Information Processing Letters 116 (2016) 595–602

Contents lists available at ScienceDirect

Information Processing Letters

www.elsevier.com/locate/ipl

Genetic algorithm-based parameter selection approach to single image defogging

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ARTICLE INFO

Article history:
Received 20 April 2014
Received in revised form 18 March 2016
Accepted 28 April 2016
Available online 4 May 2016
Communicated by X. Wu

Keywords:
Single image defogging
Genetic algorithm
Parameter selection
Defogging effect assessment
Performance evaluation

ABSTRACT

Image defogging is widely used in many outdoor working systems. However, owing to the lack of enough information to solve the equation of image degradation model, existing restoration methods generally introduce some parameters and set these values fixed. Inappropriate parameter setting will lead to difficulty in obtaining the best defogging results for different input foggy images. This letter proposes a novel defogging parameter value selection algorithm based on genetic algorithm (GA). We mainly focus on the way to select optimal parameter values for image defogging. The proposed method is applied to two representative defogging algorithms by selecting the two main parameters and optimizing them using the genetic algorithm. An assessment index of image defogging effect is used in the proposed method as the fitness function of the genetic algorithm. Thus, these parameters may be adaptively and automatically adjusted for the defogging algorithms. A comparative study and qualitative evaluation demonstrate that the better quality results are obtained by using the proposed method.

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 letter, we thus focus on the genetic algorithm-based adaptive parameter adjustment for single image defogging.

The motivation of using genetic algorithm for image defogging is that the parameter selection and function maximization can be closely related problems, since acquired the best parameter values also simultaneously solved the function maximization problem, and constructing a good object function actually ensures the best parameter values for image defogging effect. The essence of genetic algorithm is its global optimization performance, that is, the

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http://dx.doi.org/10.1016/j.ipl.2016.04.013
0020-0190/

Fig. 1. Fog removal results with fixed parameter value. (a) Original image. (b) Unpleasing contour effect with $\omega = 0.95$. (c) No obvious visibility improvement with $\omega = 0.65$. (d) Smoother sky region using $\omega = 0.12$.

fitness function may reach its maximum with the optimal parameter values, and using genetic algorithm the probability of finding out the global optimization solution is the highest in most intelligent search algorithms. It is widely used to generate useful solutions to optimization problems and it can be also used for digital image processing, such as image segmentation [8], image enhancement [9], etc. Therefore, the parameter value selection of image defogging is simulated as an optimization problem, and the genetic algorithm is used to optimize the sensitive parameters in the proposed method. Experimental results demonstrate that the better quality defogging results can be obtained by using the genetic algorithm.

However, due to the lack of proper objective criterion of defogging effect as the fitness function, present defogging algorithms seldom 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 image, 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 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) [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.

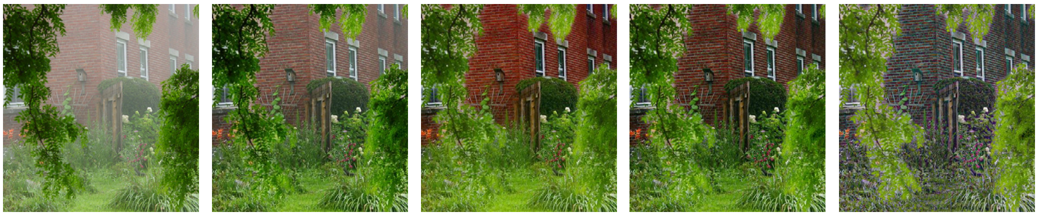
In this letter, we mainly focus on the way to select parameter values for single image defogging. Here, the defogging effect assessment index presented in our previous work [12] is taken as the fitness function of the proposed GA-based method to adaptively adjust the parameter values for different input foggy images. In Section 2 of the letter, the limitation of existing methods are described. Section 3 introduces the proposed parameter value selection approach to single image defogging. Experimental results and conclusions are presented in Sections 4 and 5, respectively.

