Research on Warning System of Dense foggy Days Based on Image Processing

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Abstract. On dense foggy days, the visibility is low. In order to increase the driving safety of vehicles, this paper studies a set of image-based dense foggy day discrimination method and warning system, which provides early technical supports for the intelligent start and stop of fog lamps. Firstly, by analysing and comparing image characteristics of sunny and dense foggy days, finding out the obvious distinction between images on sunny days and dense foggy days: the dark channel features. And then using the support of vector machine to obtain the judgment model of sunny/dense foggy day images. Finally, using MATLAB GUI to build a set of dense foggy day warning system which is based on image processing. After testing, the system is able to effectively distinguish between sunny and dense foggy day images with certain accuracy.

1. Introduction

When the vehicle is driving in low visibility weathers such as dense foggy and heavy rain, the driver is not easy to find the forward and surrounding changes of traffic environment, which is likely to cause traffic accidents. Therefore, fog lamps are installed on the vehicle. However, most of the current fog lamps require manual opening, which highly depends on the driver’s driving habits and mental states. Sometimes vehicles have traffic accidents on the highway, which is caused by not turning on the fog lamps on dense foggy days. Therefore, if the intelligent control of automotive fog lamps can be realized, that is, by judging whether the current weather is foggy or rainy, and then automatically control the turn-on and turn-off of the automotive fog lamps according to the judgment results. It will not only ensure the correct use of fog lamps but also simplify the driver's operation, which contributes to improve the safety and comfort of automobile driving. However, there are relatively few studies on the intelligent control of automobile fog lamps. This paper will mainly focus on a set of image-based identification method and warning system which aims at providing technical supports for the fog lamp’s intelligent start-up and stop.

The key to the intelligent control of fog lamp is to accurately judge whether the fog lamp needs to be turned on or off in current weather conditions. At present, domestic and overseas scholars have put forward some researches on the identification of weather conditions. M. Roser et al. [1] analyzed the characteristics of HIS spatial histograms to identify weather phenomena such as sunny or rainy weathers from the monochromatic images. X. S. Yan et al. [2] proposed three sets of gradient magnitude histogram, HSV color histogram and road information based on the images captured by the
vehicle vision system, and then combined these features with the algorithm based on Real AdaBoost to realize the classification and recognition of sunny, rainy and cloudy weather. C. H. Chen et al. [3] realized the recognition of fog image by analyzing the average brightness gray level of input image and the result of Sobel image processing, and combining the experience value of relevant characteristic parameters. H. J. Song et al. [4] used the image obtained by the roadside workstation and the initialized image to carry on the difference operation, got the difference image, and then extracted the texture and other image features of the obtained image, finally identified the fog by dynamic clustering method. Y. Xiang et al. [5] researched a method of super highway fog detection based on two - way neural network fusion model. The research methods in references [4] and [5] can identify foggy days relatively accurate, but they are often used to detect dense foggy days at fixed locations, which are neither suitable for dynamic analysis and detections on automobiles nor conducive to intelligent control of fog lamps. W. X. Zhu et al. [6] estimated the visibility and other information reflected in the image by comparing the differences between the vanishing point of the road and the vanishing point of the actual road, and then recognized the foggy day. However, this method must know the vanishing point of the actual road in advance or be in the situation where the markings on both sides of the road are clearly visible. Therefore, the universal use of the method is constrained. Y. F. Zhou [7] calculated the cumulative distribution function by obtaining the histogram of the gray image, and substituted the upper and lower saturation points of the function into the contrast formula to calculate the contrast, and then determined whether it is a foggy day or not. But the shortcoming of this method is that the up and down saturation point of cumulative distribution function is not easy to obtain. Z. Zhang [8] selected different features of different weathers to identify the images of outdoor surveillance scenes, and used multi-core learning algorithms to select and fuse different weather features, and then trained the classification model based on support vector machine to achieve classification of different weathers. M. Xu [9] combined the dark channel prior principle with the parallax characteristics of the human eye binocular vision, and studied a visibility detection algorithm based on dark channel prior, which can effectively detect the fog visibility distance. In summary, there have been many studies using image processing to judge foggy days, and the judgment methods have their own characteristics, but most of these studies have not been used in fog warning systems. Z. J. Lai [10] developed a vehicle-mounted moving fog detection test system and a safety warning method by using a light-emitting diode and a photo resistor which are combined with a single-chip microcomputer. But the system was tested in the "environment fog" which created by the fog generator other than tested in real dense foggy day, which was lack of verification and tests on the road.

