Grey Wolf Optimizer-Based Automatic Focusing for High Magnification Systems

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***Abstract*—High-quality astronomical images significantly affect the results of astronomical scientific research. Since the accurate focus is one of the principal factors that vary the observation quality, automatic focusing is essential. The automatic focusing finds the best position by measuring the images' focus level at different positions and considering the best one. It applies a focus measure operator to evaluate the focus level. However, the astronomical images suffer from high blur due to the high magnification of the telescope. Thus, a proper focus measure is tricky due to a high blur. In this paper, we firstly investigate a focus operator based on fuzzy logic because of its ability to deal with imprecise data. We secondly optimized the parameters of the membership functions using the grey wolf optimizer (GWO). We acquired two data sets using the 74-inches telescope of the Kottamia astronomical observatory (KAO) at good seeing conditions and composed of in-focus and out-of-focus images. After that, we compare the measures using four criteria. The results show that the optimized one outperforms the other operators.**

***Index Terms*—Grey wolf optimizer, fuzzy logic, focus measure, astronomical images**

I. Introduction

The precise automatic focusing for high magnification systems like the telescope is principle due to the significant effect on the observation quality, which is principal for astronomical scientific research. The automatic focusing systems search the positions until it finds the best one which has the highest focus level. In the best one, the maximum amount of the light converges, while in out-of-focus, the light rays are spreading on a large area on the charge-coupled device (CCD) resulting, in the loss of faint celestial objects and improper image for scientific research. The automatic focusing estimates the focus level by applying a focus level operator into the image.

Various focus measure operators (FM) are investigated for automatic focusing. The focus measures are traditionally classified into five main categories [1], which are Gradient-based, Auto-correlation-Based, Statistical-Based, Transform-Based, and Edge-Based. However, a proper focus measure for high-magnificent images like astronomy images is tricky due to a high blur. A focus measure based on fuzzy logic [2] obtains attention because of the ability of fuzzy to deal with imprecise data. It is based on applying fuzzy logic into the images then calculating a statistical called Modified Histogram as a focus measure. In this research, we firstly investigate the focus measure based on fuzzy logic on astronomical images. Besides, we compare the Modified Histogram focus measure with other traditional operators on two data sets of astronomical images. We acquired two star-clusters sequences using the 74-inches telescope of the Kottamia astronomical observatory (KAO) at good seeing conditions.

It is well-known that the parameters' values of the membership functions are selected depending on experience. As a result, an optimization technique for optimizing the fuzzy parameters has been widely used to ensure better performance [3], [4]. In literature, several optimization techniques have been introduced, such as genetic algorithm (GA) [5], ant colony optimization (ACO) [6], particle swarm optimization (PSO) [7], and so on. However, the grey wolf optimizer (GWO) [8] achieves a competitive result. The GWO algorithm imitates the leadership structure and hunting ways of grey wolves in nature. Four types of wolves, alpha, beta, delta, and omega, are manipulated to mimic the leadership hierarchy. They are hunting by firstly searching for prey, then they surround it for the attack.

In this context, we secondly propose an optimization of the fuzzy parameters using GWO. The remainder of this paper is organized as follows. Section II presents the common focus measure operators. In Section III, the description of the modified histogram focus measure is introduced. The methodology is presented in Section IV. Finally, the analysis of experimental results and conclusions are presented in Section V and VI, respectively.

II. Focus Measure Operators

In the state-of-the-art, several comparative studies, including various focus measures, have been introduced [1], [9], [10]. In this work, we investigate several existing focus measures, such as absolute gradient [11], squared gradient [12], Tenengrad [13], Brenner [15], auto-correlation [16], amplitude [17], histogram [18], discrete cosine transform (DCT) [19], and fast Fourier transform (FFT) [20].