2. Limitation of the existing defogging methods

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 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 may all have fixed values in the defogging algorithms. Therefore, the proposed approach first split the set of algorithm parameters into two sets: sensitive parameters set and less sensitive parameters set. Then a criterion is used to select the best sensitive parameters using a genetic algorithm. The reason why the parameter selection is needed for the proposed method is that optimizing too many parameters will cost too much computing time. Therefore, we choose two main sensitive parameters which have significant effect on the final defogging results to optimize, and other less sensitive parameters are set with fixed values. However, if time permits, all the algorithm parameters can be optimized using the proposed approach.

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 given in Fig. 1 using He's algorithm [3] 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 show that ω sometimes needs to be decreased when an image contains substantial sky regions, otherwise the sky region may wind up having artifacts. An example showing the need to decrease ω is presented in Fig. 1. The defogging result with $\omega = 0.95$ is shown in Fig. 1(b). One can clearly see that the sky looks contoured since the fog removed by He's algorithm was too strong in this region, and the defogging result has no obvious visibility improvement with $\omega = 0.65$. If setting $\omega = 0.12$, the sky region becomes brighter and smoother, which makes the whole image look more natural.

Most defogging algorithms have introduced some parameters, which lead to user interaction and make the fi-



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

Fig. 2. Fog removal results with many fixed parameters. (a) Original image. (b) Defogging result with $p = 0.7$, $b = 0.5$, $s_v = 19$, $s_i = 1$, $g = 1.3$. (c) Defogging result with $p = 0.99$, $b = 0$, $s_v = 19$, $s_i = 1$, $g = 1$. (d) More pleasing result with $p = 0.96$, $b = 0.5$, $s_v = 19$, $s_i = 1$, $g = 1.3$. (e) Less pleasing result with $p = 0.99$, $b = 1$, $s_v = 19$, $s_i = 1$, $g = 1$.

nal 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 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. Fig. 2 shows the defogging results obtained with different parameter values using Tarel's algorithm [4]. One can clearly see that the restoration is too light with $p = 0.7$, $b = 0.5$, $s_v = 19$, $s_i = 1$, $g = 1.3$ and too strong with $p = 0.99$, $b = 0$, $s_v = 19$, $s_i = 1$, $g = 1$. It seems better with $p = 0.96$, $b = 0.5$, $s_v = 19$, $s_i = 1$, $g = 1.3$. One the right, most of the colors are removed due to a too large value of $b = 1$, and $b = 0.5$ leads to better results. 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.

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 image. However, the defogging evaluation results obtained using image quality evaluation criteria is 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 realizing adaptive adjustment of the algorithm parameters by the defogging results is very hard due to the lack of an effective assessment index. Therefore, a GA-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.

The main advantages of the proposed method are as follows: (i) compared with the results obtained by most existing defogging methods which use fixed default parameter values, better image defogging effect can be obtained by using the auto-adaptive parameter values; (ii) the static, open-loop parameter estimation issue can be transformed into a dynamic parameter adjustment issue. Thus, there is no need to manually adjust parameter values for different input images, and the optimal values can be automatically determined with no user-interaction. This is quite essential in automatic fog removal.

3. The proposed parameter value selection approach

Since most defogging algorithms may produce oversaturated or undersaturated colors with fixed parameters, the two main parameters that directly affect the defogging results are first selected. And then a generic 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. In this section, the detailed descriptions of the two main parameters selection approach to various representative defogging algorithms are first given in Subsection 3.1. Then, the assessment index for measuring defogging effect is reported in Subsection 3.2. Finally, the GA-based parameter value selection method is presented in Subsection 3.3.

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 et al.'s method [3] is recognized as one of the most effective ways to remove fog, and Tarel et al.'s method [4] is regarded as one of the fastest defogging algorithms at present.

