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Toward an improvement of UAV-aerial image using non-linear image enhancement

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***Abstract*—Unmanned aerial vehicle (UAV)-vision applications are increasingly widespread in recent years, however, the UAV-aerial image causes a blurred condition because there is no power in the high-frequency component of aerial image. To improve the quality of such a blurred image, the image enhancement is an indispensable post-processing method. In this paper, the opportunity cost can be used to improve the non-linear image enhancement method for the UAV blurred image. In addition, a modified non-linear image enhancement scheme by cubic splines and opportunity cost will be proposed. The different non-linear image enhancement methods such as Gaussian-Pyramid and FSD-Pyramid are also compared with the proposed enhancement method.**

Keywords- UAV; image enhancement; opportunity cost; aerial image

I. Introduction

With the gaining popularity of camera lens and UAV (Unmanned Aerial Vehicle) technologies, aerial images are not only used in military but also have been widely used in daily lives in recent years such as geographical research, traffic infrastructure, hydraulic engineering, emergency relief, media broadcast, and police tracking, etc. However, the UAV-aerial image because of aerial flight factors and image compression process leads to a blurred problem caused by the loss of high-frequency components [1], as shown in Fig.1. To improve the quality of such a blurred image, the image enhancement is an indispensable post-processing method. The principle of image enhancement is to process a given blurred image so that it is more suitable for visual quality or image analysis [2].

(a) Aerial color image (JPEG) (b) Aerial gray-scale images
Figure 1. UAV-aerial train track image

Nonlinear image enhancement [3][4], which uses low-pass filter and non-linear operator technique to predict a high-frequency component, can enhance the visual quality of a blurred image. In addition, it uses the Gaussian-Pyramid [3] or the filter subtract and decimate (FSD)-Pyramid [4] representation of an image to extract the high-frequency component of input (blurred) image shown in Fig.2. In [4], it is also shown that a tradeoff exists between the perceived ringing side-effects and the sharpness of the edges in the nonlinear image enhancement. That is, the exact relationship between the *c* (clipping) and *s* (scaling) parameters to the blurring and ringing deviations is very complex.

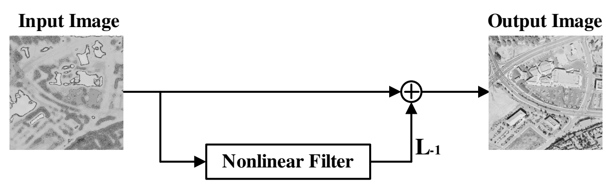

Figure 2. Basic operation of nonlinear image enhancement

Opportunity cost [5][6] is a well-known theory. This paper shows how to use this economic concept in the area of UAV-aerial image processing. That is, we present an idea that uses the concept of opportunity cost to improve the nonlinear image enhancement for the blurred problem of UAV-aerial images. However, it is believed that the best values of enhancement parameters in [4] vary with the types of images. Since one solution for *c* and *s* parameters cannot fit all occasions, this paper is mainly inspired by the principles of opportunity cost, and presents an approach to improve the blurred image problem, which simulates the image enhancement for different combinations of the *c* and *s* parameters. Furthermore, the authors in [7] developed a modified nonlinear image enhancement with cubic B-spline filter [8][9] and using the idea of opportunity cost to improve the conventional nonlinear image enhancement [3][4]. In the theoretical analysis, the proposed enhancement method that uses the opportunity cost needs to calculate *c* and *s* for every image of every *c* and *s*. Therefore, in this paper, an optimal parameter combination algorithm is proposed how to select the *c* and *s* values as best as possible for a set of image enhancement to get the optimal solution. Since, the calculation time required for the training process is slightly complexity, but in the experimental part, using the optimal

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solution obtained in the training process, the calculation time required for the proposed enhancement method is very fast and similar to the original nonlinear image enhancement method in [6]. Finally, we conclude with the experimental results that the proposed method can provide a better subjective quality and better PSNR on objective non-linear aspect, in comparison with other image enhancement methods.

II. BACKGROUND OF THIS WORK

It is well known that the cubic B-spline filter [8] is a very smoothing filter. The authors in [7][9] show that this cubic B-spline filter can be used to improve the conventional nonlinear image enhancement method. In this paper, a cubic B-spline filters [8] with the form: [1, 4, 1; 4, 16, 4; 1, 4, 1]/36 are used to improve the nonlinear image enhancement method which is shown in Fig.3.

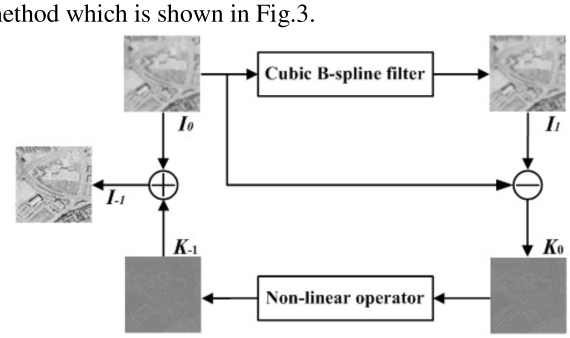


Figure 3. The proposed nonlinear image enhancement

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,

$$I_{-1} = I_0 + K_{-1}, \tag{1}$$

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

$$NL(K_0) = s \times Clip(K_0) \tag{2}$$

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

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

where x is the pixel of the high-frequency image K_0 , $T = c \times K_{0max}$, K_{0max} 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 high-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 to find the most suitable combination of clipping and scaling parameters for the proposed nonlinear image enhancement method with cubic B-spline filter.