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A. Absolute gradient

The absolute gradient [11], which is also known as sum modulus difference (SMD), is the sum of absolute of image gradients, horizontal and vertical, along image M rows and N columns in Eq. (1), where FM is the focus measure and $I(x,y)$ is the image intensity at pixel located at (x,y). The horizontal gradient is the intensity differences between neighboring pixels along image rows. However, the vertical gradient is the intensity differences between neighboring pixels along image columns.

$$\begin{aligned}\mathrm{FM} = \sum_{x=1}^{M}\sum_{y=1}^{N}(&|I(x,y+1)-I(x,y)| \\ &+|I(x+1,y)-I(x,y)|).\end{aligned} \tag{1}$$

B. Squared gradient

The squared gradient [12] is the sum of squares of gradients, horizontal and vertical. It is computed as shown in Eq. (2). Indeed the absolute gradient is similar to the squared gradient. However, the larger gradients have more influence on the squared gradient than the absolute gradient. Whereas, the absolute gradient is computed much faster than the squared gradient measure.

$$\begin{aligned}\mathrm{FM} = \sum_{x=1}^{M}\sum_{y=1}^{N}(&\left|I(x,y+1)-I(x,y)\right|^2 \\ &+|I(x+1,y)-I(x,y)|^2).\end{aligned} \tag{2}$$

C. Tenengrad

Tenenbaum and Schlag are proposed focus measure similar to the squared gradient called Tenengrad [13]. However, the horizontal and vertical gradients are obtained using the Sobel operator [14]. The Tenengrad focus measure can be expressed as

$$\mathrm{FM} = \sum_{x=1}^{M}\sum_{y=1}^{N}(I_x^2+I_y^2), \tag{3}$$

where $I_x(x,y)$ and $I_y(x,y)$ are the horizontal and vertical gradient at pixel located at (x,y), respectively, and can be given by

$$\begin{aligned}I_x(x,y) &= I(x,y)\times g_x(x,y),\\ I_y(x,y) &= I(x,y)\times g_y(x,y),\end{aligned}$$

$$g_x = \begin{pmatrix} -1 & 0 & 1\\ -2 & 0 & 2\\ -1 & 0 & 1\end{pmatrix},\ g_y = \begin{pmatrix} 1 & 2 & 1\\ 0 & 0 & 0\\ -1 & -2 & -1\end{pmatrix}.$$

D. Brenner

Another measure was developed by Brenner, which was devised for automated microscopy. The author [15] notes that the differences between the image pixels and their neighbors that are located two pixels away increase as the focus increases. The focus measure can be expressed by

$$\mathrm{FM} = \sum_{x=1}^{M}\sum_{y=1}^{N}\left|I(x,y)-I(x+2,y)\right|^2. \tag{4}$$

E. Auto-correlation

The correlation family is based on the evaluation of neighboring pixels' dependency. The image auto-correlation is expected to contain sharpness information. The auto-correlation [16] focus measure is computed as presented in Eq. (5).

$$\mathrm{FM} = \sum_{x=1}^{M-1}\sum_{y=1}^{N} I(x,y)I(x{+}1,y) - \sum_{x=1}^{M-2}\sum_{y=1}^{N} I(x,y)I(x{+}2,y). \tag{5}$$

F. Amplitude

The sum of the absolute of differences between image intensities and image mean ($\bar{I}$) is suggested in the amplitude focus measure, which is also known as absolute central moment [17]. Eq. (6) and (7) show the Amplitude focus measure and the image mean.

$$\mathrm{FM} = \sum_{x=1}^{M}\sum_{y=1}^{N}\left|I(x,y)-\bar{I}\right|, \tag{6}$$

$$\bar{I} = \frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N} I(x,y). \tag{7}$$

G. Histogram

The histogram focus measure is proposed in [18]. It is defined as the difference between the maximum and minimum grey levels in Eq. (8).

$$\mathrm{FM} = \max\{k|P_k>0\} - \min\{k|P_k>0\}, \tag{8}$$

where k is the grey level and P_k is the relative (normalized) frequency.

H. Discrete cosine transform

In [19], the DCT is used to transform the image into the DCT domain, and the average of alternative current (AC) components $E_{AC}(x,y)$ is used as an indication of the focus measure. It is equivalent to the image variance and can be calculated as

$$\mathrm{FM} = \frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N} E_{AC}(x,y), \tag{9}$$

where

$$\begin{aligned}E_{AC}(x,y) &= \left(\sum_{u=1}^{8}\sum_{v=1}^{8} I(u,v)^2\right) - I(1,1)^2,\\ I(u,v) &= \frac{4c(u)c(v)}{8^2}\sum_{i=1}^{8}\sum_{j=1}^{8}\Bigg[I(i,j)\times\\ &\quad \cos\left(\frac{(2i+1)u\pi}{2\times 8}\right)\cos\left(\frac{(2j+1)v\pi}{2\times 8}\right)\Bigg],\\ c(u) &= \begin{cases}\frac{1}{\sqrt{2}}, & \text{if } u=1\\ 1, & \text{if } u>1\end{cases}.\end{aligned}$$

