Single image defogging based on particle swarm optimization*

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Due to the lack of enough information to solve the equation of image degradation model, existing defogging methods generally introduce some parameters and set these values fixed. Inappropriate parameter setting leads to difficulty in obtaining the best defogging results for different input foggy images. Therefore, a single image defogging algorithm based on particle swarm optimization (PSO) is proposed in this letter to adaptively and automatically select optimal parameter values for image defogging algorithms. The proposed method is applied to two representative defogging algorithms by selecting the two main parameters and optimizing them using the PSO algorithm. Comparative study and qualitative evaluation demonstrate that the better quality results are obtained by using the proposed parameter selection method.
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Most automatic systems assume that the input images have clear visibility, so 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 describes 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 letter, we thus focus on the particle swarm optimization (PSO)-based adaptive parameter adjustment for single image defogging.

It is widely agreed that PSO algorithm can be used for digital image processing, such as image retrieval[8], image segmentation[9], etc. However, due to the lack of proper objective criterion of defogging effect as the fitness function, present defogging algorithms seldomly use genetic algorithm 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 images, such as image denoising results and image 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 cannot 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 a degraded image, such as the structural similarity (*SSIM*)[10], the peak signal-to-noise ratio (*PSNR*)[11], 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. In this letter, we mainly focus on the parameter values selection for single image defogging. Here, the defogging effect assessment index presented in our previous work[12] is taken as the fitness function of the proposed PSO-based method to adaptively adjust the parameter values for different input foggy images.

Most current defogging methods recover the scene radiance by solving the image degradation model. Since the model contains three unknown parameters and the solving process is an ill-posed inverse problem, it is thus

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inevitable to introduce many application-based parameters used in various assumptions for image defogging. A large number of experimental results show 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 cause 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 alters the amount of haze kept at all depths, c is the patch size for estimating transmission map, and t_0 restricts the transmission to a lower bound to make a small amount of fog preserved in very dense fog regions. All these parameters have fixed values suggested by the authors, such as the fog parameter ω, which is set to be 0.95 in the algorithm[3]. For He's algorithm[3], if ω is adjusted downward, more fog will be kept, and vice versa. Using ω=0.95 can keep a slight amount of fog effect around at all depths. However, the experimental results show that ω sometimes needs to be decreased when an image contains substantial sky regions. Otherwise the sky region may wind up with artifacts.

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[4] in which p is the percentage of removed atmospheric veil, s_v is the assumed maximum size of white objects in the image, b is the white balance control for global or local process, s_i is the maximum size of adapted smoothing to soften the noise amplified by the restoration, and g is 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 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.

In order to solve the "fixed parameter value" problem, on the one hand, we should choose two main parameters and optimize them for different defogging algorithms, and on the other hand, we must use an effective defogging effect assessment index to automatically determine the parameter values for different input images. However, the defogging evaluation results obtained using image quality evaluation criteria are often inconsistent with human visual conception, and the existing enhancement assessment methods are mainly from image contrast and do not consider the color restoration effect of the defogging results.

It can thus be seen that "fixed parameter value" is the most common problem existing in most fog removal methods. However, it is hard to realize adaptive adjustment of the algorithm parameters by the defogging results due to the lack of an effective assessment index. Therefore, a PSO-based parameter value selection algorithm using proper defogging effect assessment index is proposed in this letter to select the parameter values for single image defogging.

Since most defogging algorithms may produce oversaturated or undersaturated colors with fixed parameters, the two main parameters that directly affect the defogging results are firstly selected. And then a PSO algorithm combined with a proper defogging assessment index is used here to enable these defogging methods to adaptively set the required two parameters for different input images, and enhance the visibility of scenes with natural color and the best defogging effect.

The task of optimal parameter selection is to distinguish 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 is recognized as one of the most effective ways to remove fog, and Tarel's method is regarded as one of the fastest defogging algorithms at present.

