# Application of Multi-Scale Convolution Neural Network Optimization Image Defogging Algorithm in Image Processing

Weihan Zhu
School of Electrical and Information Engineering-Jiangsu University, Jingjiang College, Zhenjiang, 212000, China

***Abstract*—To improve the ability to detect and identify smog images in complex road traffic scenes, smog images need to be defogged, and an optimized image defogging algorithm on the basis of multi-scale convolutional neural network (MCNN) is proposed. The physical model of road traffic scene smog scattering is constructed, and the image is divided sky area, road surface area and road sky boundary area. The road sky boundary line is the boundary line between road surface and sky area. The dark channel of traffic scene smog image is established by Canny edge detection and MCNN optimization, and the smog image is subjected to detail compensation and gray enhancement processing through prior knowledge. After substituting the atmospheric light value and transmittance map into the atmospheric scattering model (ACM), the MCNN learning model is combined to realize the filtering processing and defogging optimization of smog images in complex road traffic scenes. The color saturation, defogging degree, peak signal-to-noise ratio (PSNR), texture effect as well as other aspects of the image are taken as test indexes for the simulation experiment. The simulation results show that the color saturation, defogging degree and image definition of the defogged haze images in complex road traffic scenes are higher by using this method, which improves the output PSNR of the defogged haze images in complex road traffic scenes, and has a good application value in image defogging.**

***Keywords*—*Multi-scale convolution neural network; complex road traffic scene; Image defogging; dark passage; Gray enhancement***

## I. INTRODUCTION

Nowadays, the society has entered the information age, and the way that human beings know and transform the world depends not only on language and characters, but also on images, which gradually become the main medium for transmitting real-world information. According to scientific statistics, in the process of people learning and recognizing social changes, most of the effective information comes from images, which means that image research has a significant role in production and life. In actual scenes, image semantics is often changed due to the introduction of some noises, and some directions related to computer vision are just born for solving this kind of image tasks, such as common image denoising and image enhancement, etc. This paper mainly focuses on the research of the related methods of image defogging. Recently, daily transportation, aerospace and road monitoring are all seriously affected by smog weather due to rapid development of domestic industrial production,. Fog refers to tiny water droplets suspended in the air, which are formed by condensation of water vapor in the ground layer; Haze, which consists of dust, sulfuric acid, organic hydrocarbons and other particles in the air, leads to atmosphere turbid. In foggy scenes, natural light will be absorbed or scattered by these suspended water droplets and particles in the process of transmission, which will cause the outline of the shot scene to be blurred, the image clarity and color saturation to decrease, thus affecting the overall visual effect of images. Especially when the smog concentration is high, the information of the real image will be seriously lost. Hinder the subsequent application of images. For example, in daily traffic

The main goal of image defogging algorithm is to reduce the noise caused by haze impurities to the image, increase the image's clarity and color saturation, and repair the image details. Traditional image defogging methods are mainly divided into two types. The first type is the defogging algorithm on the basis of non-physical model, which only depends on enhancing the image to enhance the image visual effect. This kind of method does not involve the principle of fog formation and the process of image imaging, but only enhances some information in the foggy image according to the actual needs. The second kind is the defogging algorithm on the basis of physical model. This method, on the basis of the ACM, estimates the undetermined parameters in the model by statistical methods to recover the fog-free image. Recently, the deep learning theory has been extensively applied in image defogging. Some scholars use a large number of foggy image data sets to train and learn, so that they can achieve defogging more efficiently.

The early defogging algorithm did not consider the objective physical model of image degradation in foggy environment, but was guided by the subjective feeling of human vision. By enhancing the contrast of foggy images, the visual feeling of images was natural and clear, and the details of images were richer. This kind of method can improve the subjective quality of images to some extent[1]. However, there is no fundamental analysis of the factors affecting image degradation, so some prominent information may cause some losses. This kind of algorithm mainly includes: histogram equalization algorithm. And wavelet homomorphic filtering algorithm, Re tinex algorithm, etc. Among them, literature [2] puts forward an image defogging algorithm for complex road traffic scenes, which adopts the smooth transition of abrupt points in the image. Because of the unknown a priori, it is difficult to build a statistical model. Literature puts forward a simple defogging model on the basis of physical laws. Through constructing the scene's physical texture features, the atomization points are virtually reconstructed. The method is simple and easy, but the accuracy is not high. Literature analyzes the defogging algorithm of atomized images collected on the water surface, and mainly adopts the defogging algorithm of complex road traffic scenes on the basis of constrained evolutionary time-frequency weighted filtering. The algorithm is limited by the scattering interference of edge fog points, so the defogging effect of complex road traffic scenes and other images is not good.

To solve the above problems, this paper puts forward a haze image defogging algorithm on the basis of MCNN. Firstly, the paper builds a physical model of haze scattering in road traffic scenes, and builds an ACM according to the sky brightness estimation and road sky line segmentation method. By using MCNN method, the largest line segment is found out based on the calculated length of each straight line segment, so as to recover the image scene and defog the image in complex road traffic scenes. Finally, the performance of this algorithm is checked by simulation experiment, indicating that his algorithm has superior performance.