I. Fast Fourier transform

A focus measure based on the FFT has been suggested in [20]. The idea in using this criterion is that sharp edges have high spatial frequencies. So measuring frequencies provides an image focus level. The focus measure using the FFT is defined as the sum of absolute of product of image magnitude spectrum ($\text{Mag}(u, v)$) and phase ($\text{Ang}(u, v)$), and can be expressed as

$$\text{FM} = \sum \left| \text{Mag}(u, v) \times \text{Ang}(u, v) \right| . \tag{10}$$

III. Modified Histogram Focus Measure

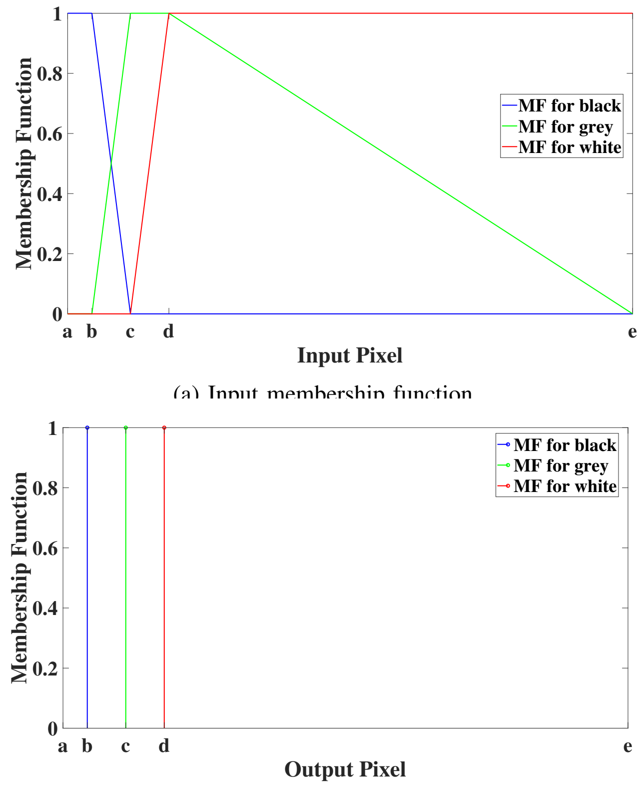
In [2], the authors propose a focus measure called modified histogram. It is based on firstly applying fuzzy logic to the image, then the focus measure is estimated from the output of the fuzzy logic (fuzzy image). The modified histogram is a modification of the Histogram focus measure, which has the advantage of simplicity and fast computation. The basic idea of the histogram is that as the image goes focus, its maximum increases, which consequently increases the difference between the maximum and minimum. Indeed, the image minimum is assumed to be fixed since it is affected by the sky background. The maximum may not be increased due to the effects of the observation conditions like temperature, cloud, and humidity. Consequently, the authors substitute the minimum with the median of maximum, and the focus measure can be expressed by

$$\text{FM} = \max\{k | P_k > 0\} - \text{med}\left\{ \max_{(x,y)\in S_i} I(x, y) \right\}, \quad i = 1, 2, 3, \ldots, N_S, \tag{11}$$

where N_S is the number of samples. Samples S_i from the image are randomly selected, then the maximum of samples is found, and the median of those values is calculated.

A. Fuzzy logic

The fuzzy logic is a single-input-single-output system. The linguistic values are black, grey, and white. The adopted membership functions (MF) of the input and the output are trapezoids and singletons, as shown in Fig. 1a and 1b, respectively. **a** is the image minimum, **b** is the mean of minimum, **c** is the median of maximum, **d** is the mean of maximum, and **e** is the image maximum. The mean of minimum and maximum is computed similarly to the median of maximum, except the mean is used. The fuzzy rules are as follows. If the input is dark, make it darker. If it is bright, make it brighter. Finally, if it is grey, make it grey. In conclusion, the defuzzification is calculated by the center of gravity method (CoG) [21].