For He et al.'s method [3], 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 parameters. For example, the influence of the large patch size c can be ef-

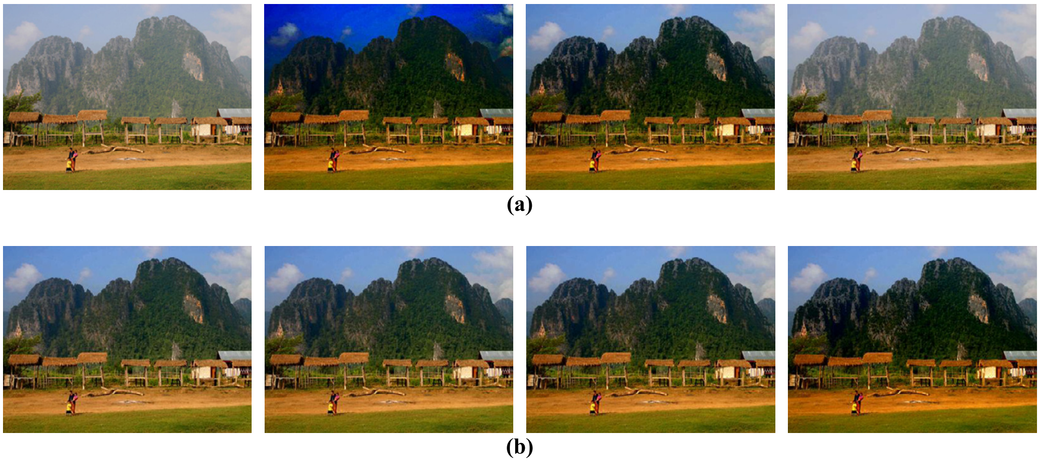


Fig. 3. He's defogging results with different parameter values. (a) The influence of two main parameters on final results with $\omega = 0.95$, $c = 7$. From left to right: original foggy image with size of 400×300, the results obtained with $t_0 = 0.1$, 0.5, 1, respectively. (b) The influence of parameter c on the final results with $\omega = 0.95$, $t_0 = 0.5$. From left to right: the results obtained with $c = 30$, 15, 9, 3, respectively.

