**Multi-feature based Foggy Image Classification**

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Abstract. Classifying the density of foggy images is an important step in further processing for foggy images. In this paper, we propose a fog density estimation algorithm from the multi-feature perspective. Based on the analysis of the characteristics of foggy images with different levels of density, three features of color, edge gradient and transmittance are adopted to construct the feature-pool. During the process of feature constructing, the type of color space is firstly determined via the linear discriminant analysis (LDA). Then the histograms of the three features are extracted to form the whole feature. Finally, classification is completed by training a support vector machine classifier. Experimental results show that the method can accurately classify the density of foggy images, which has certain theoretical and practical significance.

1. Introduction

When a computer vision task is executed in a foggy situation, the imaging result is severely degraded due to suspended particles in the atmosphere, which makes it difficult to effectively perform computer vision tasks [1–3]. Therefore, defogging the foggy image has become an important issue [4–7]. Judging whether there is fog in the image and giving the degree of fog density has an important enlightening effect on image defogging. Because the subsequent processing can be selectively performed after obtaining the fog density in the image, it helps to improve the understanding of images.

Most of the current fog density classification algorithms compose of two steps. In the first step, the image feature is extracted, and then the classifier is trained to perform classification task in the second step. In [8], the author first converts the image from RGB space to HSI space, and then uses the distribution variance of the three channels as the color feature respectively. Besides color feature, they also adopt the atmospheric scattering model to calculate the angular deviation of the image as the second feature. On this basis, the classifier is trained to classify the fog density. In [9], the Gaussian mixture model is introduced to model different fog densities, and the model parameters are learned by the EM algorithm. In [10], the characteristics of color, edge and dark channel distribution are used to judge whether the image is foggy, but it does not classify the fog density. In [11], the normalized RGB color and the gray co-occurrence matrix after discrete cosine transform are used to decide whether there is fog in the image or not. In [12], the dark channel distribution, wavelet features and mean subtracted contrast normalized features are used to form a mixed feature vector to study the fog density classification. However, the recognition rate of dense fog images is less than 80%, which needs further improvement.

From the perspective of multiple features, the classification of fog density is studied in this paper. Based on the analysis of the characteristics of foggy images with different levels of density, firstly, LDA is used to select the color space with the best discriminative performance to serve as color features, and then the gradient intensity of the image canny edge points is obtained to construct image sharpness feature, finally, the image transmittance is modeled to obtain the transmittance distribution,
and then the above three features are combined to obtain the final image representation features. At the same time, we also construct the train and test dataset in this work. The designed multi-feature model is verified by the support vector machine classifier. Experimental results show that the method can accurately classify the density of foggy images which has certain theoretical and practical significance.

![Foggy image and fog-free image](image)

**Figure 1:** Foggy image and fog-free image.

2. **Feature Construction**

Designing effective features to describe the characteristics of images is a key factor in accurately classifying the fog density. A comprehensive comparison of the foggy image and the fog-free image is shown in Fig. 1 which reveals that there is a difference in color distribution between them, for that the color of the fog-free image is more distinct, and the color of the foggy image is more uniform. Secondly, the edges of the fog-free image are sharp, while the foggy image is relatively smooth. In addition to the difference in appearance, from the physical model of the fog, the fog-free image has a high transmittance and the image is clear, while the foggy image is affected by the scattering of the haze particles, the transmittance is low, and the imaging is unclear. Based on the above considerations, in this paper, the image features are constructed from three perspectives of color, sharpness and transmittance, and the three features are integrated as the final feature. For convenience, all of the three features are expressed in the form of histogram.

2.1 **Color characteristics**

When modeling the color characteristic, firstly we should choose the type of color space. Here, three color models are investigated which include RGB, HSV and YCbCr. For convenience of expression, the color features are described in the form of a histogram. Assuming that the color space used is $C = \{c_1, c_2, c_3\}$, then for the $i$th channel $c_i$, the corresponding histogram is:

$$ H_i^c = \sum_{u=1}^{M} \text{count}(\text{im}(x) == u) $$

(1)

where $u = 1: M$ is the index of the histogram, and $n$ is the number of pixels. From the above formula, the histogram of the changed color space can be obtained as:

$$ H^c = \{H_1^c, H_2^c, H_3^c\} $$

(2)

In the actual application, the $H^c$ is normalized in order to ensure the regularity of the data. Fig. 2 shows the histogram distribution of the fog-free (the first line) and foggy images (the last line) shown in Fig. 1 in three color spaces. It can be seen from the figure that there are obvious differences between them.
Figure 2: Histogram of fog-free image and foggy image in different color spaces.