In this paper, image processing technology will be used to judge dense foggy days, and then it will use MATLAB GUI to build a set of dense foggy warning system for the future intelligent control of fog lamps for the preliminary study of algorithms and related procedures.

2. Select typical characteristics of dense foggy image

In order to study images of sunny days and foggy days, firstly should be analyzed and compared the contrast and brightness, the grayscale mean and the dark channel values of the image. And find out the maximum difference between foggy and sunny day images.

2.1. Contrast and brightness

Contrast is a common feature in image analysis. The Mechelson formula is usually used to calculate the contrast of image, that is:

$$C = \frac{L_{\text{max}} - L_{\text{min}}}{L_{\text{max}} + L_{\text{min}}}$$

In this formula, $L_{\text{max}}$ is the maximum pixel value of pixels in the image, $L_{\text{min}}$ is the minimum pixel value of pixels in the image.

In the research, 14 sets of pictures of sunny and foggy days were selected, as is shown in Figure 1. By comparing the contrast characteristics of these 14 sets of images, the differences between sunny and dense foggy day images were shown in Figure 2. It can be seen from Figure 2 that the image
contrast value of the dense foggy day is relatively low compared with the image of the sunny day, but among the 14 sets of images, the contrast of the dense foggy images of the 1st group, the 8th group and the 13th group are larger or closer to the sunny image; and the contrast of the sunny and dense foggy images of 3th group, 9th group and 12th group are not much different. Since the above method does not consider the pixel value of the noise point contained in the image, the calculated image contrast may have a large error, so it is also necessary to calculate the image brightness standard deviation. The calculation method of the brightness standard deviation of the image is shown in Formula (2).

\[
C = \left\{ \frac{\sum L_{(x,y)}^2 - \left( \sum L(x,y) \right)^2}{N_f} \right\}^{\frac{1}{2}} \tag{2}
\]

In this formula, \( L(x, y) \) is the pixel values of arbitrary pixel point \((x, y)\) in images, \( N_f \) is the total number of pixels point in images.

![Figure 1. Picture groups of sunny and foggy days](image)

Figure 1. Picture groups of sunny and foggy days

Figure 3 shows the comparison of the brightness standard deviation between the sunny day picture and the foggy day pictures. It can be seen from Figure 3 that there is a certain difference in the standard deviation of brightness between the image of sunny days and dense foggy days, but the law is not obvious.

![Figure 2. The contrast of sunny and foggy day images](image)

![Figure 3. Brightness standard deviation of sunny and foggy day images](image)

2.2. Gray mean value

The gray mean value is the average of the sum of the gray values of all the pixels in a gray image, and the calculation formula is:

\[
g = \frac{\sum_{i=1}^{m} \sum_{j=1}^{n} G(i, j)}{N} \tag{3}
\]

\( g \) is the gray level mean of the image; \( G(i, j) \) is a pixel point gray value at the position of \((i, j)\); \( m \) and \( n \) are the pixel coordinates in the image.
is the number of transverse pixels of the image; $n$ is the number of longitudinal pixels of the image; $N$ is the total number of image pixels.

Figure 4 shows the comparison result of the gray mean values of sunny and foggy day images. It can be seen from Figure 4 that the gray mean value of the sunny day image and the dense foggy day image are mostly different, but the law is not obvious as well.

![Figure 4. Gray mean value of sunny and foggy day images](image)

2.3. Dark channel feature

The dark channel feature is obtained by statistics on a large number of outdoor sunny day images. In most of the non-sky partial areas of these sunny day images, some pixels always have at least one color channel with a very low value, even close to zero, which also equivalent to the minimum brightness intensity of the block is close to zero. These pixels are called dark pixels. In a foggy image, the dark pixel does not have the above characteristics, and the minimum channel value at each of the three channels has a large brightness value due to the action of light in the air. For any image $J$, the dark channel $J_{\text{dark}}$ calculation method is shown in Equation (4).

