Parameter Selection of Image Fog Removal Using Artificial Fish Swarm Algorithm

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Abstract. Although image defogging is widely used in many working systems, existing defogging methods have some limitations due to the lack of enough information to solve the equation of fog formation model. To overcome the limitations, a novel defogging parameter selection algorithm based on artificial fish swarm algorithm (AFSA) is proposed in this paper. Two representative defogging algorithms are used to test the effectiveness of the method. The proposed method first selects the two main parameters and then optimizes them using the AFS algorithm. An assessment index of image defogging effect is used as the food concentration of the AFSA. Thus, these parameters may be adaptively and automatically adjusted for the defogging algorithms. A comparative study and qualitative evaluation demonstrate that better quality results are obtained by using the proposed method.

Keywords: AFSA · Defogging effect assessment · Parameter selection Single image defogging

1 Introduction

Most automatic systems assume that the input images have clear visibility, therefore removing the effects of bad weather from these images is an inevitable task. In the past decades, extensive research efforts have been conducted to remove fog or haze from a single input image. Most of these methods [1–4] intend to recover scene radiance using the image degradation model that describe the formation of a foggy image. Tan [1] removed fog by maximizing the local contrast of the restored image. Nishino et al. [2] proposed a Bayesian probabilistic method that estimates the scene albedo and depth from a foggy image with energy minimization of a factorial Markov random field. He et al. [3] estimated the transmission map and the airlight of the degradation model using the dark channel prior. Tarel et al. [4] introduced an atmospheric veil to restore image visibility based on the fast median filter. However, these methods are controlled by a few parameters with fixed values that cannot be automatically adjusted for different foggy images.

In recent years, people are quite interested in automatic fog removal, which is useful in applications such as surveillance video [5], intelligent vehicles [6], and outdoor object recognition [7]. In this paper, we thus focus on the AFSA-based adaptive parameter adjustment for single image defogging.

D.-S. Huang et al. (Eds.): ICIC 2018, LNCS 10954, pp. 25–37, 2018.
https://doi.org/10.1007/978-3-319-95930-6_4

Artificial fish swarm algorithm (AFSA) was first presented by Li et al. [8]. This algorithm is a technique based on swarm behaviors that were inspired from social behaviors of fish swarm in nature. AFSA works based on population, random search, and behaviorism. The fish swims towards locations where food concentration is highest. As a typical application of behaviorism in artificial intelligence, AFSA can search for the global optimum [9]. It is widely agreed that AFSA can be used for digital image processing, such as image segmentation [10, 11], image enhancement and restoration [12], image matching [13], image quantization [14], etc. However, due to the lack of proper objective criterion of defogging effect as the fitness function, present defogging algorithms seldom use AFSA to effectively remove fog from a single image. Though the objective image quality evaluation methods have achieved some promising results, they are just applied to assess the quality of degraded image, such as image denosing results and deblurring results. The aim of defogging algorithm is to recover color and details of the scene from input foggy image. Unlike image quality assessment, the fog can not be addressed like a classic image noise or degradation which may be added and then removed. Meanwhile, there is no easy way to have a reference no-fog image, and the quality evaluation criteria of degraded image, such as the structural similarity (SSIM) [15], the peak signal-to-noise ratio (PSNR) [16], and the mean square error (MSE), are not suitable for assessing image defogging effects. This makes the problem of adaptive parameter adjustment of defogging algorithm not straightforward to solve.

The main contribution of this paper is we propose a way to select parameter values for single image defogging, which can help to overcome the limitations of existing defogging algorithms. Here, the defogging effect assessment index presented in our previous work [17] is taken as the food concentration of the proposed AFSA-based method. Thus, the parameter values can be adaptively and automatically adjusted for different input foggy images. A comparative study and qualitative evaluation demonstrate that the better quality results are obtained by using the proposed method.

2 Limitations of the Existing Defogging Methods

Most current defogging methods recover the scene radiance by solving the fog formation model. Since the model contains three unknown parameters and the solving process is an ill-posed inverse problem, it is thus inevitable to introduce many application-based parameters that used in various assumptions for image defogging. A large quantity of experimental results shows that the selection of the algorithm parameters has direct influence on the final defogging effect. However, there exists a major problem for the parameter setting in most defogging algorithms, i.e. the parameters always have fixed values in the defogging algorithms.