III. THE OPTIMAL PARAMETER COMBINATION ALGORITHM

For an input image, first it is blurred to low-resolution image, and then it is enhanced by the nonlinear image enhancement 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, 0.3, …, 0.9, 1.0 and s = 1, 2, 3, …, 9, 10, respectively. Consequently, 100 different combinations can be generated. The costs for different combinations of c and s refer to their corresponding opportunity costs. That is, for one image, when we choose the option of a set of parameters c = 0.1 s = 1 and give up the choice of the other sets of 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.

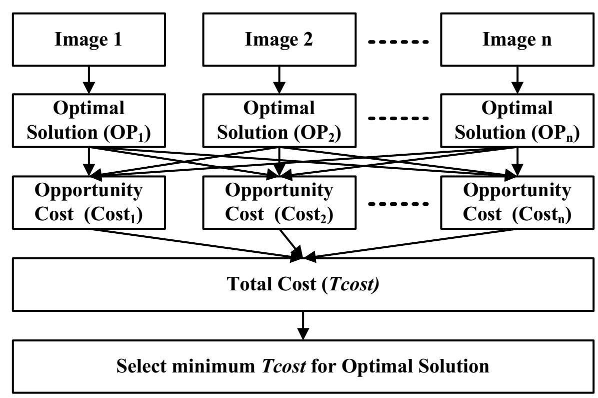


Figure 4. The optimal parameter combination algorithm

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 summation of opportunity costs with respect to each set of parameter, n total costs. We can obtain the optimal combination of parameters to minimize the total opportunity cost, as illustrated in Fig.4. [7]

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

1) **Input.** Calculate the values of $PSNR_{i,j}$ for n input images with m combinations, where i is the index of images and j is the index of distinct combination of c and s parameters for $1 \le i \le n$, $1 \le j \le m$ and $n \le m$.

2) **Optimal solution for each input image.** Each input image will have an optimal solution *OP*, and we obtain n optimal solutions for n input images. Therefore, totally we will have $n \times n$ of *PSNR* (*Optimal_PSNR*), as in (4) and (5).

$$OP(i) = \max(PSNR_{i,j}) \tag{4}$$

$$Optimal\_PSNR_{i,j} = \max(OP(i)) \tag{5}$$

3) **Opportunity cost.** By the optimal solution for each input image, we can decide the opportunity costs, as in (6).

$$Cost_{i,j} = OP(i) - Optimal\_PSNR_{i,j} \tag{6}$$

4) **Optimal c and s parameters.** After the cost calculation, we can obtain the opportunity cost of each input image, given the same parameter values. At last, we add the opportunity costs altogether and obtain the total cost (*Tcost*), select the combination of c and s parameters of the minimum *Tcost*, which is deemed the optimal combination parameters, as in (7).

$$\begin{aligned} Tp\cos t &= \min_j (T\cos t_j) \\ &= \min_j \left(\sum_{i=1}^{n} Cost_{i,j}\right) \end{aligned} \tag{7}$$

IV. Experimental Results

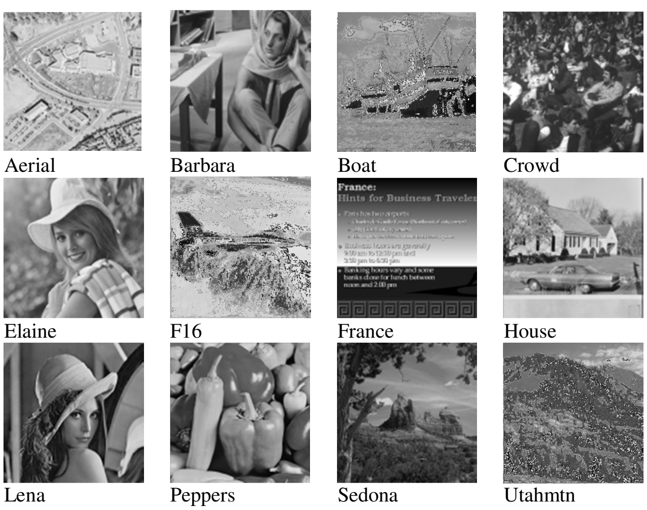
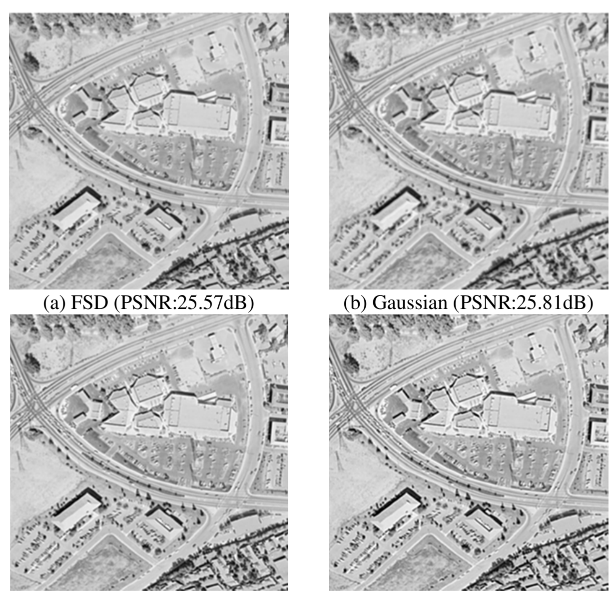


