

Improved Roberts focusing evaluation method for an autofocus system

AIJUN YIN^{1*}, ZONGXIAN DAI¹, BENQIAN CHEN², KONGJING LI³

¹The State Key Laboratory of Mechanical Transmission, Chongqing University, Chongqing 400044, China

²XJ Jingrui Science and Technology Co., Ltd, Xuchang, Henan, 461000, China

³School of Electrical, Electronic and Computer Engineering, Newcastle University, Newcastle upon Tyne, NE1 7RU, UK

*Corresponding author: yinaijun2001@yahoo.com.cn

In this paper, a new focusing evaluation method based on local 2/8 center windows is proposed for an autofocus system. We have proposed an evaluation function which improved the Roberts function with eight-neighborhood or four-neighborhood. The approximate optimal criteria window is selected by a 2/8 rule. Comparative experiments implemented with other methods have shown that the 2/8 rule method not only can find the approximate optimal evaluation window quickly, but also has better generality. This evaluation function of improved Roberts' function has higher sensitivity and better real-time performance.

Keywords: focus evaluation function, evaluation window, autofocusing.

1. Introduction

Focusing evaluation method is one of the key issues in an autofocus system. It should have non-bias, unimodality, higher sensitivity and higher signal-to-noise ratio, lower computational cost, and so on. There are two primary approaches to autofocusing: *i*) image content sharpness measurements, wherein the image quality is maximized directly to achieve the best focus; *ii*) position sensing, which is usually based on the light reflection-off of specimen surface substrates [1, 2].

Evaluation methods are usually divided into spatial domain methods and frequency domain methods. Some spatial domain evaluation methods have been proposed previously based on edge information and gradients. These include the Sobel gradient function, Roberts function, Vollath function [3] and the minimum entropy criteria method [4], as well as others [1, 5–10]. The Roberts method has better robustness and real-time performance, but its sensitivity is general. The Sobel method has good sensitivity in a near focus region, a wide effective range of a far focus region, but it is influenced by noise. Vollath's method has general accuracy and real-time perfor-

mance. The minimum entropy method has a small amount of calculation apart from fast response, but its unimodality and sensitivity are poor.

The most commonly used frequency evaluation functions include the mid-frequency discrete cosine transform (MF-DCT) focus measure [11], the evaluation function based on improved power spectral in frequency-domain (IPSPD) [12], and so on. The robustness and accuracy of MF-DCT are better for images with Gaussian and impulse noise, but its sensitivity is general. The IPSPD function has better robustness and real-time performance, but it has a poor single apex. Recently, many focusing evaluation functions have been investigated based on the wavelet transform with the continuous development of the wavelet transform theory and its applications. In the discrete wavelet transform (DWT) domain, ZONG *et al.* first proposed a focus measure based on the energy of wavelet coefficients [13]. Various methods have been discussed such as the function based on DWT and the autocorrelation operator based on the continuous wavelet transform (CWT) filtering [14], wavelet packet transform [15], lifting wavelet transform [16] and the function based on the M_{WT}^2 operator and others [17]. If the target object is in the center of the focus window or in a low-noise environment, it can achieve good focusing performance through these existing methods. Otherwise, the focusing performances are poor. The improved weighted evaluation function based on the wavelet transform with the daubechies (db) wavelet function was proposed [18]. However, this method is time-consuming. To solve the above problems, this paper presents an improved Roberts' evaluation function.

An image includes not only a target object but also background information. Consequently, the selection of the focus evaluation window would directly affect the accuracy and speed of the focus. The common selection methods of a criteria window include the central window selection measure, multi-window choice method, interactive measure, tracking method, and so forth [19–21]. The adaptive genetic algorithm (AGA) is used to search the approximately best criteria window automatically [17]. The obvious shortcomings of these methods are simplicity, blindness, and poor generality and complex processing. To address these problems, in this paper, the 2/8 center window method is used through a 2/8 general principle.

The paper is organized as follows. Section 2 provides the brief review of the Roberts method and the window analysis. Experimental results are shown in Section 3. Finally, Section 4 summarizes the conclusions.