## II. Related Works

The work of removing smoke from traffic scene images belongs to image denoising, and people have carried out a lot of research in this field before. With the development and maturity of artificial intelligence technology, it is increasingly used in image denoising. Jian J et al. found that the image denoising algorithm based on sparse expression has good denoising effect. Therefore, a convolutional neural network algorithm based on sparse expression is designed and applied to image denoising. The experimental results show that the algorithm significantly improves the image quality and the denoising effect is significantly better than the algorithm model without sparse expression [3]. Jh A et al.'s desert images tend to contain noise caused by large amounts of sand and dust in the air. In order to improve the quality of images taken in desert areas, an improved neural network algorithm was designed. The test results show that the algorithm has better image denoising effect than the current algorithm [4]. Liu Y's research team found that the quality of polarized images is easily affected by the noise in the images obtained by the polarization camera. A denoising method using pulse coupled neural network to optimize polarization images is proposed. The calculation results show that compared with the most advanced image denoising algorithm, the proposed optimized image denoising method effectively suppresses the noise in polarized images [5]. Golilarz NA et al. designed a neural network algorithm incorporating adaptive Gaussian distribution to solve the noise problem in remote sensing satellite images. The test results show that, compared with the common denoising algorithm, the denoised image signal-to-noise ratio of this algorithm is significantly higher [6].

To sum up, in order to denoise the image to improve the image quality, people have proposed many improved image appearance processing methods, but few studies have involved removing the influence of fog caused by weather in the image, which is crucial to improve the image recognition quality of the transportation industry, which is the main purpose of this study.

## III. Construction of Atmospheric Scattering Physical Model and Image Pre-Processing of Image Environment on the Basis Of GIS

### A. *Physical Model of Haze Scattering in Road Traffic Scenes*

Firstly, a physical model of smog scattering in road traffic scenes is established[7]. When light travels, some of it will deflect due to contact with suspended particles in the atmosphere[8-9]. Besides, the deflection intensity is closely related to the suspended particle's size, type and distribution. Generally, the camera equipment receives two types of light sources: one is the reflected light of the target object. During reflected light propagation from the target object to the imaging equipment, the light received by the equipment is attenuated due to the absorption and scattering of impurities, resulting in the decrease of imaging brightness and contrast; Second, the ambient atmospheric light, the main sources of which are direct sunlight, atmospheric scattered light and ground reflected light, etc. Atmospheric light will also experience the process of being absorbed or scattered by particles, but when it propagates to the imaging equipment, the original image may be blurred because the intensity of this split light is larger than the target's reflected light. Therefore, the light intensity which is received by the imaging sensor is mainly from the superposition of the above two remaining light intensities after being influenced by impurities. They can be respectively expressed by the incident light attenuation model (ILAM) and the atmospheric light imaging model. Seen from image processing, the contrast of degraded images in foggy days is enhanced. Aiming at the characteristics of clear boundary line between highway and sky and large sky area, the image is segmented first, and the pre-processing of image defogging is realized [10]. The schematic diagram of the physical model of water surface atmospheric scattering is shown in Fig. 1.

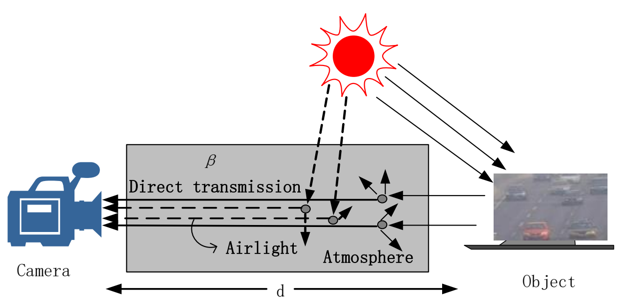


Fig. 1. Physical model of atmospheric scattering

Fig. 1 shows Narasimhan ACM. On the basis of this, a monochromatic ACM under fog and haze weather conditions is obtained. Depending on the physical model, the weather degradation image restoration method, the human eye observes the object depending on the reflection phenomenon formed when the light meets the target scene[11-12]. During the reflection process, the light will collide with the suspended impurities in the atmosphere, resulting in the deflection of some light propagation directions and attenuation of the incident light actually entering our eyes or imaging equipment[13]. At the same time, the scattering degree of the incident light is relevant to the distance between the measured object and the imaging equipment. The larger the distance, the stronger the scattering ability, and the less the light that finally enters the camera[14]. The atmospheric scattering process and image degradation process during the generation of the incident ACM are described by the model state equation:

$$I(x) = J(x)t(x) + A(1 - t(x)) \tag{1}$$

Wherein, $A$ indicates the environmental light effect component of smog image in complex road traffic scene, $t(x)$ indicates the atomization transmittance of smog image in complex road traffic scene, and $J(x)t(x)$ indicates the attenuation factor of smog image atomization process in complex road traffic scene. According to the above equation, it is assumed that $A$ represents the sky brightness, $\rho(x)$ represents the scene albedo of the smog image of the complex road traffic scene at the spatial coordinate $d(x)$, and S $x$ represents the spatial coordinate, so that the pixel of the smog image of the complex road traffic scene captured by $I(x)$ is expressed as:

$$I(x) = A\rho(x)e^{-\beta d(x)} + A(1 - e^{-\beta d(x)}) \tag{2}$$

Wherein, $\beta$ represents the scattering degree of incident light. In the complex road network environment, the transmission wavelength coefficient of smog image imaging in the atmosphere of complex road traffic scenes is:

$$L = J\left(w,e\right) - \sum_{i=1}^{N} a_i \left\{ w^T \varphi\left(x_i\right) + b + e_i - y_i \right\} \tag{3}$$

Wherein, $J\left(w,e\right)$ represents the distance between the measured object and the imaging equipment, $a_i$ represents the unit cross-sectional thickness through which the incident light vertically passes, $b$ represents the wavelength of the incident light, and $e_i$ is the scene depth. When the reflected light of the target scene propagates to the imaging equipment, the impurities suspended in the natural environment will scatter the reflected light, resulting in the attenuated incident light, direct sunlight and scattered light of other objects entering the image acquisition equipment simultaneously. This process is named atmospheric light imaging. Therefore, contrary to the ILAM, the acquisition equipment in the atmospheric light imaging model can not only receive the target object's reflected light, but also have more types of atmospheric light. With the fluctuation of light and the change of probability density distribution model, the objective optimization function of atomization image processing and defogging is expressed as:

$$\left.\begin{aligned} J_1\left(w,e\right) &= \frac{\mu}{2} w^T w + \frac{1}{2}\gamma \sum_{i=1}^{N} e_i^2 \\ s.t. y_i &= w^T \varphi\left(x_i\right) + b + e_i, \quad i = 1,\cdots,N \end{aligned}\right\} \tag{4}$$

In the above formula, φ () is the wavelength kernel space mapping function of the local light spot information of the haze image in the complex road traffic scene, and $w^T \varphi\left(x_i\right)$ is the atmospheric penetration factor of the haze image in the complex road traffic scene. The partial derivative of the above formula is obtained as follows:

$$\left.\begin{aligned} \frac{\partial L}{\partial w} &= 0 \to w = \sum_{i=1}^{N} \alpha_i \varphi\left(x_i\right) \\ \frac{\partial L}{\partial b} &= 0 \to \sum_{i=1}^{N} \alpha_i = 0 \\ \frac{\partial L}{\partial e_i} &= 0 \to \alpha_i = \gamma e_i \\ \frac{\partial L}{\partial \alpha_i} &= 0 \to w^T \varphi\left(x_i\right) + b + e_i - y_i \end{aligned}\right\} \tag{5}$$

In the above formula, $i = 1,\cdots,N$ , streamline amplification processing is performed on the smog image of complex road traffic scene in the Z-axis direction of each vertex of the entity constructed by the atomized environment model, and the LOD with the highest resolution is used to form the entity environment object model of the smog image of complex road traffic scene. During the propagation of the reflected light of the smog image of complex road traffic scene, because of the scattering effect of atmospheric particles, some reflected light on the surface of the object is lost due to the scattering of the particles of the smog image of complex road traffic scene, and the fog point scattering loss of the smog image of complex road traffic scene is obtained as follows:

$$J(x) = \frac{I(x) - A}{\max(t(x), t_0)} + A \tag{6}$$

Wherein, $A$ represents the opposite of the ILAM, which is collected in the atmospheric light imaging model, $I(x)$ represents the reflected wavelength of the received target object, and $\max(t(x), t_0)$ is the wavelength of the reflected light scattered by the suspended impurities in the natural environment. Therefore, through the ACM, a scene picture is formed, and the reflected light intensity will decrease exponentially with the propagation distance. On this basis, this paper adopts the defogging method on the basis of the physical model, which essentially uses the ACM to solve the scene albedo and realize the image defogging.

### *B. Mathematical Model Construction and Preprocessing of Image*

On the basis of the prior knowledge, the smog image is subjected to detail compensation and gray enhancement. After substituting the atmospheric light value and transmittance map into the ACM, the MCNN learning model is combined to construct the defogging processing model of the smog image in the complex road traffic scene, and the mathematical model of the image is obtained. Collecting image information by block processing method, and selecting initial block size as a fixed value: 15*15; determining the image processing template by the image size m*n. And solving the dark primary color of the scattered atomized image in the 3*3 template of the haze image of complex road traffic scene, where $t(x)=e^{-\beta d(x)}$ indicates the propagation function or transmittance of the medium at the image position $0<t(x)<1$, so as to obtain the new features of the haze image of complex road traffic scene. The solution process is described as follows: Assume that the signal form of the haze image information of a complex road traffic scene is:

$$s(t)=\sum_{m=-\infty}^{\infty}\sum_{n=-\infty}^{\infty}a_{mn}g_{mn}(t) \tag{7}$$