Fig. 5 Twelve standard 512×512 gray images

In this section, we are also based on the authors in [10] improved the nonlinear image enhancement method by using opportunity cost with image classification for blurred images. Therefore, twelve standard gray images (Aerial, Barbara, Boat, Crowd, Elaine, F16, France, House, Lena, Peppers, Sedona, and Utahmtn), shown in Fig. 5, of size 512×512 are selected for the classification of UAV-aerial images. In order to verify the performance of the proposed opportunity cost method, these twelve images are blurred into low-resolution ones as input-blurred images (I_0). Using the optimal parameter combination algorithm based on the opportunity cost method, we can find two optimal parameters of c = 0.1 s = 7 and c = 0.3 s = 7 for these twelve images. In addition, the proposed opportunity cost method and the methods in [3] and [4] are applied on these input-blurred images, and we make a comparison on the *PSNR* generated in each method in Table I [10]. These input images are originally blurred, and we use the Gaussian [3], FSD [4] and proposed opportunity cost methods for image enhancement. It follows from Table I that the PSNR values of the enhanced images using the proposed opportunity cost method with c = 0.1 s = 7 and c = 0.3 s = 7 are better than those of methods given in [3] and [4].

TABLE I. PSNR(DB) OF GRAY ENHANCED IMAGES FOR GAUSSIAN, FSD, AND OPPORTUNITY COST WITH IMAGE CLASSIFICATION

Image Name	**Blurred Image**	**FSD [4] c=0.45 s=3**	**Gaussian [3]**	**Opportunity cost with c=0.1 s=7**	**Opportunity cost with 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	26.98	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



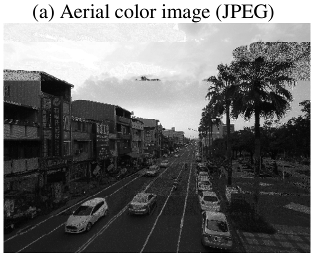
(a) FSD (PSNR:25.57dB) (b) Gaussian (PSNR:25.81dB)
(c) Proposed c=0.1 s=7 (PSNR:27.73dB) (d) Proposed c=0.3 s=7 (PSNR:28.80dB)

Fig. 6 Comparison of enhanced gray Aerial images

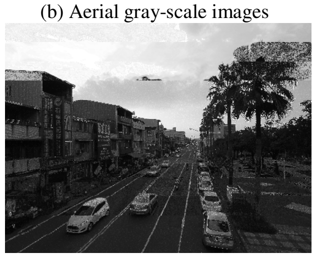
In Fig.6 [10], one observes that the gray Aerial enhanced images in Fig.6(c) and Fig.6(d) processed by the proposed method obtain a better subjective quality and an objective *PSNR* value than other nonlinear enhancement methods in Fig.6(a) and Fig.6(b). That is, those images enhanced by the FSD and Gaussian methods are relatively worse in visual and *PSNR* quality. Furthermore, Fig. 7 shows an example of the enhanced gray UAV-aerial image in Pingtung city, it is easy to found that the proposed method with c=0.1 s=7 in Fig. 7(c) and c=0.3 s=7 in Fig. 7(d) obtains a better subjective quality to the blurred image. In addition, the car number in Fig.7(e) can be seen clearly by the proposed enhancement method with c=0.1 s=7 (zoom in).

(a) Aerial color image (JPEG)

(b) Aerial gray-scale images



(c) Proposed method with c=0.1 s=7



(d) Proposed method with c=0.3 s=7

(e) Proposed method with c=0.1 s=7 (zoom in)

Fig. 7 Comparison of enhanced UAV-aerial gray image in Pingtung city

V. CONCLUSIONS

In this paper, we present that the nonlinear image enhancement combined with a simulation and identification process of clipping and scaling parameters can provide the optimal parameter combination for UAV-aerial images. The experimental results show that the proposed enhancement method by using cubic B-spline filter with c=0.1 s=7 and c=0.3 s=7 yields a better subjective quality and objective PSNR value than other nonlinear enhancement methods for the enhanced image.

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