For He's method, a small amount of haze for distance objects is kept to make the final defogging results 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 example, the influence of the large patch size c can be effectively reduced by the soft matting used in He's method[12]. Therefore, the patch size suggested by the author is reasonable. In our experiment, we find that t_0 has significant influence on the final results, while the patch size c on the contrary has little influence.

For Tarel's method, the most important two steps that determine the final defogging effect are atmospheric veil removal and gamma correction. Since the value of p ($0<p<1$) controls the amount of atmospheric veil that can be removed, this parameter is useful to make a compromise between highly restored visibility where colors may be 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 results. Experimental results show that the larger the value of g, the clearer the defogging result. Compared with the two parameters p and g, other parameters b, s_v and s_i have less effect on the final defogging results.

Therefore, the two main parameters generally have significant influence on the final results, and also have definite physical meanings, while other parameters, such as the patch size or the window size of smoothing, have much less effect on the results and can thus be considered as fixed values. The conclusions can be applied to other defogging algorithms to select the key parameters for them.

The CNC index, an effective defogging evaluation indicator proposed in our previous work[13], is used here to guide the parameter adjustment process. For the input foggy image $\boldsymbol{x}$ and its corresponding fog removal image $\boldsymbol{y}$, 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) caculate the image color naturalness index (CNI) and color colourfulness index (CCI) to measure the color naturalness of the defogging image $\boldsymbol{y}$, and (iii) combine the three components e, CNI and CCI to yield an overall defogging effect measure:

$$\mathrm{CNC}(\boldsymbol{x},\boldsymbol{y}) = h\left(e(\boldsymbol{x},\boldsymbol{y}), \mathrm{CNI}(\boldsymbol{y}), \mathrm{CCI}(\boldsymbol{y})\right) . \qquad (1)$$

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 overenhanced, 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, the peak of CNC curve can be more close to the real best effect point. Meanwhile, the value variation of CNI is small, while those of e and CCI are relatively big. Thus, the effect of e and CCI on the CNC index needs to be weakened. The CNC index between images $\boldsymbol{x}$ and $\boldsymbol{y}$, i.e., the function h in Eq.(1), can be defined as

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

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

The PSO is one of the most important swarm intelligence paradigms[14], and its searching is based on the simulations of social behaviors, such as animals herding, fish schooling, and birds flocking, where the swarms search for food in a collaborative manner. The PSO is easy to implement, and therefore, it is employed to solve the optimization problems in many applications. Using PSO, the two main parameters of various defogging algorithms can be automatically determined on the basis of the CNC index. The simple but effective PSO-based parameter selection consists of the following steps:

(1) Parameter initialization

Initialize the beginning parameters, such as swarm populations, and the number of training iterations. Also, the particles are randomly located and the movement vector is randomly assigned. To prevent the blind search of particles, the particle's position and velocity are constrained in a certain range.

The task using the PSO is to find the best combination of the two main parameters according to an objective criterion. Therefore, the initial position of a particle can be expressed as a 1×2 matrix with random value RV, and each element of it follows $RV \in (0,1)$. $X_{\min}$ and $X_{\max}$ are the minimum and maximum range values for the position of the two parameters. $X_{\min}$ is set to 0, and the value of $X_{\max}$ depends on the value ranges of the two parameters. For example, the value ranges of p and g in Tarel's method are (0, 1) and (0, 10), respectively, so these values can be written as $p=RV$ and $g=10\times RV$.

(2) Fitness function

Let *Gbest* be the best known position of the entire swarm and let *Pbest* be the best known position of particle *i*. Store *Gbest* and all *Pbest* locations at the current iteration by using an evaluation process employing the fitness function for all particles.

For image defogigng, the fitness is measured by the CNC index (see Eq.(2)) of a defogged image obtained by the method presented above, because a color image with good defogging effect includes many visible edges and its color must be natural and colorful. The best fitness value is the one with the largest CNC value. Therefore, using the CNC index, the *Gbest* and *Pbest* can be obtained by selecting the highest fitness.