Wherein, $a_{mn}$ is the extra luminous flux of the imaging acquisition equipment, $g_{mn}(t)$ is haze images of miscellaneous road traffic scenes , the included angle projected in the imaging acquisition equipment is fixed, and the atmospheric light source is the cross section of the vertebral body, and the largest pixel value of the imaging acquisition is determined as the estimated value of sky brightness, which is expressed as:

$$J^{dark}(x)=\min_{c\in\{r,g,b\}}(\min_{y\in\Omega(x)}(J^c(y))) \tag{8}$$

Wherein, $J^c$ represents a channel of smog image information of complex road traffic scene. A dark original smog image distribution area is set in the 3*3 template with X as the center. The edge of the smog image of complex road traffic scene is detected by Canny operator, and the smog image of complex road traffic scene is counted in blocks to find out the candidate sky area, and the intensity of the smog image of complex road traffic scene is close to 0. Based on the above processing, the haze image mathematical model in complex road traffic scene is obtained, and the atmospheric dissipation function is further defined, and the haze image in complex road traffic scene is defogged. The atmospheric dissipation function represents the extra part of ambient light to the image. In this way, the atmospheric dissipation function is simplified to $U(x)=1-e^{-\beta d(x)}$, which apparently has the characteristic resolution of the haze image in complex road traffic scene. Therefore, the captured image pixels is simplified as follows:

$$I(x)=J(x)t(x)+AU(x) \tag{9}$$

Wherein, $J(x)$ is the regular quantity of incident light attenuation of a point light source, $A$ is the illumination amplitude and $U(x)$ is the radiance of the light source. For a color image, $J^c$ is defined to represent a certain color component $J$, namely one of the three channels of RGB. The global non-significant mutation information extraction method is adopted to increase the sampling accuracy. The information sampling plane of smog image in complex road traffic scene is composed of single-layer square grid in color space. In the above-mentioned modeling coordinate system of background information of smog image in complex road traffic scene, the formula for collecting atomization information of smog image in complex road traffic scene is as follows:

$$y=\bar{y}+R_t d \quad , \quad z=\bar{z}+R_h d \tag{10}$$

Among it, $R_t$ indicates the transmittance estimation value of the haze image in the complex road traffic scene, $R_h$ is the estimation of the edge change pixels of the haze image Grid structure in the complex road traffic scene is the change rate of the abrupt information texture after the image is disturbed by haze. Through the above processing, the ACM is constructed according to the sky brightness estimation and highway sky line segmentation method, and the haze scattering image of road traffic scene is defogged.

## IV. Scale Convolution Neural Network Method and Improved Implementation of Defogging Algorithm

### A. MCNN Learning

Narasimhan and Nayar explained the elements contained in foggy images and the imaging process by establishing a mathematical model. The model considered that the reasons for the image quality degradation in foggy days mainly included two aspects: first, the energy attenuation caused by the influence of suspended particles in the atmosphere on the absorption and scattering of the target's reflected light, and finally reduced the imaging brightness; Second, atmospheric light imaging, where ambient light like sunlight is scattered by atmospheric media to form background light, and its intensity is too high, which affects the imaging clarity and causes the image color to be unnatural. Therefore, the MCNN learning method is applied to learn the image defogging. Fig. 2 shows the MCNN learning model.

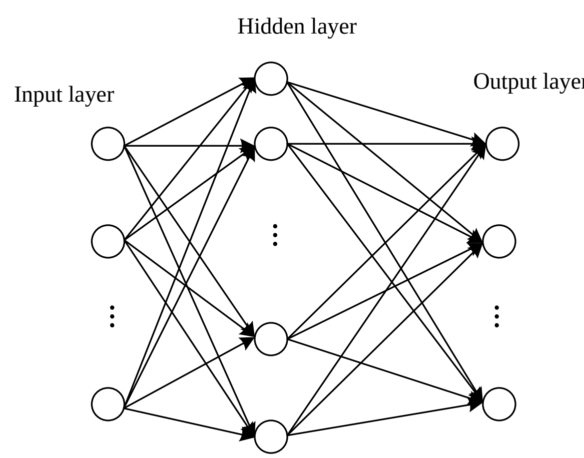


Fig. 2. MCNN

In this study, a smog image defogging algorithm on the basis of MCNN for complex road traffic scenes is adopted. The improved idea and key technology realization of the algorithm are described as follows. Firstly, the texture information features of smog images in complex road traffic scenes are calculated. Assuming that the transmittance of smog in complex road traffic scenes is the same in a local area, the 3*3 median filter is used to preprocess the smog in complicated scenes of road traffic and filter out the noise in the smog in complex road traffic scenes, and the texture information of smog in complex road traffic scenes is obtained as follows:

$$pk = \left\langle x_0, (x_i)_{0\le i\le\tau}, (x_i')_{0\le i\le l-1}, (\Pi_i)_{0\le i\le l-1} \right\rangle \quad (11)$$