In our experiments, we find that the fixed parameter values caused that the fog removal algorithms just have good defogging effect for a certain kind of foggy image, and the algorithms may not work well for the images captured under other foggy conditions. For example, He's algorithm [3] has mainly three parameters to control: ω which alters the amount of haze kept at all depths, c the patch size for estimating transmission map, and t_0 restrict the transmission to a lower bound to make a small amount of fog preserve in very dense fog regions. All these parameters have fixed value suggested by the authors, such as the fog parameter ω, which is set to be 0.95 in the algorithm [3]. Our experimental results show that, if ω is adjusted downward, more fog will be kept, and vice versa. Using $\omega = 0.95$ keeps a slight amount of fog effect around at all depths. However, the experiments also show that ω sometimes needs to be decreased when an image contains substantial sky regions, otherwise the sky region may wind up having artifacts.

Besides, most defogging algorithms have introduced some parameters, which lead to user interaction and make the final defogging effect hard to control as well. For example, Tarel's algorithm [4] is controlled by five parameters in which p is the percentage of removed atmospheric veil, s_v the assumed maximum size of white objects in the image, b the white balance control for global or local process, s_i the maximum size of adapted smoothing to soften the noise amplified by the restoration, and g an extra factor during final gamma correction. It is obvious that the controllability can be greatly improved and the user-interaction can be also largely reduced if defogging algorithm has no more than two parameters. Therefore, distinguishing between main parameters which directly affect the results and other less important parameters which can be considered as fixed values, and then automatically adjusting their values are very important for the defogging algorithms.

3 The Proposed Parameter Value Selection Approach

3.1 Optimal Parameter Selection

The task of optimal parameter selection is to distinguish between two main parameters which directly affect the results and other less important parameters which can be considered as fixed values for various defogging methods. There are two ways to select the two main parameters: one is to analyze the related parameters from the perspective of physical mechanism, and the other is to tune one of algorithm parameters by fixing the rest to see whether the defogging results have significant change. Two representative fog removal methods [3, 4] are taken as examples to describe the parameter selection process in this paper. Since He's method [3] is recognized as one of the most effective ways to remove fog, and Tarel's method [4] is regarded as one of the fastest defogging algorithms at present.

For He's method [3], the dark channel prior with the haze imaging model is used to directly estimate the thickness of the haze and recover a high-quality haze-free image. In the method, a small amount of haze for distance objects is kept to make the final defogging results seem more natural and preserve the feeling of depth as well. There are two key parameters for the fog preservation purpose: ω $(0 < \omega < 1)$ and t_0 $(0 < t_0 < 1)$. Other parameters have less influence on the final defogging effect, and can thus be regarded as less important paramters. For Tarel's method [4], the method is based on median filter and consists in: atmospheric veil inference, image restoration and smoothing, tone mapping. The most important two steps that determine the final defogging effect are atmospheric veil inference and tone mapping. Since the value of $p\,(0 < p < 1)$ controls the amount of atmospheric veil that can be removed, this parameter is useful to compromise between highly restored visibility where colors may appear too dark, and less restored visibility where colors are clearer. The parameter g $(0 < g < 10)$ is used to perform gamma correction to achieve more colorful result. Experimental results show that the larger the value of g, the clearer the defogging result is. Compared with the two parameters p and g, other parameters have less effect on the final defogging results.

3.2 Measurement of Defogging Effect

The CNC index, an effective defogging evaluation indicator proposed in our previous work [17] is used here to guide the parameter adjustment process. For the input foggy image **x** and its corresponding fog removal image **y**, the CNC index is obtained after carrying out the following steps: (i) compute the rate e of visible edges after and before fog removal, (ii) calculate the image color naturalness index (CNI) and color colourfulness index (CCI) to measure the color naturalness of the defogging image **y**, and (iii) Combine the three components e, CNI and CCI to yield an overall defogging effect measure CNC. The mathematical formula of e can be expressed as:

$$e(\mathrm{x}, \mathrm{y}) = \frac{n(\mathrm{y})}{n(\mathrm{x})}. \tag{1}$$

where $n(\mathrm{x})$ and $n(\mathrm{y})$ denote the cardinal numbers of the set of visible edges in x and y, respectively. More details about the mathematical formula of CNI and CCI can be found in [18].

