Research on visibility detection model optimization based on dark channel prior and image entropy and visibility development trend prediction

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Abstract. In this paper, a visibility detection model based on the dark channel prior and image entropy is established to improve the lane line detection algorithm. Our algorithm does not need to preset the target, nor is it affected by the camera calibration parameters and position. It transforms the visibility calculation problem into the atmosphere transmittance calculation problem and refines the required results through the guided filter, achieving more accurate and stable visibility estimation results. In addition, based on the changing regularity of the visibility over time obtained by the detection model, a mathematical model is established to predict the change of heavy fog. We use ADF to test the visibility obtained in the visibility detection model and calculate the autocorrelation and partial autocorrelation functions. Finding the original sequence non-stationary, we perform the difference on the data, remove all insignificant factors and then incorporate the data into ARIMA model for fitting, finally getting the fitting and prediction results. The results are found similar to the actual situation, indicating that the results obtained by the visibility prediction model are robust and reliable.

1. Introduction

With the rapid development of the economic society since the reform and opening up, people’s demand of the convenient traffic is increasing day by day. The quantity of the fundamental transport infrastructure has increased dramatically, which greatly improves the traffic efficiency. However, it also brings about a large number of issues in safe driving, which have been a social problem that cannot be ignored in modern society. If we don’t take precautions, the issues will cause huge economic losses and can be even life-threatening. There are many factors threatening the safe driving. Studies have shown that the visibility of road has a great influence on drivers’ behavior. According to the statistics during the night with poor visibility, the number of the traffic accidents only accounts for 10% of the total, but the mortality is surprisingly up to 47% [1].

Promoting visibility detection serves as an important means to reduce severe weather accidents. One of methods to measure the visibility is the laser visibility meter. Unfortunately, it is trapped in such deficiencies as high production cost, low accuracy in detection, limited inspection range and high maintenance cost.

For this case, in recent years, many researchers have proposed a visibility detection method based on the videos of the road condition as a solution to replace the laser visibility instrument, which overcomes
the shortcomings of laser visibility to some extent. The method of video visibility detection is to combine atmospheric optical analysis with image processing and artificial intelligence technology. By analyzing and processing the video images, the relationship between video image and real scene can be established. Then, the visibility value is calculated indirectly according to the change of image characteristics. However, the existing visibility detection method based on video images is difficult to estimate the visibility accurately because it is calculated in an indirect way [2-3]. In this paper, we optimize the visibility detection model based on Dark channel prior and image entropy. At the same time, ARMA data, without exogenous variables, is used to predict the trend of visibility.

2. Establishment of visibility detection model

According to the visibility-estimated algorithm based on the detection of lane line, the road visibility model is obtained based on the lane detection method. The boundary between road and sky in foggy days is obtained by using the region growing method, and the boundary between road and sky can be estimated based on perspective projection transformation, then the method of estimating visibility can effectively calculate the influence of fog on visibility on expressway, but there are also some shortcomings. Specifically, not all the cameras are installed above the center line of the highway road. Overall, cameras are always on the left side of the road, which makes the video-capture distorted compared with the real road. And the angle information of the installed camera lens is not easy to get. Unfortunately, the angle makes a great influence on the visibility estimation.

In order to avoid the influence of the loss of the information on the final estimation of visibility index, on the basis of lane detection, we use a method based on dark channel prior and image entropy to estimate the visibility. This method estimates the atmospheric transmittance and avoids the problems of camera installation position and focal length. It is much closer to human’s visual observation in result, compared with that gotten in the detection model based on lane line.

2.1. Based on dark channel prior and image entropy

The model which is used to estimate visibility is based on the Koschmieder law and the dark channel transcendental theory [4-5]. The conclusion of Koschmieder law transforms the tough visibility measurement into the measurement of atmospheric extinction coefficient[6]. The priori theory of dark channel is an empirical theory, which refers to the smaller pixel values in a certain RGB channel in the local fog free area outside the sky area, which is defined as follows:

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

(1)

Where $J^c$ is a channel of the image, $\omega(x)$ is a local area containing pixels and $x$ is the pixel.