(3) Termination condition

If the number of training iterations is terminated or the accuracy is satisfied, output *Gbest* and *Pbest* locations, and the algorithm terminates. Otherwise, go to Step (4). When the number of training iterations is reached, the PSO computation is terminated.

In our experiment, the particle swarm populations *sizepop* is set to 20 and the number of iterations *maxgen* is set to 35, so the total number of parameter p or g can thus be calculated as 2×*sizepop*+(*maxgen*−1)×*sizepop*= 2×20+ (35−1)×20=720. The final optimal value of p or g corresponding to the maximum value of the 720 candidate particle values indicates the selected value for the two main parameters. The enhanced image with the two final parameter values is our final fog removal result.

(4) Iterative optimization

Calculate the movement vectors in Eq.(3) for all particles. Next, modify the locations of all particles utilizing Eq.(4) and then go to Step (2). The movement vector (location) is specified as follows:

$$\boldsymbol{V}_i(t+1)=w\boldsymbol{V}_i(t)+c_1\times r_1\times(Pbest_i-\boldsymbol{X}_i(t))+c_2\times r_2\times(Gbest-\boldsymbol{X}_i(t)), \quad (3)$$

where $V_i=(V_{i1},V_{i2},...,V_{im})\in\Re^m$, and the particle's initial velocity is $0.5\times RV$. $\boldsymbol{V}_i(t+1)$ represents the movement vector of particle i at the $(t+1)$th iteration, w indicates the inertia weight (w=1 in our experiments), c_1 and c_2 denote the acceleration coefficients which are random numbers in [0, 1], and we set $c_1=c_2=0.5$ for all results reported in this paper. r_1 and r_2 are also two randomly generated values in [0, 1]. Moreover, in Eq.(3), the first term $w\boldsymbol{V}_i(t)$ denotes the particle's inertia, the second term $c_1\times r_1\times(Pbest_i-\boldsymbol{X}_i(t))$ indicates the particle's cognition-only model, and the third term $c_2\times r_2\times(Gbest-\boldsymbol{X}_i(t))$ stands for the particle's social-only model. The location of particle i is modified by

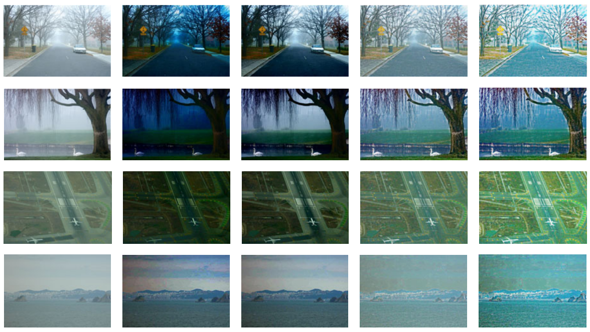
$$\boldsymbol{X}_i(t+1)=\boldsymbol{X}_i(t)+\boldsymbol{V}_i(t+1), \quad (4)$$

where $\boldsymbol{X}_i(t+1)$ represents the location of particle i at the $(t+1)$th iteration, which is used to estimate the optimal values of the two main parameters. $\boldsymbol{V}_i(t+1)$ denotes the movement vector of particle i at the $(t+1)$th iteration. Hence, the new location of particle i is to add its current location vector to its movement vector. We can deduce that the iterative optimization operation is designed to suit our needs regarding good image defogging effect with relatively large CNC index and maintaining the diversity at the same time.

To verify the effectiveness and validity of the proposed parameter value selection method, three criteria have been considered: generation number influence, qualitative comparison, and 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.

The final condition of the proposed PSO-based algorithm is to reach the given number of training iterations *maxgen*. To evaluate the influence of the iteration number *maxgen* used in the proposed method, some groups of experiments are performed by varying *maxgen* from 20 to 50. From the parameter values and the resulting absolute difference (AD) metrics of a test image, we can clearly see that the results are visually and statistically close (the value range of AD is [60.733 2, 61.950 3] for He's method, and [42.291 8, 43.757 9] for Tarel's method) when varying *maxgen* from 20 to 50. It demonstrates that the influence of the iteration number is very limited in the proposed method. The experiments on a large number of other test images also confirm the observations.