Wherein, $x_0$ is the transmittance of the window, $x_i$ is the selected brightness in the dark channel diagram of the foggy image, $\Pi_i$ is the pixel point at the same position, and the error vector of random logarithmic fluctuation is used to obtain integer vectors of haze fluctuation and cutoff as follows:

$$\boldsymbol{b} = (b_i)_{1\le i\le\tau} \in \left(-2^{\alpha}, 2^{\alpha}\right)^{\tau} \quad (12)$$

Wherein, $b_i$ is the atmospheric light value, and the image S is decomposed into an orthogonal projection sequence of smog in complex road traffic scenes by one-dimensional wavelet decomposition method. The learning function of neural network of smog in complex road traffic scenes is:

$$c = \left[\sum_{1\le i,j\le\mu} m_{i,j}\cdot x_{i,0}'\cdot x_{j,1}' + \sum_{1\le i,j\le\mu} b_{i,j}'\cdot\Pi_{i,0}\cdot\Pi_{j,1} + \sum_{1\le i,j\le\beta} b_{i,j}\cdot x_{i,0}\cdot x_{j,1}\right]_{x_0} \quad (13)$$

Wherein, $b_{i,j}'$ is the transmitted light intensity of smog in complex road traffic scene, and for the point set in the edge center area, in a local sub-block area in any channel of the original road fog image, it satisfies:

$$\min_{c\in\{r,g,b\}}(\min_{y\in\Omega(x)}(I^c(y))) = \tilde{t}(x)\min_{c\in\{r,g,b\}}(\min_{y\in\Omega(x)}(J^c(y))) + (1-\tilde{t}(x))A^c \quad (14)$$

: Wherein, $A^c$ represents the sky brightness of a certain color channel component, which is known from the previous sky brightness estimation algorithm as $A^c$, and $A>0$. The texture features of the haze image of the complex road traffic scene in the haze obtained above are uniformly traversed and addressed, and the haze on the water surface is segmented by the highway sky line to obtain two parts, the regional difference $Dif(C_1,C_2)$ of which is larger than the internal difference $Int(C_1)$ or $Int(C_2)$ of no less than one part. In the area near the highway sky boundary line, the target search area can be reduced through detecting the highway sky line, which can reduce the subsequent target detection and recognition. Here, the estimated value of transmittance is expressed by. Because of $A>0$, equation (14) is equivalent to:

$$\min_{c\in\{r,g,b\}}(\min_{y\in\Omega(x)}(\frac{I^c(y)}{A})) = \tilde{t}(x)\min_{c\in\{r,g,b\}}(\min_{y\in\Omega(x)}(\frac{J^c(y)}{A})) + (1-\tilde{t}(x)) \quad (15)$$

In the sky area of the complex road traffic scene smog image, the intensity value of the complex road traffic scene smog image with the smallest channel tends to the sky brightness $A$, that is, $\min_{c\in\{r,g,b\}}(\min_{y\in\Omega(x)}(\frac{I^c(y)}{A}))\to 1$, then $\tilde{t}(x)\to 0$ at this time, because of $A>0$, so

$$\min_{c\in\{r,g,b\}}(\min_{y\in\Omega(x)}(\frac{J^c(y)}{A})) = 0 \quad (16)$$

Substituting the formula (16) into the formula (15) gives:

$$\tilde{t}(x) = 1 - \min_{c\in\{r,g,b\}}(\min_{y\in\Omega(x)}(\frac{I^c(y)}{A})) \quad (17)$$

$$\tilde{U}(x) = 1-\tilde{t}(x) = \min_{c\in\{r,g,b\}}(\min_{y\in\Omega(x)}(\frac{I^c(y)}{A})) \quad (18)$$

Edge detection is used to get the smog image of complex road traffic scene, and Hough transform is used to detect the straight line, and the straight line segment is extracted. Here, the expression is the estimated value of atmospheric dissipation function.

## A. Haze Image Defogging Processing in Complex Road Traffic Scenes

According to the above algorithm, the prior defogging algorithm flow of dark channel can be obtained. Firstly, the foggy image is used as input, and the dark channel map is obtained in accordance with the ACM deformation. Then, the atmospheric light value is estimated, thus obtaining the transmittance map; at last, on the premise that I(x,y) is known, the clear image is inverted by t(x) and A. The defogging algorithm can restore the image color and visibility, and at the same time, it can estimate the distance of the object by using the fog concentration, which have important applications in computer vision. However, according to the experimental statistics, if the image to be searched contains a large sky scene, the restored fog-free image will have obvious excessive areas. Realize the restoration of the image scene, and realize the image defogging processing in the complex road traffic scene. The estimated atmospheric dissipation function is:

$$U(x) = 1-\tilde{t}'(x) = \omega\tilde{U}(x) = \omega\min_{c\in\{r,g,b\}}(\min_{y\in\Omega(x)}(\frac{I^c(y)}{A})) \quad (19)$$