2. Evaluation function

With the Roberts method, the Roberts gradient function is expressed as

$$F = \sum_{x=1}^M \sum_{y=1}^N \left[|g(x, y) - g(x + 1, y + 1)| + |g(x + 1, y) - g(x, y + 1)| \right] \quad (1)$$

where $g(x, y)$ is the gray value of the point of (x, y) in an $M \times N$ sized image. The structure of this image is shown in Fig.1.

$g(x - 1, y - 1)$	$g(x, y - 1)$	$g(x + 1, y - 1)$
$g(x - 1, y)$	$g(x, y)$	$g(x + 1, y)$
$g(x - 1, y + 1)$	$g(x, y + 1)$	$g(x + 1, y + 1)$

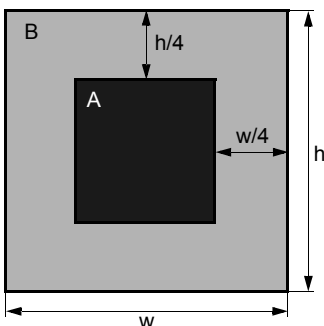
◀ Fig. 1. The changing schematic diagram of eight neighborhood pixels.

Obviously, the image details of the point (x, y) are affected by gray gradient changes of the eight directions [22]. Therefore, it is more effective to consider the gray gradient in each of the eight directions as a focusing criterion [21]. Based on these ideas, we can define the central distance between two adjacent pixels in a straight line as 1, such as the range between point (x, y) and point $(x, y - 1)$ in Fig. 1. The centre distance between two relative pixels is $\sqrt{2}$, as the distance between point (x, y) and point $(x + 1, y - 1)$. So the Roberts criterion function of Eq. (1) can be amended as

$$\begin{aligned}
 F = \sum_{x=1}^M \sum_{y=1}^N & \left\{ |g(x, y) - g(x + 1, y)| + |g(x, y) - g(x, y + 1)| + \right. \\
 & + |g(x, y) - g(x - 1, y)| + |g(x, y) - g(x, y - 1)| + \\
 & + \frac{1}{\sqrt{2}} \left[|g(x, y) - g(x - 1, y - 1)| + |g(x, y) - g(x - 1, y + 1)| + \right. \\
 & \left. \left. + |g(x, y) - g(x + 1, y - 1)| + |g(x, y) - g(x + 1, y + 1)| \right] \right\} \quad (2)
 \end{aligned}$$

considering that the multi-region focusing window could reduce the dependence on the main non-imaging objective [19, 20]. According to the art of photography and the aesthetics theory [23], there are five key human vision points. The main subjects are usually focused on the center region, especially for a vision measurement system. For fast operation, we can only consider the area A in the image as shown in Fig. 2, even only the 1/16 image area in the centre [20]. This information distribution rule was approximately concluded using other entropy-based methods [24].

There is a 2/8 basic rule valid in nature and social activities. It was firstly found by Pareto when he researched the income distribution in 1906. It is used widely in business management, economy, marketing, finance, e-government in web informa-



◀ Fig. 2. Evaluation of the multi-region focus window.

tion system [25]. According to the aforementioned discussion, we naturally think that image information distribution fits the 2/8 rule, or Pareto distribution. Therefore, the evaluation focusing window can be simplified to two regions (A, B) as shown in Fig. 2. We also think that this 20% of the image area contains over 80% of information. From Fig. 2, given the convenience of processing, A is in the centre with 25% of the image size. B is the remaining image area with 75%.

Two criterion values corresponding to the focus areas (A, B in Fig. 2) can be calculated by Eq. (2) and denoted, respectively, by F_A , F_B . So the integrated focus evaluation value F of the whole image can be defined as:

$$\begin{cases} F = k_1 F_A + k_2 F_B \\ k_1 + k_2 = 1 \end{cases} \quad (3)$$

where k_1 , k_2 denote weights of the evaluation values of two focus regions (A, B) in the comprehensive evaluation value. They are all positive. Considering the 2/8 basic rule, k_1 is 0.75, and k_2 is 0.25.