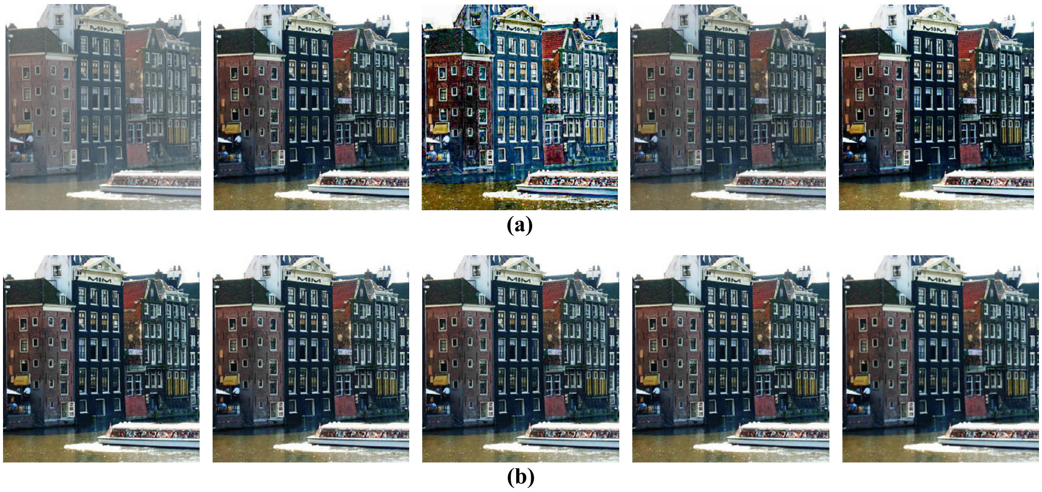


Fig. 4. Tarel's defogging results with different parameter values. (a) The influence of two main parameters on the final results with $b = 0.5$, $s_v = 17$, $s_i = 1$. From left to right: original foggy image with size of 370×400, the results obtained with ($p = 0.1$, $g = 3$), ($p = 0.95$, $g = 3$), ($p = 0.1$, $g = 3$), ($p = 0.1$, $g = 7$), respectively. (b) The influence of other three parameters on final results with $p = 0.1$, $g = 5$. From left to right: the results obtained with ($b = 0$, $s_v = 17$, $s_i = 1$), ($b = 1$, $s_v = 17$, $s_i = 1$), ($b = 0.5$, $s_v = 5$, $s_i = 1$), ($b = 0.5$, $s_v = 30$, $s_i = 1$), ($b = 0.5$, $s_v = 17$, $s_i = 10$), respectively.

fectively reduced by the soft matting used in He et al.'s method [13]. Therefore, the patch size suggested by the author is reasonable. Fig. 1 shows He's defogging results using different ω. The fog removal results using different t_0 or patch size c are shown in Fig. 3. One can clearly see that t_0 has significant influence on the final results, while the patch size c on the contrary has little influence.

For Tarel et al.'s method [4], 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 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 b, s_v and s_i have less effect on the final defogging results, as shown in Fig. 4.

From the two examples showed in Figs. 3–4, we can deduce that 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.

3.2. Measurement of defogging effect

The CNC index, an effective defogging evaluation indicator proposed in our previous work [12] is used here

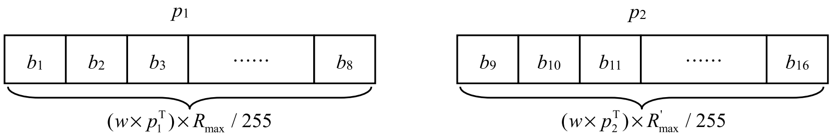


Fig. 5. Chromosome representation.

to guide the parameter adjustment process. For the input foggy image $\mathbf{x}$ and its corresponding fog removal image $\mathbf{y}$, 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 colorfulness index (CCI) to measure the color naturalness of the defogging image $\mathbf{y}$, and (iii) Combine the three components e, CNI and CCI to yield an overall defogging effect measure:

$$\mathrm{CNC}(\mathbf{x},\mathbf{y}) = h\left(e(\mathbf{x},\mathbf{y}), \mathrm{CNI}(\mathbf{y}), \mathrm{CCI}(\mathbf{y})\right) \tag{1}$$

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, 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 $\mathbf{x}$ and $\mathbf{y}$, i.e. the function h in (1) can be defined as

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

As explained above, 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 genetic algorithm

Using the genetic algorithm (GA), the two main parameters of various defogging algorithms can be automatically determined on the basis of the CNC index. The simple but effective GA-based parameter selection consists in the following steps:

(1) Representation of chromosome

The task using the GA is to find the best combination of the two main parameters according to an objective criterion. Therefore, the representation of the chromosomes is a string of 2 genes denoting the two parameters. The length of each gene L is set to 8 binary integers, and the number of individuals in the population is set to 16. This representation is given in Fig. 5, where b_i $(i = 1, 2, \ldots, 8)$ designates the 8 random binary integers that represent the first parameter p_1, the other parameter p_2 is also represented by the binary integers b_i $(i = 9, 10, \ldots, 16)$, $R_{\max}$ and $R'_{\max}$ are the maximum range values for the two parameters, and $w = [1, 2, 4, 8, 16, 32, 64, 128]$. Thus, the value of L depends on the value ranges of the two parameters. For example, the value ranges of parameters p and g in Tarel et al.'s method are $(0, 1)$ and $(0, 10)$, respectively, so the 2 genes can be expressed as $(w \times p_1^{\mathrm{T}}) \times 1/256$ and $(w \times p_2^{\mathrm{T}}) \times 10/256$.

(2) Fitness function

An individual fitness f 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. Thus, the best fitness value is the one with the largest CNC value.