Linear Discriminant Analysis (LDA) is utilized to evaluate the discriminative performance of each color space based on the training dataset. Since the training dataset contains three types of samples, multi-class LDA are used. The discriminant function is:

\[ S_b = \sum N_i (\mu_i - \mu)(\mu_i - \mu)^T \]  \hspace{1cm} (3)

where \( \mu = \frac{1}{N} \sum x \) is the mean of all samples, \( N \) is the total number of samples, \( \mu_i = \frac{1}{N_i} \sum x_i \) is the mean of class \( \omega_i \), and \( N_i \) is the number of samples of class \( \omega_i \).

The within-class variability of class \( \omega_i \) can be expressed as:

\[ S_w = \sum(x - \mu)(x - \mu)^T \]  \hspace{1cm} (4)

The total within-class variability is the sum of each class:

\[ S_w = \sum S_{wi} \]  \hspace{1cm} (5)

Figure 3: Construction of edge gradient distribution features.
Then the final discriminant function is defined as:

\[ J = \frac{S_p}{S_r} \]  

(6)

The color of the sample image is modeled by selecting the color space with the largest \( J \) value.

**Figure 4**: Transmittance image and its histogram.

2.2 Edge gradient distribution

In addition to the difference on color distribution among images with different fog densities, another more distinct feature is the image definition of them. In general, the fog-free image usually has a higher definition; in contrast, the definition of foggy image is very poor. For an image, the sharpness is essentially determined by the gradient strength of the edge, and the stronger the intensity, the sharper the edge. Therefore, the gradient distribution of the image can be used to characterize the sharpness of it. Before we achieve the gradient distribution, the gradient of each pixel in the image is usually first computed, and then the distribution of different intensity gradients is calculated in the form of a histogram. However, there is a disadvantage in this method. For that there are too many edge-independent noise gradients, especially for foggy images, the noise gradient of the haze region will account for a large proportion. In order to overcome this defect, when we estimating the image gradient distribution, the canny operator is first applied to obtain the edge of the image, then only the gradient for pixel lying in the edge region is counted, and finally the gradient distribution histogram of the image is obtained. Fig. 3 shows the results of gradient statistics for the image shown in Fig. 1. The edge image, the gradient of the edge region, and the histogram of the edge gradient intensity are given in the figure. It can be seen from the figure that although the edge definition of the foggy image is not high, due to the excellent performance of the canny operator, it is still possible to effectively detect various types of edges, thereby improving the discrimination of the gradient distribution.

2.3 Transmittance distribution

When we constructing the above two feature, only the appearance characteristics of the image are taken into consideration, and the generation mechanism of the fog is neglected. When image defogging is performed, the following formula is usually used to express the formation mechanism of the fog:

\[ I(x) = J(x)t(x) + A(1-t(x)) \]  

(7)

where \( I(x) \) and \( J(x) \) are foggy images and optimized output images, respectively. \( A \) is the global atmospheric illumination, \( t(x) \) is the transmittance. Generally speaking, \( t(x) \) has a higher value for clear fog-free images, and for foggy images, due to the scattering caused by the haze particles; \( t(x) \) is
severely attenuated. So the transmittances of the fog-free image and the foggy image have different value distributions. From this perspective, the statistical characteristics of transmittance can be well modeled for the density of fog.

To get the image transmittance, dark channel prior theory is often used. The dark channel prior theory states that there is a color channel of approximately zero in the local area except the sky area in the fog-free image [13]. That is, for any fog-free image, the J dark channel is expressed as:

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

(8)

where $J^c$ represents the three primary color channels of the outdoor image, and $\Omega(x)$ gives a local area window centered on the pixel $x$. Assume that the transmittance in each window is a fixed value, defined as $\tilde{t}(x)$, and $A$ is known. According to the aforementioned dark channel prior theory, it can be obtained as following:

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

(9)

In daily life, there often exists a small amount of fog. In order to make the restored image more realistic, the fog retention factor (usually 0.95) is introduced, and the equation (9) is modified to:

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

(10)

After the transmittance of all the pixels in the image is obtained, we can calculate the histogram of it to form the third type of feature. As shown in Fig. 4, the transmittance images and the corresponding histogram distributions of the fog-free image and the foggy image are respectively given. It can be seen from the figure that the fog-free image has a higher transmittance, while the foggy image has a lower transmittance.