For Equation (3), the normalized evaluation values F_{i_nor} of the i -frame image can be defined as:

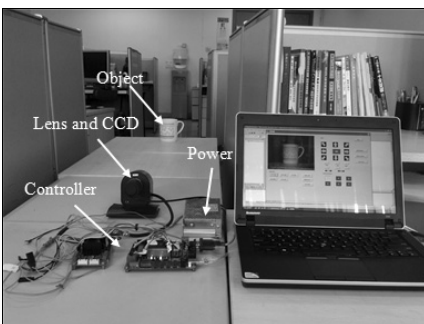
$$F_{i_nor} = \frac{F_i - F_{\min}}{F_{\max} - F_{\min}} \quad (4)$$

where F_i denote the evaluation values of the i -frame image, F_{\max} and F_{\min} denote the maximum and minimum of all frame images, respectively.

3. Experimental results

3.1. Experiments setup

The test rig is shown in Fig. 3. The imaging system consists of a camera lens with three stepper motors, CCD, 51MCU controller, power supply and PC. Images are acquired by the CCD, they are sent to the PC through USB. The focal distance, object distance and aperture of the camera are adjusted by the stepper motor with the controller. PC sends a signal to the controller according to the evaluation value, then the system achieves autofocusing.



◀ Fig. 3. Test rig.

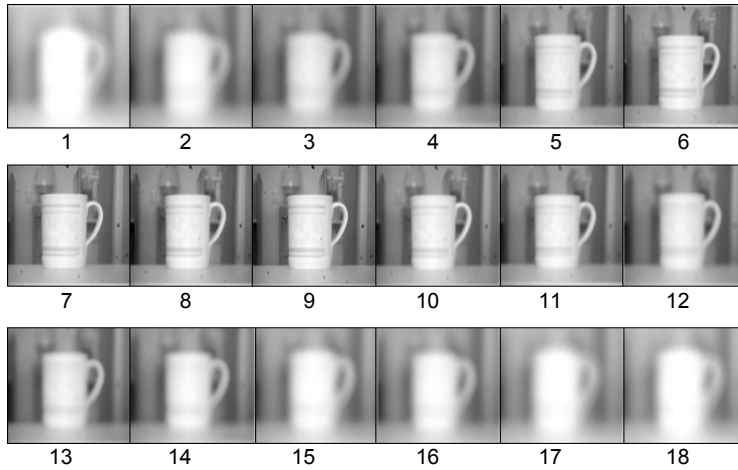


Fig. 4. Experimental images.

In this paper, a sequence of 18 frames of a defocus–focus–defocus image are used to perform contrast experiments, whose size is 640×480 , where the images are captured consecutively in natural conditions. The images are shown in Fig. 4. The proportion of image zooming is 35% of the original image size. The software Matlab is used to analyze the image.

3.2. Experimental results and analysis

3.2.1. Experiment one: criteria performance comparison using different evaluation window selection methods

The comparison of evaluation performances is shown in Fig. 5, using the same evaluation function – Eq. (2). Obviously, from Fig. 5, the performances of these three evaluation

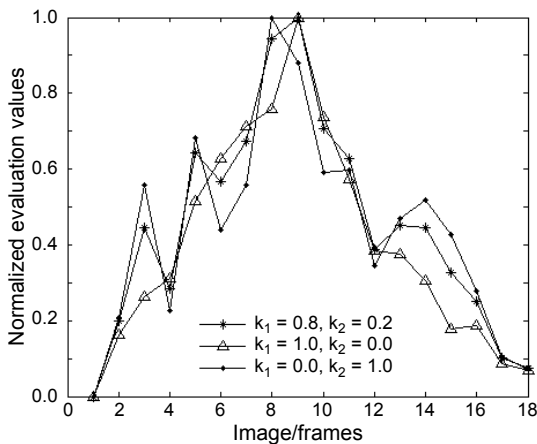


Fig. 5. Performance comparison of different evaluation window selection methods.

window selection methods are similar. Especially when the area A is selected only, the evaluation performance is not worse than the other two methods. In Figure 2, when only B is selected (as parameters $k_1 = 0$ and $k_2 = 1$), this will result error focus position (the position No. 8 in Fig. 5) because non of main objects are targeted within the image. It can be seen that there are more local extremal points if too many main non-imaging objectives are considered. This will result in bad unimodality and accuracy. At this time, the 2/8 center window should be selected, which will save time. That said, the real-time performance of the 2/8 center window is better than the global window because it evaluates only 25% of the image area.