According to Koschmieder law, $I(x) = J(x)t(x) + A(1-t(x))$ is the relationship between the input image and the clear image, where $A$ refers to the brightness of the sky. After processing the input image with Dark Channel Process, we can get:

$$\min_{c \in \{r,g,b\}} \left( \min_{y \in \omega(x)} I^c(y) \right) = t(x) \cdot \min_{c \in \{r,g,b\}} \left( \min_{y \in \omega(x)} J^c(y) \right) + (1-t(x))A$$

(2)

The formula of atmospheric transmittance can be deduced by the above method:

$$t(x) = 1 - w \min_{c \in \{r,g,b\}} \left( \min_{y \in \omega(x)} (I^c(y)/A) \right)$$

(3)

However, the transmittance obtained by this method has a certain blurring effect, so it is necessary to further refine the atmospheric transmittance map by using guided filter. The essence of guided filter is a smoothing operator to preserve edges. In a rectangular window centered on pixel $k$, there should be a linear relationship between the filtered image and the guided image:

$$\hat{i}(i) = a_k I(i) + b_k, \forall i \in \omega_k$$

(4)

The corresponding coefficients in the formula are obtained by linear regression:
\[ a_k = \frac{\text{cov}_k(I,t)}{\sigma_k^2 + \varepsilon} \]  \tag{5}

\[ b_k = \bar{T}_k - a_k \mu_k \]  \tag{6}

Furthermore, the cost function is used to find out the \( \hat{t}(i) \) which has the smallest difference with \( t(i) \) after guided filtering.

\[ E(a_k, b_k) = \sum_{i \in \Omega_k} \left( (t(i) - \bar{T}(i))^2 - \varepsilon a_k^2 \right) \]  \tag{7}

Since pixel \( i \) will be included by multiple rectangles, different rectangular windows will have different \( \hat{t}(i) \). Its mean value is taken as follows:

\[ \hat{t}(i) = \frac{1}{|W|} \sum_{k \in \Omega_i} (a_k I(i) + b_k) = \bar{a}_i I(i) + \bar{b}_i \]  \tag{8}

where: \( |W| \) represents the number of pixels in the rectangular window, \( \bar{a}_i = \frac{1}{|W|} \sum_{k \in \Omega_i} a_k \) and \( \bar{b}_i = \frac{1}{|W|} \sum_{k \in \Omega_i} b_k \).

So far, the atmospheric transmittance has been refined.

According to Koschmieder law, there should be the following relationship among the extinction coefficient \( \beta \), distance \( d \) when parallel light attenuates to 0.05 of the original luminous flux through the atmosphere, and the atmospheric transmittance \( t \):

\[ t = \exp(-\beta d) \]  \tag{9}

We obtain the road visibility model based on lane line detection, mark the two end points of the lane respectively and assume that the distance at the start point of the lane is \( d_1 \), that at the end point of the lane is \( d_2 \), and the atmospheric transmittance of the two points is set as \( t_1 \) and \( t_2 \) respectively. Then the equations:

\[ t_1 = \exp(-\beta d_1) \]  \tag{10}

\[ t_2 = \exp(-\beta d_2) \]  \tag{11}

The extinction coefficient is derived by the two formulas above:

\[ \frac{t_1}{t_2} = \exp[-\beta(d_1 - d_2)] \]  \tag{12}

\[ \beta = \ln\left(\frac{t_1}{t_2}\right) \frac{d_2 - d_1}{d_2 - d_1} \]  \tag{13}

With the formula above, the atmospheric extinction coefficient in the image can be calculated, and then the visibility index can be deduced.

2.2. Data acquisition

The test data involved in this paper is taken from the monitoring video of a certain section of a highway, which was taken from 6:30 a.m. to 7:40 a.m. on April 14, 2016. The monitoring video comes from the same sampling place and is taken continuously by the same camera. The camera parameters of the video are stable, and there is no equipment failure. The images in the video are taken under the condition of stable camera, ignoring the influence that might be made by the temperature, humidity or other factors. The difference among the varieties of camera’s lens is also not taken into consideration. Meanwhile we select the time when the weather condition does not change suddenly. In order to reduce
the amount of data, we capture the video as 100 BMP images.

It can be seen that the resolution of video screenshots is high, the features of each element required for processing are clear and recognizable, and the fog in a series of screenshots has a certain fading trend, which will be conducive to the subsequent image processing and model solving.

Because the coordinate ruler and reference object of each camera video are not uniform, the national standard of "Road Traffic Signs and Markings" (GB5768-1999) is consulted in the process of calculating visibility, and it is found that the width of the traffic lane should be 15 cm, and the distance between the two lines should be 6 meters. This is taken as the reference to estimate the visibility in the highway video screenshots.

3. Solving the visibility detection model
Firstly, we mark the starting point and the end point of the lane line with lane detection method and record its coordinates as \( x_1 \) and \( x_2 \) respectively, as shown in the figures:

![Figure 1. Cropped picture.](image1)

![Figure 2. Picture of marked travel lane line.](image2)

With the method of dark channel, we can get the smaller pixel value of the original image in a channel of RGB. The result of dark processing of the original image is shown in the figure 3[7]:

![Figure 3. Figure after the dark processing.](image3)

According to the national standard of "road traffic signs and markings" (GB5768-1999), the length interval of lane lines of expressways is 6m. So the formula \( \beta = \frac{\ln(t_1/t_2)}{d_2 - d_1} \) used to calculate the atmospheric extinction coefficient in the model establishment can be simplified as \( \beta = \frac{\ln(t_1/t_2)}{6} \).