In some scenes, it is difficult to extract features manually. Convolutional neural network is used to learn image features automatically. The influence weight in the field of image vision is gradually increasing. Following the example of human visual system, CNN obtains local features of data through local receptive fields, and gradually expands receptive fields by convolution kernel stacking. The restored image can be expressed as follows:

$$\begin{aligned} J(x) &= [I(x) - AU(x)]/(1-U(x)) \\ &= [I(x) - A\omega\tilde{U}(x)]/(1-\omega\tilde{U}(x)) \end{aligned} \quad (20)$$

Wherein, $I(x)$ is the convolution layer parameter, $A$ is the input feature map size, the output feature map size size, $U(x)$ is the convolution kernel size, $U(x)$ is the abstract feature and context information. The convolution layer plays an important role in feature extraction of the input data information, and it contains multiple filters. The convolution kernel's each element has its corresponding weight coefficient and bias constant, which is similar to the forward propagation neuron. Each neuron in the convolution layer is associated with multiple neurons, and the associated area is defined as "receptive field". To restore the haze image of complex road traffic scenes more naturally, a constant $\omega$ is introduced here to improve the estimation of transmittance, where $0<\omega\leq1$, and

$$\tilde{t}'(x)=1-\omega\min_{c\in\{r,g,b\}}(\min_{y\in\Omega(x)}(\frac{I^c(y)}{A}))=1-\omega\tilde{U}(x) \tag{21}$$

Wherein, $\tilde{t}'(x)$ is the estimated value of the improved transmittance, and the value of $\omega$ relies on the fog concentration and the size of the sky area in the specific complex road traffic scene. For the atomized image, in the convolution layer, the step parameter S transformation can affect the size of the feature map. It can be seen that when S increases, the network parameters of the complex road traffic scene fog will decrease. However, setting the S value is complicated, and the pool layer can be used to achieve the same function, that is, the pool layer can also change the image size, so it is also called the sampling layer. It can not only reduce the data size, but also detect more abstract features and contextual information, thus enriching semantic information. The pool layer is generally used behind the convolution layer, and two ways of maximum pool and average pool are often adopted. Maximum pooling refers to selecting the largest element value from locally related elements, while average pooling refers to calculating the average value from these elements and returning it. The adjacent gray levels of image pixels obtained by constraining evolutionary conditions are:

$$P(t,f)=\int_{-\infty}^{\infty}s^*(u-\frac{\tau}{2})\alpha(\tau,v)e^{-j2\pi(vt+f\tau-vu)}dudvd\tau \tag{22}$$

In the above formula, when there is large sky area and thick fog, the light transmittance of smog in complex road traffic scenes is generally 0.75. When the fog is thick, the $\omega$ value is larger, and the value is smaller when the proportion of smog image features in complex road traffic scenes is larger in the sky area. Because the fog concentration of the smog in the complex road traffic scene in the same background has little change, we can only get the fog distribution map of one of the video frames in the same background, and use the MCNN to directly subtract the fog noise of other frames from this fog distribution map to achieve the effect of video clarity. To sum up, the algorithm implementation process is shown in Fig. 3.

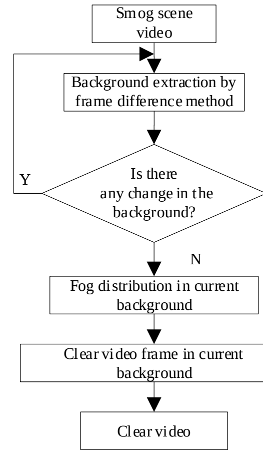


Fig. 3. Flow chart of defogging and clearing processing of road surface scattering image

## V. Simulation Experiment and Result Analysis

To test the algorithm's defogging and clearing performance after collecting smog images of complex road traffic scenes under smog, a simulation experiment was carried out. The hardware environment of the simulation is PC, the operating system is Windows 7, and the system memory is 4GB. The algorithm simulation is realized by Matlab 2012. To prove the image defogging effectiveness, it is evaluated from objective and subjective perspectives. According to the subjective visual perception of the observer, evaluate the color saturation and clarity of the restored image. Evaluation indexes are used to quantitatively analyze the restoration effect of fog-free images. Subjective evaluation refers to the subjective evaluation of the defogged image by observers on the basis of its color saturation, defogged degree and texture effect. Generally, the scoring criteria for comparison between fog-free images and restored images include: whether the color is distorted, whether the image is clear, whether there is exposure problem, and whether the information of the image is lost. Image subjective evaluation can not only reflect subjective feelings, but also the evaluation results are authentic and effective, which has certain reference significance. Although the subjective evaluation is intuitive, there are still many problems, which require repeated observation of fog-free images, and it is time-consuming. Firstly, the images in the road traffic scene under the fog scattering environment are collected. Figure shows the collected original image information, which is used as a sample for image defogging. In Fig. 4, when the road empty background image is viewed from a long distance, the image is divided into sky area, road surface area and road sky boundary area. The road sky boundary line is the boundary line between road surface and sky area, and the Canny edge detection and Hough line detection are combined to obtain the image detail enhancement image in Fig. 5.