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

In Equation (4), $J^c$ is a color channel, and $\Omega(x)$ is an image block corresponding to $x$. The dark channel is the result of two minimum operations: $\min_{c \in \{r, g, b\}}$ is performed on each pixel; $\min_{y \in \Omega(x)}$ is a minimum filter. And the operation to find the minimum is exchangeable.

The concept of using a dark channel can be described as follows: if $J$ is an outdoor fogless day image, except for the sky region, the value of $J$‘s dark channel is small, close to 0:

$$J_{\text{dark}} \rightarrow 0$$

The dark channel characteristics of the foggy and fogless images at the same location are calculated according to Equation 4, and the results are shown in Figure 5.

The dark channel mean is the average of a sum of the gray values of all pixels of a dark channel image. The calculation formula is:

$$d = \frac{\sum_{i=1}^{m} \sum_{j=1}^{n} G(i, j)}{N}$$

$d$ is the dark channel mean of image; $G(x, y)$ is the pixel point gray value at the position of $(x, y)$; $m$ is the number of horizontal pixels of the image; $n$ is the number of vertical pixels of the image; $N$ is the total number of image pixels.

Figure 6 shows the comparison between the dark channel mean values of sunny and dense foggy day images.
Figure 5. Comparison of dark channel features of sunny and foggy day images in the same location.

Figure 6. Dark channel mean value of sunny and foggy day images.

As it is seen, the dark channel mean has obvious difference between the foggy and sunny day images. Compared with the image on a sunny day, the dark channel mean of the foggy day image is relatively high overall. But the dark channel averages of the dense foggy and sunny day image in the 11th group are substantially the same, and the dark channel average of the dense foggy day image in the 14th group is lower than that of the sunny day image. However, relative to other characteristics, the difference between dark channel features of sunny and foggy day images is more obvious.

In summary, comparing the contrast, brightness standard deviation, gray mean and dark channel mean of sunny and dense foggy day images, it can be found that the dark channel mean feature has the highest distinction degree among the four image features. Therefore, the dark channel feature is used to identify dense foggy days in this study.

3. Identification algorithm for dense foggy and sunny day images

3.1. Dense foggy day recognition algorithm based on support vector machine

Support Vector Machine is an algorithm for classifying two types of data. Its basic model is a linear classifier with the largest interval defined in the feature space. It can quickly and reliably complete the classification calculation task with limited data. However, before using the support vector machine to classify the data, it needs to train the classification function with an example of a known correct answer.

Since the support vector machine is proposed for the binary classification problem, and the result of the dense foggy day image recognition is “foggy” or “fogless”, it is a binary classification problem. Therefore, this study will use support vector machine to identify dense foggy images. Assuming that the data set used for training is linearly separable, the goal of learning is to find a separate hyperplane in the n dimensional feature space, which can be used to classify instances into different classes. The separation hyperplane corresponds to Equation (6), which is determined by the normal vector \( \omega \) and the intercept \( b \), and can be represented by \( (\omega, b) \) [11].

\[
\omega^T x + b = 0
\] (6)

The geometric meaning of Equation (6) is that this hyperplane separates the two sets of data in space, and all points on one side of the hyperplane are classified as "positive" or represented by the number 1. And the other side is classified as "negative" or by the number -1. This hyperplane can be used as a geometric representation of the classification function. Let the function expression of the classification function be the Formula (7), then the expression of the point on the hyperplane is \( f(x) = 0 \). The point where the function value is not 0 must be located on both sides of the hyperplane, corresponding to the labels "1" or "-1" of the two categories.

\[
f(x) = \omega^T x + b = 0
\] (7)

In general, when the training data set is linearly separable, there are infinitely separated hyperplanes that can correctly separate the two types of data. The perceptron uses the strategy of least misclassification to find the separation hyperplane, but there are infinite solutions. The linear
separable support vector machine uses the interval maximization to find the optimal separation hyperplane. At this time, the solution is unique [11]. That is, determining two parameters $\omega$ and $b$ can uniquely determine the hyperplane that classifies the two types of data.

In this study, the dark channel feature value of the picture characterizing the dense foggy day is represented by $x$, which is an $n$-dimensional vector. The $T$ in $\omega^T$ represents transposition. And category is represented by $y$. When $y=1$, it means dense foggy day; $y=-1$ means fogless day. “1” and “-1” are used as labels of two classes.