The proposed method works well for a wide variety of real captured foggy images. Fig.1 shows some examples of the defogging effects obtained by using the default parameters of He's method, the default parameters of Tarel's method and the proposed parameter selection method for both He's method and Tarels' method. These foggy images are captured under different conditions, such as vehicle assistant driving image, natural scene image, aerial image and ocean image, etc. One can clearly see that the defogging results obtained using auto-adaptive parameter values seem more visually pleasing compared with those obtained using the default values for both He's method and Tarels' method, which demonstrates that the proposed parameter selection method can greatly improve the performance of defogging algorithms. The auto-adaptive parameter values for the four testing images in Fig.1 are shown in Tab.1. The testing results on other real captured foggy images also confirm the conclusion.



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

Fig.1 Visual comparison of defogging results for real captured foggy images: (a) Foggy images; (b) He's results obtained using default parameter values (ω=0.95, t_0=0.1, c=3); (c) He's results obtained using auto-adaptive parameter values; (d) Tarel's results obtained using default parameter values (p=0.95, b=0.5, s_v=9, s_f=1, g=1.3); (e) Tarel's results obtained using auto-adaptive parameter values

Tab.1 The auto-adaptive parameter values for the testing images in Fig.1

Image	He's method		Tarel's method	
	ω	t_0	p	g
Fig.1 (Row #1)	0.969 7	0.49	0.997 3	9.9
Fig.1 (Row #2)	0.990 0	0.50	0.990 0	8.2
Fig.1 (Row #3)	0.986 4	0.66	0.962 0	8.7
Fig.1 (Row #4)	0.953 8	0.37	0.994 7	9.4

For the two representative defogging algorithms, the most time-cosuming 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 $M\times N$, so He's algorithm involves a $(M\times N)\times(M\times N)$ matting Laplacian matrix. Therefore, the time complexity of He's algorithm TC_{H} is about $O(M^2\times N^2)$, while that of Tarel's algorithm TC_{T} is about $O(MNs_v^2\ln s_v)$, 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 $O((M/s)^2\times(N/s)^2)$, where s is the subwindow size used for patch segmentation. For PSO optimization algorithm, csuppose the number of particles in the ith iteration is N, and m is the number of iterations. Let the running time of each particle in each iteration is T_p, so the total running time of the proposed PSO-based algorithm can be written as $N\times m\times T_p$. Thus, the time complexity of PSO algorithm can be reflected by the number of particle swarms and the running time of each particle in an iteration. Since the particle swarm populations is set to 20 and the number of iterations is set to 35 in our experiment, and the ideal defogging results are obtained by appling the determined optimal parameter values to defogging algorithms, we can thus deduce that the whole time complexity of the proposed method is about $20\times35\times(TC_H+TC_{CNC})\times T_p+TC_H$ for He's algorithm, and about $20\times35\times(TC_T+TC_{CNC})\times T_p+TC_T$ for Tarel's algorithm.

Generally, the average running time of the proposed parameter selection method for He's algorithm is about 760 s for an image with a size of 200×150, and about 150 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 benifit much from the proposed method. That's because for surveillance video, once the optimal parameter values are determined by an 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.

In this letter, a novel PSO-based single image defogging method is proposed. Different from the most defogging methods which generally fix the parameter values, the proposed approach can help defogging methods to automatically select optimal parameter values for different foggy images. In the proposed method, the two main parameters which directly affect the results are firstly distinguished from other less important parameters which can be considered as fixed values. Then, the two parameter values are adaptively determined by using the PSO algorithm. The proposed parameter selection method has been applied to two representative defogging algorithms, which demonstrates the superior performance of the proposed scheme both qualitatively and quantitatively. Although the proposed method provides a new way to solve the parameter adjustment problem for single image defogging, in the future, we will try to investigate the parameter value selection issue based on mmore advanced assessment index, since the CNC index may be not the best one to measure image defogging effect.

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