Fig. 4. Original image sample

Fig. 5. Image feature enhancement extraction diagram

Using the prior information of the sky area position, a connected component above the image is selected as the sky area to segment the road sky, and the final road sky boundary line graph is obtained, so as to pre-process image defogging. Through the above processing, on the basis of this, the fog processing of road fog image is carried out. To compare the performance of the algorithm, this algorithm is compared with the traditional Retinex algorithm and MCNN algorithm.

The analysis results in Fig. 6 show that most of the fog in the image is removed by using this algorithm, and the image is realistic with good visual effect. The algorithm in this paper has obvious defogging effect on smog, especially suitable for the processing of images with obvious road-sky boundary lines. Test the convergence of the image and get the convergence curve as shown in Fig. 7.

(a) Retinex

(b) Time-frequency weighting algorithm

(c) Algorithm in this paper

Fig. 6. Comparison of simulation results of image defogging algorithm

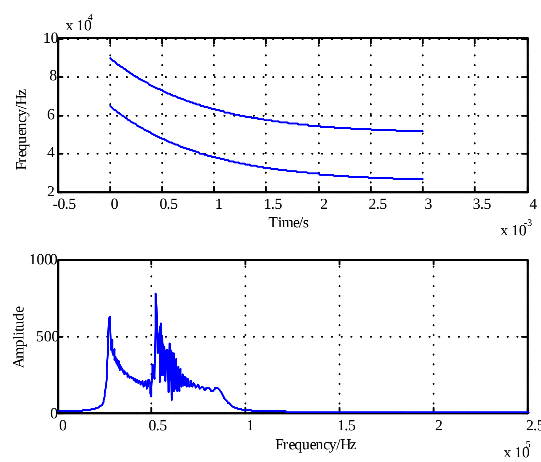


Fig. 7. Convergence test of image defogging

The output SNR is tested. The comparison results are shown in Fig. 8 and Table I. The results in Fig. 8 and Table I show that this method has higher color saturation, higher defogging degree and better image definition, which improves the peak SNR of the defogged haze images in complex road traffic scenes, and has a good application value in image defogging.

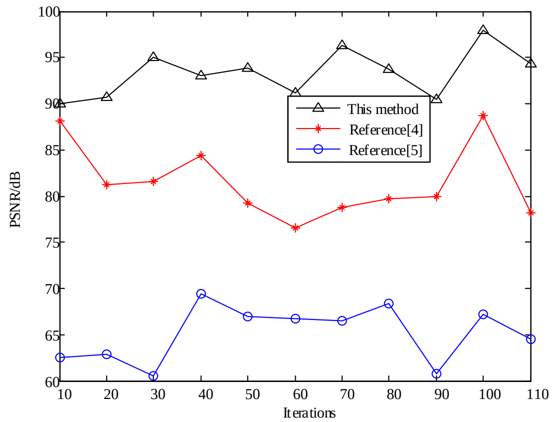


Fig. 8. Signal-to-noise ratio of image defogging output

TABLE I. OUTPUT PSNR OF IMAGE DEFOGGING (UNIT: DB)

| Test frame | This method | Retinex | Time-frequency weighting algorithm |
|---|---|---|---|
| 10 | 90.05 | 88.09 | 62.54 |
| 20 | 90.76 | 81.27 | 62.87 |
| 30 | 95.06 | 81.62 | 60.54 |
| 40 | 93.06 | 84.35 | 69.45 |
| 50 | 93.85 | 79.19 | 66.97 |
| 60 | 91.17 | 76.56 | 66.70 |
| 70 | 96.36 | 78.77 | 66.44 |
| 80 | 93.71 | 79.68 | 68.32 |
| 90 | 90.47 | 79.92 | 60.76 |
| 100 | 97.90 | 88.77 | 67.18 |
| 110 | 94.31 | 78.22 | 64.55 |

## VI. DISCUSSION

The existence of smoke in complex traffic scenes will further reduce the image clarity, which will affect the efficiency of the image recognition system in traffic scenes. In this study, a smoke denoising algorithm for traffic scene images is proposed, which combines multi-scale idea and Canny edge detection. The test results show that, from a qualitative point of view, the part of the image that is occluded by smoke using the improved algorithm is clearer by naked eyes, and the definition and color saturation of the entire image are significantly higher than those of the image denoised by the contrast algorithm. The research results of WANGFS also show that the denoising ability of the denoising algorithm has been improved to a certain extent by using the fusion multi-scale idea [15].

From a quantitative perspective, as the number of training iterations of each algorithm increases, the peak signal-to-noise ratio of the denoised image of each algorithm gradually increases, but on the whole, the peak signal-to-noise ratio of the image processed by the improved algorithm designed in this study is the highest. When the number of iterations exceeds 100, the peak signal-to-noise ratio of the test set image after denoising based on the improved multi-scale convolutional neural network algorithm, Retinex algorithm, and MCNN algorithm is about 94dB, 81dB, and 65dB respectively. This is mainly because Canny edge detection can retain more feature information of the original image. Suyu WANG's research results show that the improved algorithm using Canny edge detection has a lower peak signal to noise ratio, which is mainly because the algorithm has too few computational levels to fully extract image features [16].