3.2.2. Experiment two: criteria performance comparison between the proposed evaluation function and other functions

In Figure 6a, the evaluation effect is shown between the function proposed in this paper and other functions mentioned in Refs. [5–8, 12]. And in Fig. 6b, the evaluation effect is shown between the function proposed in this paper and the 3×3 mask based on the first and second derivatives methods as presented in Ref. [1]. The time performance is shown in Tab. 1. According to the Reference [1], the peak widths at 50% and 80%

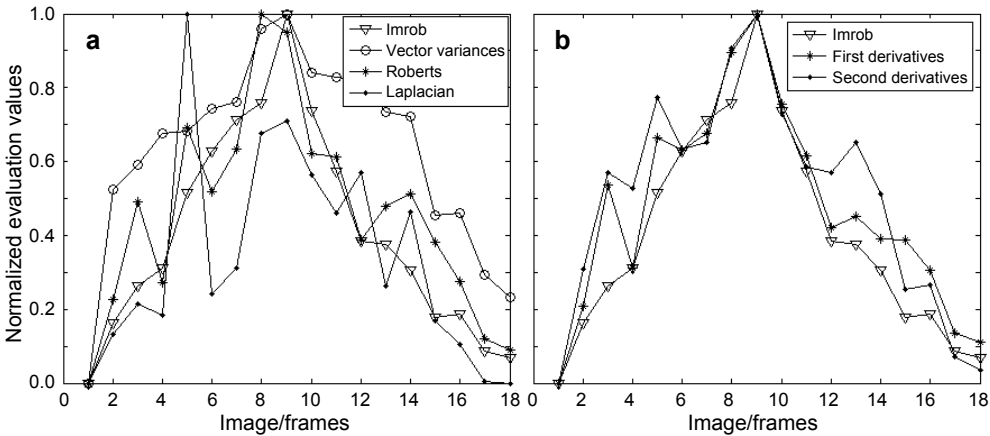


Fig. 6. Performance of improved Roberts, vector variances, Roberts and Laplacian (a), and performance of improved Roberts, first and second derivatives (b).

Table 1. Time performance of different functions.

Method	Execution time [s]
Imrob 4 neighborhood	0.402
Grayscale vector variance	0.247
Roberts	0.309
Laplacian	0.358
3×3 first derivatives	0.594
3×3 second derivatives	0.451

Table 2. Peak width at 50% and 80% of the maximum value

Method	50% (frame number)	80% (frame number)
Imrob 4 neighborhood	7	1
Grayscale vector variance	9	5
Roberts	8	2 (error focus)
Laplacian	5	1 (serious error focus)
3×3 first derivatives	8	2
3×3 second derivatives	12	2

of the maximum value are shown in Tab. 2 [1]. From these figures and tables, it can be seen that the Roberts function and Laplacian function are less accurate and less effective, although they have good real-time performance. These evaluation curves have many local extremal points. Obviously, they have bad unimodality, which even resulted in the error focal point. The peak value is also not obvious using the variance function; in other words, it is less sensitive and less reproducible. Compared with the proposed method, the 3×3 derivatives methods have also bad unimodality. The evaluation curve based on the proposed method has good unimodality, reproducibility, accuracy, and monotonicity with a sharp top of the extremum, which is important in the auto-searching focus procedure in the vision system.