(a) Input membership function

(b) Output membership function

Fig. 1: Input and output membership functions.

$$\begin{aligned}
\mathbf{a} &= \min_{(x,y)\in(M,N)} I(x, y), \\
\mathbf{b} &= \frac{1}{N_S} \sum_{i=1}^{N_S} \min_{(x,y)\in S_i} I(x, y), \\
\mathbf{c} &= \text{med}\left\{ \max_{(x,y)\in S_i} I(x, y) \right\}, i = 1, 2, 3, \ldots, N_S, \\
\mathbf{d} &= \frac{1}{N_S} \sum_{i=1}^{N_S} \max_{(x,y)\in S_i} I(x, y), \\
\mathbf{e} &= \max_{(x,y)\in(M,N)} I(x, y).
\end{aligned}$$

B. Grey wolf optimizer

Grey wolf belongs to the family Canidae, and they are considered apex predators [8]. The leadership hierarchy of the grey wolves is manipulated into four types, alpha, beta, delta, and omega. The alpha is liable for making decisions about hunting, accommodation, and wake time. The beta is the second level in the hierarchy, and they play the role of advisor to the alpha in decision-making. The omega is the lowest rank grey wolf, and they always have to capitulate to all the other powerful wolves. However, the omegas seem insignificant internal problems have been observed in the case of losing the omegas. Finally, the delta is a wolf who is not an alpha, beta, or omega, and they have to obey alphas and betas; however, they control the omegas.

The grey wolves search for prey by making use of the position of the alpha, beta, and delta. In the beginning, they diverge from each other to find it, then they converge to attack it. The GWO algorithm runs as follows. Firstly, a random population of grey wolves (candidate solutions) is initiated. Throughout iterations, alpha, beta, and delta wolves estimate the probable position of the prey, then each wolf (solution) updates its distance from it. Eventually, the GWO algorithm is stopped by an end criterion. In this context, we use the GWO to optimize the parameters of the fuzzy membership functions, which are $\mathbf{b}$, $\mathbf{c}$, and $\mathbf{d}$, to maximize the fitness function modified histogram focus measure. The search interval for each parameter is $\mathbf{a} \leq \mathbf{b} \leq \mathbf{c}$, $\mathbf{b} \leq \mathbf{c} \leq \mathbf{d}$, and $\mathbf{c} \leq \mathbf{d} \leq \mathbf{e}$.

IV. Methodology

In this paper, we firstly investigate the focus measure based on the modified histogram on two sequences of star-clusters observations, which are M103 and N7067. Then, we optimize the parameters of the fuzzy membership functions using the GWO. The data sets are acquired using the 74-inches telescope of the KAO [23] shown in Fig. 2. Each sequence contains in-focus and out-of-focus images of size 2K. The M103 and N7067 sequences consist of 66 and 55 images, respectively. In addition, we use an exposure time of 60 (sec/frame).

The modified histogram and the proposed optimized modified histogram are compared to the operators mentioned in section II. In literature, various ranking criteria are used. In [22], they are ranked according to four criteria as follows.

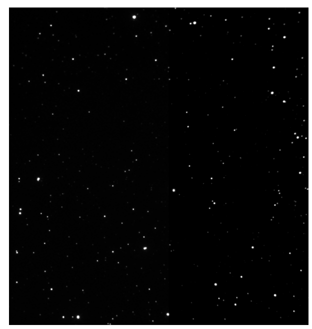
- Accuracy: This determines how the operator is distant from the best position. It is the distance between the operator's best position and the data set's best one.
- Range: This measures the distance between two neighboring local minimums around the global maximum. In other words, it describes the region where exists no local maximums.
- The number of false maximum: This counts the spurious maximum arising in a focus function.
- Width: This indicates the rate of change of the focus function. It is the width of the focus function at half of the height.

The operator's rank depends on its score, which is the mean of normalized criterion values. Hence. A lower score indicates higher performance.

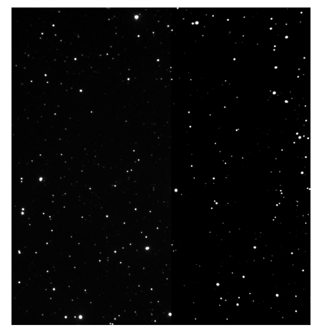
V. Experimental Results and Analysis

In this paper, we firstly investigate the effect of the fuzzy logic introduced in Section III on the astronomical data sets described in Section IV. We find it has a significant improvement in image contrast, as shown in Fig. 3. The fuzzy enhance the image's sharpness beside the faint details appearing. Furthermore, we optimize the parameters of the fuzzy membership functions using GWO. Fig. 4 shows a representative example of optimized membership functions for inputs and outputs.

Fig. 2: 74-inches Kottamia telescope.