3.2. Verification of dense foggy day recognition algorithm

In the study, dark channel mean values of 50 fog day images and 50 fogless day images were extracted at 1200×900 pixel size and 600×450 pixel size. The first 45 sets of image data are used to train the classification function, and the remaining 5 sets are used to test the accuracy of the classification function. Figure 7 shows the dark channel mean scatter plot for the selected 100 images.

In this study, the svmtrain and svmclassify functions in the MATLAB SVM toolbox were used to train and test the classification function.

The calling format of the svmtrain function is:

$$\text{SVMStruct}=\text{svmtrain}(\text{Training}, \text{Group})$$

In the formula, “Training” is the data to be trained.

In the process of training the classification function, the dimension of the data matrix is 90×2, which represents 90 sets of data, and each set of data has 2 eigenvalues. “Group” is the category label of the data. The category label of the foggy day image is "1", and the category label of the fogless day image is "-1". After calling the svmtrain function, it will return a structure variable, which includes the parameters of the trained classification function.

The calling format of the svmclassify function is:

$$\text{Group}=\text{svmclassify}(\text{SVMStruct}, \text{Sample})$$

In the formula, SVMStruct is the classification function to be used, and Sample is the data point to be classified.

In the process of testing the classification function, the dimension of the data matrix is 10×2, which means that 10 groups of data should be classified, and each group of data has two eigenvalues for judging. After calling the svmclassify function, it will return to the classified category label. This calculation will return to a column vector of 10×1 dimension, representing the category label after the classification of 10 image data groups. When the label is "1", it means that the image is judged as "foggy"; and when the label is "-1", it means the image is judged as "fogless".

Table 1 shows the results of the final test of 10 images (5 sunny day images and 5 dense foggy day images) used to verify the algorithm. The test accuracy rate is 100%. The feasibility of the algorithm is proved initially.

![Figure 7. The scatter plot for the dark channels mean value of the 100 images](image)

| Images Number | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---------------|---|---|---|---|---|---|---|---|---|----|
| Definition Label | -1 | -1 | -1 | -1 | -1 | 1 | 1 | 1 | 1 | 1 |
| Predict Label | -1 | -1 | -1 | -1 | -1 | 1 | 1 | 1 | 1 | 1 |
4. Construction of dense fog warning system

4.1. System design goal
The design goal is to build a set of dense foggy day warning system which is based on image processing. This system can judge the image extracted in the driving recorder and display the judgment result. If the judgment result is a dense foggy day, the system will give a warning message, such as a beep. In addition, in order to avoid meaningless repeating weather judgment, the system should also have the function of setting the time interval to read image information and setting the manual on/off system according to the user or enterprise requirements.

4.2. System design flow
In order to achieve the design goal, the dense foggy day recognition algorithm based on image processing and the warning system are combined, and a set of image fog warning system based on image processing is built by MATLAB GUI. The workflow of the whole system is shown in Figure 8.

![Figure 8. Workflow diagram of the system](image)

As can be seen in Figure 8, the workflow of the system is:
(1) Input image;
(2) Extract the features of the image;
(3) Put the dark channel feature value of the extracted image into the judgment model, and judge whether it is a dense foggy day image. If yes, the system outputs "foggy" and makes the warning, such as beeping. If not, outputs "fogless".
(4) Determine whether or not to continue executing the warning program. If needs to continue, return to process (1); if does not need to continue, end the system work and exit the program.

4.3. Extraction of recognition features of dense foggy images
First, the image size is adjusted so that the length × width is unified to 600×450 pixels. Then the Gaussian pyramid transform is performed on the image to establish 6 groups of 6-layer Gaussian pyramids.

The next step is to calculate the dark channel image of the Gaussian pyramid image at each scale, and then calculate the dark channel mean of the Gaussian pyramid image at each scale after segmentation.
The dark channel mean values of each image are connected in series to form a 36-dimensional feature vector, which is used as the image feature to be extracted. Calculating the mean value of the dark channel of images at multiple scales is to study the features of images from different scales to improve the discrimination of image features.