For the overall variation trend of the three indexes, the statistical results show that the peak of CNI curve stands for the most natural result, but it is not necessarily the best defogging effect. However, the best effect must have good naturalness (high CNI value). When the image is over enhanced, the color is distorted, and CNI goes down rapidly. For e and CCI, they achieve the best effect before reaching their peaks. When the image is overenhanced, the curves continue ascending. After reaching their peaks, these curves begin to go down. Therefore, if the uptrend of e and CCI (from their best effect points to their curve's peaks) can be largely counteracted by the downtrend of CNI, and the peak of CNC curve can be more close to the real best effect point. Meanwhile, the value variation of CNI is small, while that of e and CCI is relatively big. Thus, the effect of e and CCI on the CNC index needs to be weakened. The CNC index between image **x** and **y**, *i.e.* the function CNC can be defined as

$$\mathrm{CNC}(\mathbf{x}, \mathbf{y}) = e(\mathbf{x}, \mathbf{y})^{1/5} \cdot \mathrm{CNI}(\mathbf{y}) + \mathrm{CCI}(\mathbf{y})^{1/5} \cdot \mathrm{CNI}(\mathbf{y}) \tag{2}$$

A good result is described by the large value of CNC. Therefore, the optimal value of the two main parameters of defogging algorithms can be obtained when the CNC index (2) achieves the largest value.

3.3 Parameter Value Selection Using Artificial Fish Swarm Algorithm

Artificial fish (AF) is a fictitious entity of true fish, which is used to carry on the analysis and explanation of problem. The AF realizes external perception by its vision. Suppose X is the current state of an AF, Visual is the visual distance, X_v is the visual position at some moment, and N is the population size. If the state at the visual position is better than the current state, it goes forward a step in this direction and arrives the X_{next} (X_i (t +1)) state; otherwise, continues an inspecting tour in the vision. Using the artificial fish swarm algorithm (AFSA), the two main parameters of various defogging algorithms can be automatically determined.

Specifically, the AF model includes two parts (variables and functions). The variables include: X (X_i (t)) is the current position of the AF, *step* is the moving step length, *visual* represents the visual distance, *try_number* is the try number, and δ is the crowd factor ($0 < \delta < 1$). The functions include the behaviors of the AF: AF_Prey, AF_Swarm, and AF_Follow. In each step of the optimization process, AF looks for locations with better fitness values in problem search space by performing the previous three behaviors based on algorithm procedure. The pseudo-code of the AFSA-based method that is used for image defogging is presented in Algorithm 1 (see Fig. 1).

Algorithm 1. The AFSA used for image defogging

Begin
  Initialize the population: N, visual, *step*, *maxgen*, δ, *try_number*.
  While running do
    For 1 to N do
      Calculate the CNC function value for the two parameters represented as an initial fish swarm with the size of 2 × N
    Execute the basic fish behaviors
    Generate the new individuals
  End while
  The optimal solution is the selected parameter value for the defogging method.
  The enhanced image with the optimal parameter values is our final defogging result.
End

Fig. 1. Algorithm 1: The AFSA used for image defogging

The simple but effective AFSA-based parameter selection consists of the following steps:

(1) **Fish swarm initialization**

Each artificial fish in the swarm is described by a random array that generated within a given range. For He's defogging algorithm, suppose the size of fish swarm is N, ω $(0<\omega<1)$ and t_0 $(0<t_0<1)$ are the two parameters that need to be optimized. Thus, the individual's status of each artificial fishes can be expressed as a vector $X = \{x_1, x_2\}$, in which the $x_i (i = 1, 2)$ represents ω and t_0. For Tarel's algorithm, p and g are the two key parameters, where $p \in (0,\ 1)$ and $g \in (1,\ 10)$. Similarly, the x_i(i = 1, 2) here represents the parameters p and g. In initialization phase, the AFSA will produce an initial fish swarm with the size of $2 \times N$ for both algorithms, and each column represents the two parameters of an artificial fish for the defogging algorithms.