(a) Input image



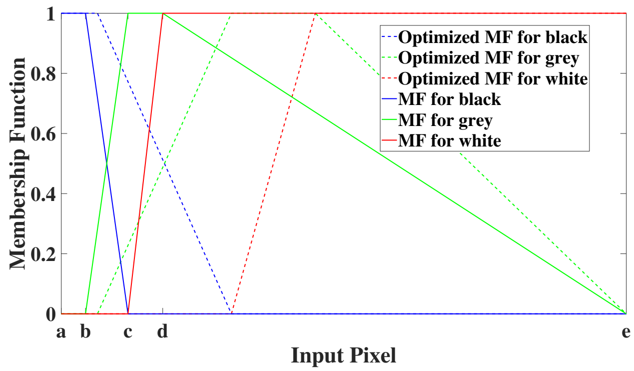
(b) Fuzzy logic output image

Fig. 3: A representative example of sequence M103.

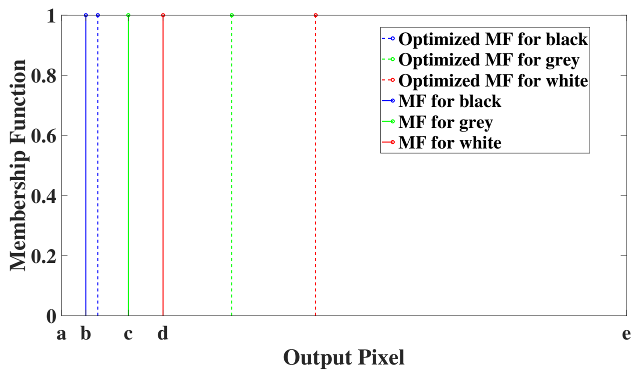
TABLE I: Rank summary for sequence M103.

Measure operator	Accuracy (μm)	Range (μm)	# of false	Width (μm)	Score
Optimized modified histogram	0	5800	13	3842.272	2.188442
Modified histogram	0	5800	13	4276.637	2.277336
Absolute gradient	0	5800	18	3627.112	2.329595
DCT	0	6200	20	3567.982	2.45506
Auto-correlation	0	6200	20	3701.837	2.482454
Squared gradient	800	6300	20	3372.492	2.738618
FFT	800	6200	20	3469.49	2.742596
Brenner	800	6200	20	3490.649	2.746926
Tenengrad	800	6300	20	3574.423	2.779943
Histogram	1200	5900	20	4886.36	3.138787
Amplitude	2600	6100	27	1970.705	3.371561

In addition, we analyze the performance of the optimized modified histogram compared to the operators described in Section II. The operators are ranked according to their score. Table I shows the rank summary for all mentioned operators for the sequence M103. The results show that the optimized modified histogram exceeds the others according to the ranking criteria. That is, the modified histogram before optimization achieves the highest performance. The rank summary for the sequence N7067 is presented in Table II. The results clarify that the optimized modified histogram also obtains the best performance.



(a) Membership function of the input



(b) Membership function of the output

Fig. 4: A representative example of the optimized memberships functions of the fuzzy inputs and outputs.

TABLE II: Rank summary for sequence N7067.

Measure operator	Accuracy (μm)	Range (μm)	# of false	Width (μm)	Score
Optimized modified histogram	0	2600	2	2737.269	0.756599
Modified histogram	0	2600	2	2742.576	0.756651
Squared gradient	0	2600	3	1988.294	0.811725
Tenengrad	0	2600	3	2078.289	0.812611
Brenner	0	2600	4	2133.232	0.875652
Auto-correlation	0	2600	4	2237.403	0.876678
FFT	0	2800	4	2648.115	0.927233
Histogram	700	3500	7	3009.135	1.540337
Absolute gradient	0	4300	9	2926.615	1.591312
DCT	0	4300	12	2649.596	1.776084
Amplitude	2700	2700	16	101578	3.627907

VI. Conclusion

Precise automatic focusing for the high magnification astronomical system significantly affects the observation quality. In this paper, we firstly investigate a focus measure based on fuzzy logic, namely modified histogram on two star-clusters sequences. The data sets are acquired using the 74-inches telescope of the KAO at good seeing conditions and different focus positions. We apply the modified histogram and other common operators into the data sets and compare them based on four evaluation criteria. In addition, we have presented the parameter optimization of the fuzzy membership functions using GWO. The results show that the optimized modified histogram can achieve the highest performance compared to other operators.

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