4.4. Judgment model of dense foggy day images

According to the dense foggy day recognition algorithm obtained in the previous, the obtained sunny/dense foggy images classification model is:

\[ f(x) = \sum_{i=1}^{22} \alpha_i k(x_i, x) + b \]  

(8)

\( k(x_i, x) \) is linear kernel function representing the point multiplication of two vectors; \( x_i \) is a 22×6 dimensional matrix, representing 22 support vectors; \( x \) is the feature data of image to be judged, which is a 1×36 dimensional vector; \( b \) is the intercept, \( b=0.1341 \).

The classification model based on support vector machine has 22 support vectors, and the weight of each support vector is \( \alpha_i \), and its value is shown in Table 2. Combined with Formula (8) and Table 2, a complete foggy day image classification model can be obtained.

| \( \alpha_i \) | \( \alpha_{i+1} \) | \( \alpha_{i+2} \) | \( \alpha_{i+3} \) | \( \alpha_{i+4} \) | \( \alpha_{i+5} \) | \( \alpha_{i+6} \) | \( \alpha_{i+7} \) | \( \alpha_{i+8} \) | \( \alpha_{i+9} \) | \( \alpha_{i+10} \) | \( \alpha_{i+11} \) | \( \alpha_{i+12} \) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Value | 1 | 1 | 1 | 1 | 0.92 | 1 | 1 | 1 | 0.66 | 1 | -1 |
| \( \alpha_i \) | \( \alpha_{i+13} \) | \( \alpha_{i+14} \) | \( \alpha_{i+15} \) | \( \alpha_{i+16} \) | \( \alpha_{i+17} \) | \( \alpha_{i+18} \) | \( \alpha_{i+19} \) | \( \alpha_{i+20} \) | \( \alpha_{i+21} \) | \( \alpha_{i+22} \) |
| Value | -0.99 | -1 | -1 | -0.60 | -1 | -1 | -1 | -1 | -1 | -1 |

4.5. The design layout of system GUI

The GUI layout of the system is shown in Fig 9. It mainly consists of four parts: input part, image display part, control part and output part.

- **Input section**: it can input the interval time between images, that is, how often collects an image to make weather judgment.
- **Image display portion**: Its function is to display the image being analyzed.
- **Control section**: Control the the program run and end.
- **Output part**: It is used to display the judgment result whether it is foggy.

4.6. System test verification and analysis

Re-collect 50 sunny day images and 50 dense foggy day images, and use them to test and verify the built-up image-based foggy warning system.

First, arbitrarily select multiple experimenters (7 were selected in this study), and let them identify the weather of each image. Then create a “foggy” or “fogless” label for each image based on the experimenters’ results. It will be used later to compare with the system judgment results.
Second, input the image into the system. The system will judge the input image one by one, and output the judgment result to the lower right corner of the system. For fogless images, the identification results of the system are shown in Figure 10. As for the dense foggy image, the recognition result is shown in Figure 11. When the output result is foggy, the system will also give a buzzer alarm to remind the driver that the current weather is foggy.

![Figure 10. The recognition result of a no fog weather image](image)

![Figure 11. The recognition result of a dense fog image](image)

Finally, the results of the system judgment are counted as shown in Table 3. Compared with the previously identified image tags, it can be known that the correct rate of the foggy identification system reaches 93%.

| Image tag | Image number | The system judges the right number | Accuracy |
|-----------|--------------|-----------------------------------|----------|
| Foggless  | 50           | 45                                | 90%      |
| Fogy      | 50           | 48                                | 96%      |

5. Conclusion
This study first analyzes the characteristics of sunny and dense foggy day images to find out their obvious distinction - dark channel features. Then use the support vector machine to obtain the judgment model of the sunny/dense foggy day images. Finally, a set of image-based foggy day warning system was built by MATLAB GUI. After testing, it has been found that the system can effectively distinguish between sunny and foggy days. When the current image is a dense foggy day image, the system can automatically alarm. This study provides an early technical support for the intelligent control of fog lamps.

The shortcoming of this study is it focuses on algorithm and program exploration, and has not yet combined hardware to achieve warning of foggy day. In addition, the system is currently only suitable for images collected during the daytime. Moreover, the identification accuracy rate of the system for foggy day is about 93 percent, and there is still a certain misjudgment. So the accuracy rate of the system needs to be improved.

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