3.2.3. Experiment three: criteria performance comparison between the proposed evaluation function and other functions after adding salt and pepper noise

The experimental images are shown in Fig. 7 after adding salt and pepper noise, with noise density d equal to 0.05. Figure 8 shows the evaluation performance comparison between the proposed evaluation function and other evaluation functions after adding

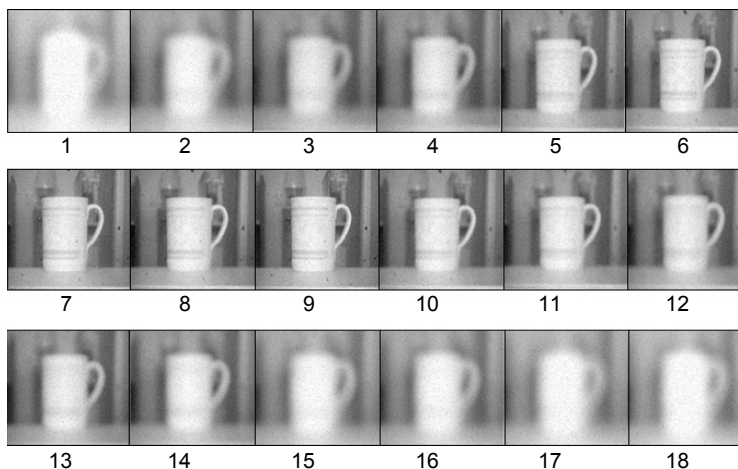


Fig. 7. Performance comparison of different neighborhood improved Roberts functions.

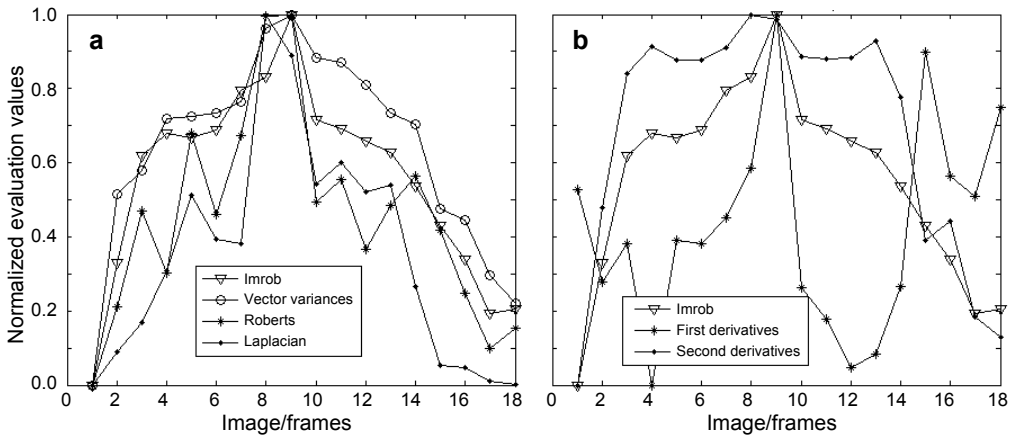


Fig. 8. Performance comparison of different functions after adding *salt and pepper* noise. Performance of improved Roberts, vector variances, Roberts and Laplacian (a). Performance of improved Roberts, first and second derivatives (b).

salt and pepper noise. From these figures, it can be seen that all of the evaluation curves have fluctuated after adding noise. However, the method proposed in this paper shows better accuracy, sensitivity, and higher unimodality than other functions. And the evaluation curves of other functions exhibit an obvious variation, especially in the derivative methods, which indicates that the autofocus process could be easily disturbed.

4. Conclusions

There are many commonly used focusing evaluation functions. Recently, evaluation methods based on the wavelet transform have been studied thoroughly. These methods still have some problems, such as sensitivity, unimodality, real-time performance and evaluation window selection, *etc.* To solve these problems, the presented paper has reviewed the advantages and disadvantages of the existing methods and put forward a novel focus evaluation method that contains the improved Roberts function and the approximate optimal criteria window based on the $2/8$ rule. This method can also be applied to non-destructive testing and measurement based on images to achieve better performance [5, 26, 27].

Experiments show that the proposed method has better reproducibility, accuracy, real-time performance and unimodality, except higher sensitivity compared with conventional functions. At the same time, the proposed method has a good capacity of resisting disturbances. In addition, the criteria window selection using the $2/8$ rule has been proved useful.

Those problems still need additional research. The proposed method requires the target object to be located at the center of the image. For a window selected, a center position of the image is artificially defined before autofocusing if the target

object is not located at the center. This window selected using the 2/8 rule is still being further analyzed.

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