As the fitness value of the objective function, the food concentration of the current location about the artificial fish is actually the CNC index value for image defogging. Therefore, the food concentration can be expressed as $Y = \mathrm{CNC}(X)$. The other parameters such as the visual field of the artificial fish, the maximum moving step, the maximum generation, the crowd factor and the maximum number of tries in every forage are expressed as *visual*, *step*, *maxgen*, δ and *try_number*. Note that the crowd factor δ can be used to limit the fish swarm size of the artificial fish swarm so as to make more artificial fish individuals gather in the region with better state rather than the neighborhood with suboptimal state. For the proposed approach, the parameters of ASFA are set as following, $N = 10$, $visual = 1$, $step = 0.1$, $maxgen = 20$, $\delta = 0.5$ and $try\_number = 10$. In our experiment, we find that the parameter settings can make algorithm get better optimization performances.

(2) **Prey behavior**

This behavior is an individual behavior that each AF performs independently and performs a local search around itself. Every AF by performing this behavior attempts *try_number* times to move to a new position with better food concentration. Here, the better food concentration is corresponding to the higher CNC value. Suppose AF_i is in position X_i, then within the visual area S, it randomly chooses another position X_j. AF_i will swim towards X_j. This process can be written as:

$$X_j = (X_i + visual \times \mathrm{rand}(0,1)) \times \frac{1}{2} \tag{3}$$

Since Y represents the food concentration, if $Y_j > Y_i$, position of AF_i is updated to the next step by Eq. (4).

$$X_i(t+1) = X_i(t) + \frac{X_j - X_i(t)}{\left\|X_j - X_i(t)\right\|} \times step \times \mathrm{rand}(0,\ 1) \tag{4}$$

The above two steps are repeated *try_number* times. If AF_i could not move toward better positions, it moves with a random step in its visual using Eq. (5), and the food concentration of Y_{next} (Y_i $(t+1)$) state can also be obtained by means of CNC index.

$$X_i(t+1) = (X_i(t) + visual \times \mathrm{rand}(0,1)) \times \frac{1}{2} \tag{5}$$

(3) **Swarm behavior**

Fish usually assembles in groups to capture colonies and/or to avoid dangers. There are n_f neighbors within the visual area S. X_c is the center of those neighbors. AF_i will swim a random distance towards X_c. If $(n_f/n) < \delta$ (where n is the number of artificial fishes) and $Y_c > Y_i$ which means that the companion center has more food (higher CNC value) and is not very crowded, it goes forward a step to the companion center (Eq. 6). Otherwise, AF_i will resume the behavior of Prey.

$$X_i(t+1) = X_i(t) + \frac{X_c - X_i(t)}{\|X_c - X_i(t)\|} \times step \times \mathrm{rand}(0,\ 1) \tag{6}$$

(4) **Follow behavior**

When some fishes find food through the moving process of swarm, their neighborhood partners tend to follow them to the best food concentration location. Let X_i be the AF current state, and it explores the companion X_j in the neighborhood ($\|X_j - X_i(t)\| <$ Visual), which has the greatest Y_j. If $Y_j > Y_i$ and $(n_f/n) < \delta$, which means that the companion X_j state has higher food concentration (higher CNC value) and the surrounding is not very crowded, it goes forward a step to the companion $X_{j.}$ Otherwise, AF_i will resume the behavior of Prey.

$$X_i(t+1) = X_i(t) + \frac{X_j - X_i(t)}{\|X_j - X_i(t)\|} \times step \times \mathrm{rand}(0,\ 1) \tag{7}$$

The collective behaviors of Prey, Follow and Swarm of all fishes are simulated in each generation. The fishes will choose the behavior that has the best position (concentration). AFSA is independent on the initial condition. A termination criterion can be added for each specific problem. For the proposed method, when the maximum number of generations is reached, the AFSA computation is terminated. The optimal solution of X indicates the selected value for the two main parameters. The enhanced image with these parameter values is our final fog removal result. Figure 2 shows the optimal value (food concentration) variation for a test foggy imag. One can clearly see that the best food concentration value is 0.4762 for He's algorithm [3], and its