(3) Selection and crossover

Both the selection and crossover of the GA are applied to insure a steady convergent and exploitative behavior of the GA. Since only individuals that have higher fitness are selected in the population, the best fitness in each generation f_{best} is thus used in the selection operation. The crossover operator is designed to better mix the fitness f in the chromosomes and to suit our needs regarding good image defogging effect with relatively large CNC index value and maintaining the diversity at the same time. Thus, the individual chromosomes with smaller fitness value have less chance to exist, and the chromosomes with higher fitness value have more chance to exist.

Specifically, the procedure of selection and crossover operations can be described as follows: Firstly, for the individuals in each generation, we use certain defogging algorithm to obtain the fog removal images with the initial parameter values represented by the chromosome shown in Fig. 5. Then, the CNC index is applied to these fog removal images to calculate the corresponding fitness function f. The maximum value of the fitness function f in the individuals is denoted as f_{best}, and the minimum value of f is denoted as f_{worse}. If f_{best} equals f_{worst}, the value of E_{new} in (3) is much smaller (equals zero), compared with the E_{new} value in case that f_{best} is not equal to f_{worst}. The crossover process can be written as:

$$E_{new} = \begin{cases} \alpha(f_{best} - f) = 0 & \text{if } f_{best} = f_{worst} \\ \alpha(f_{best} - f)/\lambda & \text{otherwise} \end{cases} \tag{3}$$

where α is a updating factor $\alpha = 7L/24 \in (L/4, L/3)$, and λ is a small value (10^{-2} in our experiments). E_{new} is the function of the fitness value, which is used for the

Table 1
AD metrics of the two representative defogging methods under G from 20 to 50.

	Gen.	20	25	30	35	40	45	50
He et al.'s method	AD	30.4318	30.3989	30.3739	30.3696	30.1313	30.3783	30.8986
Tarel et al.'s method	AD	43.4687	43.4299	43.9709	43.4705	43.0922	43.3210	43.2229

crossover operation. Since the value of E_{new} is either zero or a positive integer number (larger than 1), it can thus be also regarded as a "switching function" for the next mutation operation.

(4) Mutation

The general method by reversing bits is used as the mutation method. A bit is selected at random at mutation rate $P_{mut} = 0.5$ for the bits of all individual chromosomes and the bit is reversed. The mutated genes are obtained by the following expression.

$$GN_{mut} = \begin{cases} 1 - GN & \text{if } P_{mut} \times E_{new} \times P_{num} < RN \\ GN & \text{otherwise} \end{cases} \tag{4}$$

where GN_{mut} is the calculated mutated genes, GN is the input genes. P_{num} is the number of genes (parameters) and $P_{num} = 2$ here, RN is a random number and $RN \in (0, 1)$.

The population is evolved by the genetic algorithm using the evolutionary rules described above. An random gene information is given to each individual in the first generation. The individual which has the best fitness is selected in the population in every generation. When the number of generations (40 in our experiments) is reached, the genetic algorithm computation is terminated. The gene information of the individual with the best fitness in all generations indicates the selected value for the two main parameters. The enhanced image with the final parameter values is our final fog removal result.

4. Experimental results

The publicly available dataset frida2 [14] 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, and (iii) quantitative evaluation. 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

The final condition of the proposed GA-based algorithm is to reach the given number G of generations. To evaluate the influence of the generation number G used in the proposed method, some group experiments are performed by varying the generation number G from 20 to 50, the parameter values and the resulting AD metrics of a test image are presented in Table 1. One can clearly see that the results are visually and statistically close (the value range of AD are [30.1313, 30.8986] for He et al.'s method, and [43.0922, 43.9709] for Tarel et al.'s method) when varying G from 20 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.