3. Experiment And analysis

In order to verify the validity of the designed features, experiments were performed in this section. Before we carry out experiments, we first establish the training and testing dataset. All of the sample images included in our experiments are downloaded from the network randomly. According to the density of fog, the images are divided into three classes: fog-free image, thin fog image and dense fog image. The dataset composed of 777 sample pictures, including 421 fog-free pictures, 141 thin fog images, and 215 dense fog images. We select 358 fog-free images, 120 thin fog images and 182 dense fog images to form the training set, while the remaining 117 sample images were used as the testing set. Some example pictures in the three classes of samples are shown in Fig. 5. It can be seen from the figure that the fog-free image is clearly, the thin fog image is clearly for close-range scene, and the dense fog image has poor overall clarity.

Considering the number of samples and the computational complexity, the support vector machine (SVM) is selected as the classifier. All experiments were performed on an AMD A10 2.3 GHz 8GB machine. MATLAB 2012a is used as the test platform, and the widely used LIBSVM toolkit is adopted to train the SVM classifier. During the training process, we found that the classification performance using the radial basis kernel function is the most prominent. Therefore, this type of kernel function is used for performance testing.

At the beginning of the experiment, the LDA algorithm is first applied to determine the color space used. We perform the LDA algorithm on the training set to complete this task. The J values in the three types of color spaces, RGB, HSV and YCbCr, are calculated by equations (1) and (2), respectively. The YCbCr space is found to give the largest J value, and is chosen to serve as the color feature.
In this work, histogram is adopted to represent all of the features. For this, another parameter we should decide before performing experiment is the dimension of the histogram. In order to select the best histogram dimension, experiments with histograms of different size is performed under the same SVM parameters. For the sake of convenience, in the experiment we let the entire features represented by histogram with the same dimension. In our proposed algorithm, a total of five channel features are used, which include three channels of YCbCr, one channel for image gradient and one channel for image transmittance, that is, if the length of histograms on one channel is h, then the finally combined feature dimension is 5h. Fig. 6 shows the classification performance when the dimension of histogram on one channel is 8, 16, 32, 64, 128 and 256, respectively. It can be seen that as the dimension of histogram increases, the recognition rate generally increases too; this indicates that high dimension of the histogram can provide more abundant feature information.

Since three types of features are combined to form the multi-feature histogram, when we take different combining strategies we can get different classifying performance. In Table 1, the classifying performances with different combining strategies are given. It can be seen from the table that when single feature is used, that is to say, only one feature has a weight of 1 and the rest is 0. In this case the classification results for the three different features are very uneven. As the number of features used increases, the recognition performance is also improved. When the weights of the three features are 1, 2.5, and 2.5, respectively, the system achieves optimal performance. In this case, a more than 98% accuracy rate is achieved both on training set and testing set, which also indicates the foggy image classification system designed in this paper is feasible.
Table 1: Classification performance when different features are combined

| Weight of feature | Class accuracy for test dataset % | Overall accuracy % |
|-------------------|----------------------------------|--------------------|
| color gradient    | Fog-free | Thin fog | Dense fog |  |
| 1 0 0 100 0 100   | 100      | 0        | 100       | 81.82 |
| 0 1 0 100 100 0   | 100      | 100      | 0         | 72.42 |
| 0 0 1 100 0 100   | 100      | 0        | 100       | 81.82 |
| 1 1 0 98.41 80.95 100 | 97.12  |
| 0 1 1 100 100 90.91 | 94.39  |
| 1 0 1 100 80.95 90.91 | 91.52  |
| 1 1 1 100 85.71 93.94 | 94.87  |
| 1 2.5 3 100 100 93.94 | 99.84  |

4. Conclusions
If we can obtain the density of foggy image, then more strategies can be taken for computer vision problems such as target detection and image defogging. In this work, we aim to solve the problem of foggy image classification. Firstly, the fog-free image and foggy image are compared and analyzed, then, from the perspectives of image appearance and fog formation mechanism, three features including color, edge gradient and image transmittance were selected to construct the multi-features. The LDA technique is used to quantitatively evaluate different color spaces, so as to select the optimal color space. In order to increase the convenience of feature combination, all features are expressed in the form of histogram. Finally, the foggy image dataset is established, and the SVM classifier is trained to complete the classification of the haze image. Experimental results show that it is possible to accurately classify the density of foggy images under the premise of effective combination of multiple features, which has certain theoretical and practical significance.

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