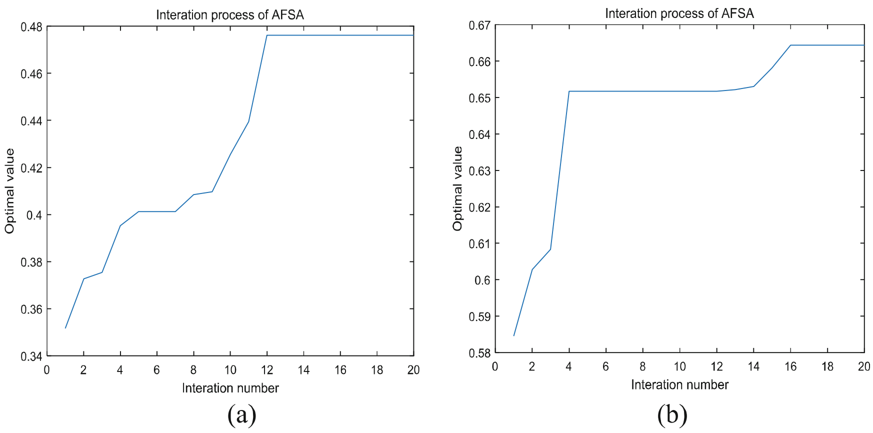


Fig. 2. The optimal value variation for a test foggy image. (a) He's result. (b) Tarel's result.

corresponding X value is (0.9977, 0.56) for the parameter value of (ω, t_0) in the method. For Tarel's algorithm [4], the best food concentration value is 0.6643, and its corresponding X value is (0.9765, 8.5) for the parameter value of (p, g). In our experiments, we find that the defogging results obtained by the two optimal parameter values seem quite promising in most cases. Thus, the effectives of the proposed approach can be verified.

4 Experimental Results

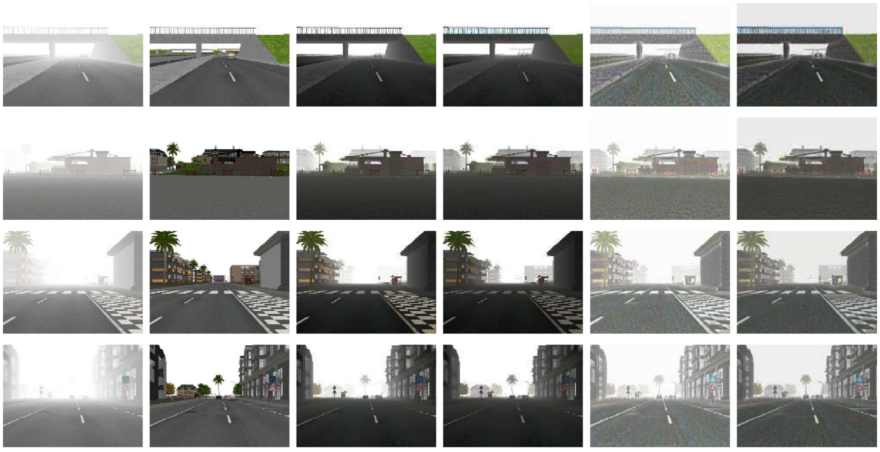
The publicly available dataset frida2 [19] is used to evaluate image defogging methods. This dataset contains synthetic no-fog images and associated foggy images for 66 diverse road scenes. The absolute difference (AD) on the images between defogged images and target images without fog is used as performance metrix, and good results are described by small value of AD. To verify the effectiveness and validity of the proposed parameter value selection method, three criteria have been considered: (i) generation number influence, (ii) qualitative comparison, (iii) quantitative evaluation, and (iv) time complexity. In the experiments, all the results are obtained by executing Matlab R2008a on a PC with 3.10 GHz Intel® CoreTM i5-2400 CPU.