4.2. Qualitative comparison

For further evaluation of the GA-based method for selecting the most proper parameter values, the image dataset provide by Tarel et al. [14] 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. For each image, we obtain the fog removal results with the default and the auto-adaptive parameter values for He et al.'s and Tarel et al.'s algorithms. We also give the corresponding fog-free images as the reference images for comparison. An illustrative example is shown in Fig. 6. One can clearly see that the defogging results obtained using the auto-adaptive values achieve a better enhancement effect compared to the results obtained using the default values for both defogging algorithms. Table 2 shows the auto-adaptive sensitive parameter values of the two representative defogging methods selected by the proposed algorithm for the four original foggy images in Fig. 6(a). The less sensitive parameters are all set with fixed values for different input foggy images, as shown in Table 2.

Note that the color of He et al.'s results seems much dark than that of no-fog reference images, and there are some halo artifacts in Tarel et al.'s results. All these problems are caused by the defogging algorithm itself, not the proposed parameter selection method. The accuracy of the GA-based parameter selection can be validated by determining the most proper parameter values and producing the best results for each defogging method.

4.3. Quantitative evaluation

To quantitatively assess the proposed parameter value selection method, we compute the AD index value for the images in Fig. 6, and the statistical results are shown in Table 3. 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. 6.

Fig. 6. Visual comparison of defogging results for public database frida2 [14]. (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.

Table 2
The parameter values selected by the proposed algorithm for Fig. 6(a).

Fig. 6(a)	He et al.'s method ($c = 3$)		Tarel et al.'s method ($b = 0.5$, $s_v = 9$, $s_i = 1$)	
	ω	t_0	p	g
Row #1	0.9570	0.2813	0.9961	8.5938
Row #2	0.9492	0.0430	0.9336	8.0078
Row #3	0.9688	0.2617	0.9727	9.9219
Row #4	0.9716	0.0547	0.9648	9.0243

Table 3
AD index between enhanced images and no-fog images for the testing images in Fig. 6.

Img	Method				
	Foggy image	He et al.'s method (default value)	He et al.'s method **(adaptive value)**	Tarel et al.'s method (default value)	Tarel et al.'s method **(adaptive value)**
Fig. 6 (Row #1)	44.6932	42.4912	**31.6455**	20.9098	**18.0832**
Fig. 6 (Row #2)	92.4735	67.4302	**63.5522**	77.8565	**72.9543**
Fig. 6 (Row #3)	75.2671	39.0186	**33.9407**	54.1371	**46.8244**
Fig. 6 (Row #4)	64.4941	31.1257	**29.4453**	46.1748	**35.4265**

The AD index is also tested for more test images in public database frida2 (66 images). Fig. 7(a) shows the statistical results of the AD for He et al.'s method and Fig. 7(b) shows the AD results for Tarel et al.'s method. In Fig. 7, circle "○" 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 AD index values and vertical axes are the image number index. 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 value 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.

5. Conclusions

In this letter, a novel genetic algorithm-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 optimal 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 that can be considered as fixed values. Then, the two parameter values are adaptively determined by using the genetic 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. Although the proposed method provided a new way to solve the parameter adjustment problem for single image defog-