## VII. CONCLUSION

In the haze scene, the images taken by the imaging equipment will have some problems. Therefore, the research of fog removal technology is of great significance. An image defogging optimization algorithm based on MCNN is proposed. In the real fog image experiment, qualitative observation with the naked eye shows that the defogging image processed by the improved MCNN algorithm can better process the details on the basis of maintaining the integrity of the image information, and the defogging effect is better than the comparison algorithm. In addition, the contrast and brightness of the real fog image can be closer to the natural and clear image. From a quantitative point of view, the improved algorithm designed in this study has the highest peak signal to noise ratio of the image after processing. When the number of iterations exceeds 100, the peak signal-to-noise ratio of the test set image after denoising based on the improved multi-scale convolutional neural network algorithm, Retinex algorithm, and MCNN algorithm is about 94dB, 81dB, and 65dB, respectively. The above research results show that the image smoke removal algorithm based on the improved MCNN algorithm proposed in this study for the application of traffic scenes has certain application potential. However, due to the limitations of research conditions, this study failed to select more data sets for experiments, which is also the part that needs to be improved in subsequent experiments.

## REFERENCES

[1] Kai LI, Jie LI. Structure-fuzzy multi-class support vector machine algorithm on the basis of pinball loss[J]. Journal of Computer Applications, 2021, 41(11): 3104-3112.

[2] Xiaoqing ZHANG, Chenxi WANG, Yan LYU, Yaojin LIN. Hierarchical classification online streaming feature selection algorithm on the basis of ReliefF algorithm[J]. Journal of Computer Applications, 2022, 42(3): 688-694.

[3] Jian J , Ren F , Ji H F , et al. Generalised non-locally centralised image de-noising using sparse dictionary[J]. Iet Image Processing, 2018, 12(7):1072-1078.

[4] Jh A , Jh B , Jw A , et al. Deterministic and probabilistic wind speed forecasting with de-noising-reconstruction strategy and quantile regression based algorithm[J]. Renewable Energy, 2020, 162(12):1208-1226.

[5] Liu Y , Liu Y , Hong Y , et al. An optimized pulse coupled neural network image de-noising method for a field-programmable gate array based polarization camera[J]. Review of Scientific Instruments, 2021, 92(11):113703-113706.

[6] Golilarz N A , Gao H , Pirasteh S , et al. Satellite Multispectral and Hyperspectral Image De-Noising with Enhanced Adaptive Generalized Gaussian Distribution Threshold in the Wavelet Domain[J]. Remote Sensing, 2020, 13(1):101-108.

[7] GAN J Y,ZHAI Y K,XIANG L,et al. Spatial-temporal texture cascaded feature method for face liveness detection[J]. Pattern Recognition and Artificial Intelligence,2019,32(2):117-123.

[8] GUO Qingrong, JIA Zhenhong, YANG Jie, Nikola KASABOV. Synthetic aperture radar image enhancement method on the basis of combination of non-subsampled shearlet transform and fuzzy contrast[J]. Journal of Computer Applications, 2018, 38(9): 2701-2705.

[9] LI Ping, XU Xin, DONG Hao, DENG Xu. Polarimetric SAR image feature selection and multi-layer SVM classification using divisibility index[J]. Journal of Computer Applications, 2018, 38(1): 132-136.

[10] SODHRO A H,OBAIDAT M S,ABBASI Q H,et al. Quality of service optimization in an IoT-driven intelligent transportation system[J]. IEEE Wireless Communications,2019,26(6):10-17.

[11] LENG J,LIU Y. An enhanced SSD with feature fusion and visual reasoning for object detection[J]. Neural Computing and Applications,2019,31:6549-6558.

[12] DONG Pengxin, DONG Anguo, LI Chuting, LIANG Miaomiao. Hyperspectral Image Classification on the basis of Fully Convolutional Network and Auto-Encoder[J]. Computer Engineering and Applications, 2022, 58(5): 256-263.

[13] XU Li, LU Guiming, QIU Zhenguang. Adaptive Retinex Algorithm on the basis of Detail Selection Used in Underwater Image Enhancement[J]. Computer Engineering and Applications, 2022, 58(11): 224-233.

[14] SHI Wenxu, BAO Jiahui, YAO Yu. Remote sensing image target detection and identification on the basis of deep learning. Journal of Computer Applications, 2020, 40(12): 3558-3562.

[15] WANG F S, WANG J,LI B,et al. Deep attribute learning based traffic sign detection[J]. Journal of Jilin University (Engineering and Technology Edition),2018,48(1):319-329.

[16] Suyu WANG, Jing YANG, Yue LI. Image super-resolution restoration algorithm on the basis of information distillation network with dual attention mechanism[J]. Journal of Computer Applications, 2022, 42(1): 239-244.