4.1 Generation Number Evaluation

To evaluate the influence of the generation number *maxgen* used in the proposed method, some group experiments are performed by varying the generation number *maxgen* from 10 to 50. From the parameter values and the resulting AD metrics of a test image we can clearly see that the results are visually and statistically close (the value range of AD are [36.1573, 36.9429] for He's method, and [48.0486, 48.9980] for Tarel's method) when varying *maxgen* from 10 to 50. It demonstrates that the influence of the generation number is very limited in the proposed method. The experiments on other test images also confirm the observations. Thus, to make a tradeoff between speed and accuracy, we set the maximum generation to be 20.

4.2 Qualitative Comparison

To evaluate the AFSA-based method for selecting the most proper parameter values, the image dataset provide by Tarel et al. [19] is used to validate the accuracy of the parameter selection, since this dataset provides the original image without fog and the image with fog for 66 road scenes simultaneously, thus we can use the AD index to measure the defogging effects. For each image, we obtain the fog removal results with the default and the auto-adaptive parameter values for He's and Tarel's algorithms. We also give the corresponding no-fog images as the reference images for comparison. An illustrative example is shown in Fig. 3. One can clearly see that the far-away buildings or trees which cannot be seen in He's or Tarel's results become more obvious in our AFSA-based results. Therefore, we can deduce that the defogging results obtained using the auto-adaptive values can achieve a better enhancement effect compared to the results obtained using the default values for both defogging algorithms.



(a) (b) (c) (d) (e) (f)

Fig. 3. Visual comparison of defogging results for public database frida2 [19]. (a) Foggy images. (b) Fog-free images. (c) He's results obtained using default parameter values ($\omega = 0.95$, $t_0 = 0.1$, $c = 3$). (d) He's results obtained using auto-adaptive parameter values. (e) Tarel's results obtained using default parameter values ($p = 0.95$, $b = 0.5$, $s_v = 9$, $s_i = 1$, g = 1.3). (f) Tarel's results obtained using auto-adaptive parameter values.

4.3 Quantitative Evaluation

To quantitatively assess the proposed parameter value selection method, we compute the AD index value for the images in Fig. 3, and the statistical results are shown in Tab. 1. One can notice that the AD value obtained by the auto-adaptive parameter is smaller than that of default parameters for both defogging algorithms, which means that the better defogging effect can be obtained by using the proposed method. This confirms our observations in Fig. 3.

Table 1. AD index between enhanced images and no-fog images for the test images in Fig. 3

Img	Method				
	Foggy image	He's method (default value)	He's method **(adaptive value)**	Tarel's method (default value)	Tarel's method **(adaptive value)**
Figure 3 (Row #1)	42.67	33.68	**31.65**	23.11	**16.42**
Figure 3 (Row #2)	55.73	34.46	**30.65**	38.67	**32.29**
Figure 3 (Row #3)	62.56	40.12	**32.66**	47.01	**27.92**
Figure 3 (Row #4)	66.20	31.05	**29.84**	47.27	**23.64**

The AD index is also tested for more test images in public database frida2 (66 images). Figure 4(a) shows the statistical results of the AD for He's method and Fig. 4 (b) shows the AD results for Tarel's method. In Fig. 4, symbol "◆" stands for foggy image, circle "◆" stands for the defogging image obtained using the default parameter values, and circle "◇" stands for the defogging image obtained by the auto-adaptive parameter values. The horizontal axes are the image number index and vertical axes are the AD index values. It is clear that the ADs of adaptive parameter results are smaller than that of other results for both defogging methods. This indicates that the fog removal results obtained by the proposed parameter selection method have better defogging effect for the public image database compared to the other results. This is also consistent with the assessment results of AD and human visual perception.