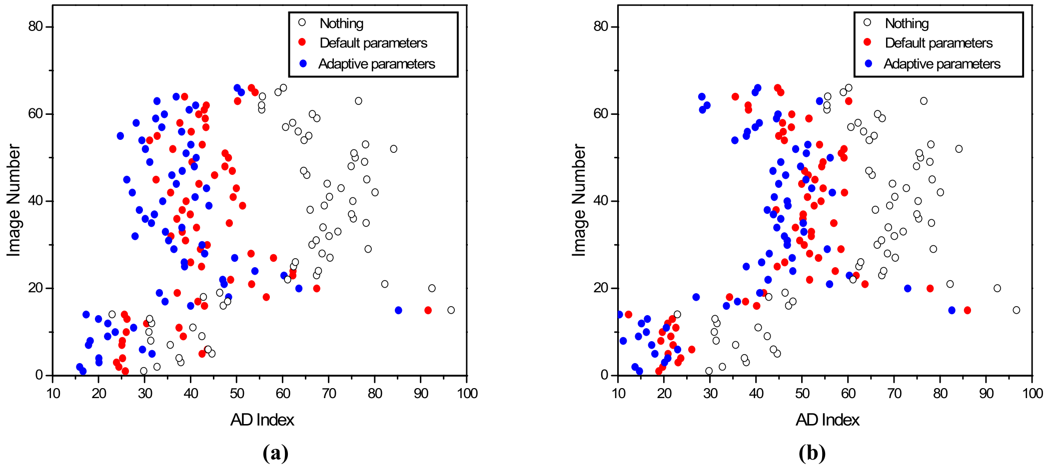


Fig. 7. AD index results for the 66 test images in public database frida2 [14]. (a) He's statistical results. (b) Tarel's statistical results.

ging, 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. The authors would like to thank the reviewers and the editors for their valuable comments. This work was supported by the National Natural Science Foundation of China (71271215, 70921001, 61502537, 61540037, and 71221061), the Collaborative Innovation Center of Resource-conserving & Environment-friendly Society, Ecological Civilization, the Postdoctoral Science Foundation of Central South University (No. 126648), and the International Science & Technology Cooperation Program of China (2011DFA10440).

References

[1] R.T. Tan, Visibility in bad weather from a single image, in: Proceedings of IEEE Conference on Computer Vision and Pattern Recognition, 2008, pp. 1–8.

[2] K. Nishino, L. Kratz, S. Lombardi, Bayesian defogging, Int. J. Comput. Vis. 98 (2012) 263–278.

[3] K.M. He, J. Sun, X.O. Tang, Single image haze removal using dark channel prior, IEEE Trans. Pattern Anal. Mach. Intell. 33 (2011) 2341–2353.

[4] J.P. Tarel, N. Hautiere, Fast visibility restoration from a single color or gray level image, in: Proceedings of IEEE International Conference on Computer Vision, 2009, pp. 2201–2208.

[5] A. Lagorio, E. Grosso, M. Tistarelli, Automatic detection of adverse weather conditions in traffic scenes, in: Proceedings of IEEE Fifth International Conference on Advanced Video and Signal Based Surveillance, 2008, pp. 273–279.

[6] N. Hautiere, J.-P. Tarel, D. Aubert, Towards fog-free in-vehicle vision systems through contrast restoration, in: Proceedings of IEEE Conference on Computer Vision and Pattern Recognition, 2007, pp. 2374–2381.

[7] N. Hautiere, J.-P. Tarel, H. Halmaoui, R. Bremond, D. Aubert, Enhanced fog detection and free-space segmentation for car navigation, Mach. Vis. Appl. 25 (2014) 667–679.

[8] E.Y. Kim, S.H. Park, H.J. Kim, A genetic algorithm-based segmentation of Markov random field modeled images, IEEE Signal Process. Lett. 7 (2000) 301–303.

[9] S. Hashemi, S. Kiani, N. Noroozi, M.E. Moghaddam, An image enhancement method based on genetic algorithm, in: Proceedings of International Conference on Digital Image Processing, 2009, pp. 167–171.

[10] Z. Wang, A.C. Bovik, H.R. Sheikh, E.P. Simoncelli, Image quality assessment: from error visibility to structural similarity, IEEE Trans. Image Process. 13 (2004) 600–612.

[11] Z.X. Ji, Q. Chen, Q.S. Sun, D.D. Xia, A moment-based nonlocal-means algorithm for image denoising, Inf. Process. Lett. 109 (2009) 1238–1244.

[12] F. Guo, J. Tang, Z.X. Cai, Objective measurement for image defogging algorithms, J. Cent. South Univ. 21 (2014) 272–286.

[13] K.M. He, Single image haze removal using dark channel prior, Ph.D. dissertation, The Chinese University of Hong Kong, 2011.

[14] J.-P. Tarel, N. Hautiere, L. Caraffa, A. Cord, H. Halmaoui, D. Gruyer, Vision enhancement in homogeneous and heterogeneous fog, IEEE Intell. Transp. Syst. Mag. 4 (2012) 6–20.