465	28.6859
Stonehse	21.5923	22.1459	22.3958	23.7554
Tahoe	22.5591	23.2861	23.7155	25.6812
Wood	25.2527	26.1833	26.2202	28.7862

All of enhanced images, obtained by the proposed and other NIE methods, are evaluated their image quality using both objective and subjective quality assessments. The measurement of PSNR is used for the assessment of objective image quality between original and enhanced images. It follows from Table I and Table II that the PSNR values of these enhanced images using the proposed method are better than those of methods given in [4] and [5]. Furthermore, one observes in Table I, the parameters of c = 0.1, s = 7 are used for eleven images of image *Class a*. One more observes from Table II, the above 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 NIE method, that is, nine 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 NIE method with image classification can achieve a superior objective performance than the proposed NIE method without image classification.

TABLE II. PSNR (dB) of Gray Enhanced Images for Gaussian, FSD, and Proposed Method by Opportunity Cost with Image Class B

Image Name	Blurred	FSD [5] c=0.45,s=3	Gaussian [4]	Using Table I c=0.1,s=7	Proposed Method c=0.3,s=7
Crowd	26.7786	28.0971	27.7077	31.9635	31.9652
Elaine	30.3007	31.0904	29.7340	32.1894	32.1895
F16	23.6234	24.4288	24.6277	26.9636	27.0062
France	18.2882	18.8792	19.1289	20.6876	20.6885
House	25.7895	26.9849	27.1659	30.3347	30.3426
Lena	28.3770	29.9516	29.3179	32.3011	32.3042
Peppers	28.9713	30.7173	29.7994	32.7840	32.8463
Sedona	24.3831	25.1516	25.5078	27.5263	27.5270
Utahmtn	20.1937	20.7645	21.1327	22.6421	22.6431

For subjective quality assessment, we use MOS (Mean Opinion Score) [10][11], which is the result of perception based on subjective evaluation. The method uses the 5-level impairment grades: 5-excellent quality, 4-good quality, 3-acceptable quality, 2-poor quality, and 1-unacceptable quality. MOS is calculated as follows:

$$MOS = \sum_{i=1}^{5} ip(i), \tag{11}$$

where *i* is grade and $p(i)$ is grade probability.

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

$$r = \frac{\sum_i (s_i - \bar{s})(o_i - \bar{o})}{\sqrt{\sum_i (s_i - \bar{s})^2 (o_i - \bar{o})^2}}, \tag{12}$$

where s_i and o_i are the series of subjective and objective image quality measurement, respectively. The possible values of *r* are between -1 and +1, the better correlation makes the closer *r* to -1 or +1. Results for PSNR, MOS, and *r* are presented in Table III for each enhanced image and the proposed method.

In Fig.3, one observes that the gray Aerial enhanced image processed by the proposed NIE method obtains a better subjective quality and objective PSNR to the blurred image. Image enhanced by the FSD, Gaussian and proposed NIE method without image classification are relatively worse in visual and PSNR quality.

(a) Original gray Aerial image

(b) Blurred image (PSNR:23.8566dB)

(c) FSD [5] (PSNR:25.5691dB)

(d) Gaussian [4] (PSNR:25.8064dB)

(e) NIE with c=0.3,s=7 (PSNR: 27.6585dB)

(f) Proposed c=0.1,s=7 (PSNR: 27.7287dB)

Figure 3. Comparison of subjective quality and objective PSNR of enhanced gray Aerial image

TABLE III. ASSESSMENT RESULTS FOR PSNR, MOS, AND CORRELATION COEFFICIENT (*r*)

Image	PSNR	MOS
Aerial	27.7287	4.15
Baboon	19.9678	3.85
Barbara	25.9393	4.05
Blackb	33.6757	4.6
Boat	30.5027	4.1
Couple	29.5293	4.1
Crowd	31.9652	4.5
Elaine	32.1895	4.3
F16	27.0062	3.9
France	20.6885	3.2
House	30.3426	4.05
Lena	32.3042	4.15
Peppers	32.8463	4.05
Portofino	31.2647	4.25
Sedona	27.5270	3.75
Stagcoch	28.6859	3.95
Stonehse	23.7554	3.8
Tahoe	25.6812	3.8
Utahmtn	22.6431	3.75
Wood	28.7862	3.75
Relability of Measurement (*r*)	0.78627	

VII. CONCLUSIONS

In this paper, we present that the NIE method combined with a simulation and identification process of clipping and scaling parameters can be improved by using opportunity cost based on image classification for blurred images. Using three-fold cross validation, some given images are separated to two image classifications. In addition, using the concept of opportunity cost with the optimal parameter combination 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 NIE method. Furthermore, objective and subjective image quality measurements such as PSNR, MOS, and correlation coefficient (*r*) are compared for all enhanced images. Experimental results show that the proposed NIE method with image classification yields a better subjective quality and objective PSNR value than other NIE methods for enhanced images.

ACKNOWLEDGMENT

This work was supported by the National Science Council, R.O.C., under Grant NSC 100-2221-E-251-011.

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