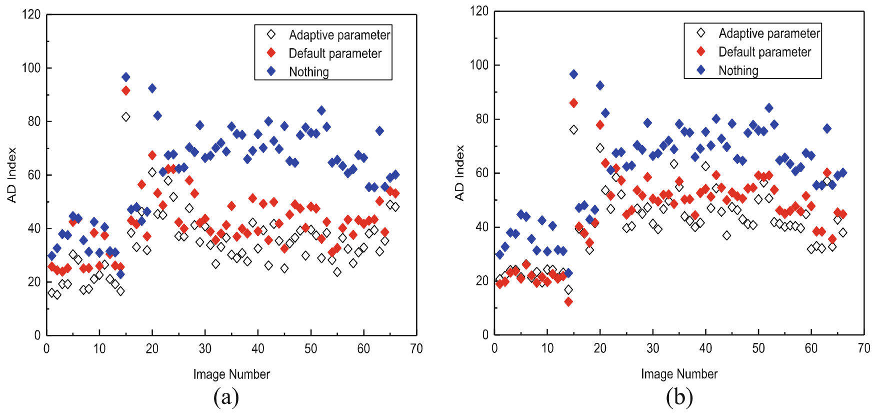


Fig. 4. AD index results for the 66 test images in public database frida2 [16]. (a) He's statistical results. (b) Tarel's statistical results.

4.4 Time Complexity

For image defogging algorithms, the computational efficiency is also an important issue. For the two representative defogging algorithms, the most time-consuming operation in He's defogging algorithm is using soft matting to obtain the refined transmission map [3]. Suppose the input image has a size of M × N, He's algorithm involves a (M × N) × (M × N) matting Laplacian matrix [20]. Therefore, the time complexity of He's algorithm TC_H is about $O\left(\mathrm{M}^2 \times N^2\right)$. While the time complexity of Tarel's algorithm TC_T is about $O\left(\mathrm{MN}s_v^2 \ln s_v\right)$, where s_v is the assumed maximum size of white objects in the image [4].

For the fitness function calculation, the time complexity of the CNC method TC_{CNC} is about $O\left((\mathrm{M}/s)^2 \times (\mathrm{N}/s)^2\right)$, where s is the subwindow size that used for patch segmentation. For AFS optimization algorithm, suppose the N artificial fishes compose a group in the target search space of two dimensions, m is the maximum generation and t_r is the maximum number of tries in every forage. Let the running time of each artificial fish in each iteration is T_f, the total running time of the proposed AFSA-based algorithm can be written as: $N \times m \times t_r \times T_f$. Thus, the time complexity of AFSA-based algorithm can be reflected by the number of artificial fishes and the running time of each fish in an iteration. Since the fish swarm populations is set to 10, the maximum number of iterations is 20 and the try number is 10 in our experiment, and the ideal defogging results are obtained by applying the determined optimal parameter values to defogging algorithms, we can thus deduce that the whole time complexity of the proposed method is about $10 \times 20 \times 10 \times (TC_H + TC_{CNC}) \times T_f + TC_H$ for He's algorithm, and about $10 \times 20 \times 10 \times (TC_T + TC_{CNC}) \times T_f + TC_T$ for Tarel's algorithm.

Generally, the average running time of the proposed parameter selection method for He's algorithm is about 50 min for an image with a size of 200×150, and about 350 s for that of Tarel's algorithm with the same size image in Matlab environment. This speed can be further improved by more efficient defogging methods or a GPU-based parallel algorithm. Besides, surveillance video defogging can also benefit much from the proposed method. That's because for surveillance video, once the optimal parameter values are determined by a image frame, the same values can be directly applied to a series of video frames to obtain the restored images whose fog density is similar in the corresponding original video frames. Therefore, the once-for-all strategy can save a lot of time for video defogging.

5 Conclusions

In this paper, a novel AFSA-based parameter value selection method was proposed. Different from the most defogging methods which generally fix the parameter values, the proposed approach can help defogging methods automatically select proper parameter values for different foggy images. In the proposed method, the two main parameters which directly affect the results are first distinguished from other less important parameters which can be considered as fixed values. Then, the two parameter values are adaptively determined by using the artificial fish swarm algorithm. The proposed parameter selection method has been applied to two representative defogging algorithms, which demonstrated the superior performance of the proposed scheme in both qualitatively and quantitatively. In the future, we will try to investigate the parameter value selection issue based on more advanced assessment index, since the CNC index may not be the best one to measure image defogging effect.

Acknowledgements. The authors would like to thank Erik Matlin and Kaelan Yee for providing He's source code, and Dr. Tarel and Dr. Hautiere for providing the Matlab code of their approach. This work was supported by the National Natural Science Foundation of China (61502537), Hunan Provincial Natural Science Foundation of China (2018JJ3681), and the National Undergraduate Programs for Innovation.

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