The results of the calculations of the atmospheric transmittance are shown in figure 4, and the guided filter is further used to refine the results, shown in figure 5.
Based on this, the atmospheric extinction coefficient of each position in the image can be obtained. We combine it with the optical visual range of information meteorology

\[ \text{MOR} = \frac{\log(F/F_0)}{-\sigma} = \frac{\log(0.05)}{-\sigma} \]

and ultimately get the curve of MOR changing with time in highway video screenshots.

Figure 6. MOR timing diagram.

4. Establishment of visibility prediction model

Based on the changing regularity of the visibility over time obtained by the above model, we establish a visibility prediction model to predict the change of heavy fog. Since we have not obtained data other than the visibility value, the only information that can be used for predicting the change of heavy fog over time in the future is the law of the evolution of heavy fog in the past[8]. Therefore, we adopt ARIMA model for prediction. The ARIMA model is composed of two parts: an autoregressive model and a moving average model, relaxing the restriction on unit root stationarity. Its basic form is as follows:

\[ (1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p) \left( 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q \right) \]

Where \( X_t \) is the time series, referring to the MOR value calculated in the visibility detection model. The ARIMA model is featured by a long memory. \( a_i \) is a white noise sequence with its mean value as 0 and variance as \( \delta^2 \). The lag operator is introduced and the simplified model is:

\[ \phi(B)X_t = \theta(B)a_t \] (15)

with:

\[ \phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p \] (16)

\[ \theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q \] (17)

When the values of \( p \) and \( q \) are 0 respectively, we can get an autoregressive model and a moving average model.

Perform the unit root test on the calculated MOR value \( X_t \) and set the model's original hypothesis \( H_0: \beta=1 \), and the standby hypothesis \( H_1: \beta<1 \), the result is:

\[ X_t = c_t + \beta X_{t-1} + \sum_{i=1}^{p-1} \phi_i \Delta X_{t-i} + e_t \] (18)
with \( c_t \) as the deterministic function of \( t \), which can be any constant or trend term and \( \Delta X_t = X_t - X_{t-1} \) as the visibility MOR difference sequence. Then we calculate the ADF value of the above regression, with its formula is as follows:

\[
ADF = \frac{\hat{\beta} - 1}{D(\sqrt{\hat{\beta}})}
\]  

(19)

We further calculate the value of \( p \) and compare it with the significance level, and decide whether to reject the original hypothesis of the model. If the sequence has unit roots, it needs to be further processed as stationary.

Then, we calculate the autocorrelation and partial autocorrelation coefficients of the original and the stationary sequence, determine the model order according to the AIC criterion and other methods, establish the model and verify the results, etc, ultimately achieving an appropriate fitting model.

After selecting an appropriate model, we begin to predict the evolution trend of heavy fog. The visibility value \( X_1, X_2, \cdots, X_{100} \) in the highway video screenshots obtained from the visibility detection and the predicted step length \( h \) are incorporated into a unified analysis framework, so as to obtain the predicted value \( \hat{X}_{101}, \hat{X}_{102}, \cdots, \hat{X}_{100+h} \) of the future sequence \( X_{101}, X_{102}, \cdots, X_{100+h} \). If all known information is stored in the information collection \( H_t \), \( \hat{X}_{101}, \hat{X}_{102}, \cdots, \hat{X}_{100+h} \) can be obtained by minimizing the mean square error \( \hat{X}_{101}, \hat{X}_{102}, \cdots, \hat{X}_{100+h} \), and the predicted value is:

\[
\hat{X}_{1t+1} = E(X_{1t+1} | H_t)
\]

with its corresponding prediction error as:

\[
e_1(t+1) = X_{h+1} - \hat{X}_{h+1} = a_{h+1}
\]

(20)

5. Solving visibility prediction model

The results of ADF test for difference sequences of \( X_t \) and \( X_t \) are shown in table 1.

|                  | \( ADF \) | Value of \( p \) |
|------------------|-----------|-----------------|
| \( X_t \)       | 0.079     | 0.633           |
| \( \text{diff}(X_t) \) | -2.24512 | 0.01783         |

It can be seen that the value of \( X_t \) sequence is too large to reject the original hypothesis. After the difference of \( X_t \), the \( p \) value is 0.01783, which is less than 0.05, indicating that the original hypothesis can be rejected at 95% level, that is, the sequence is stable after the difference. The autocorrelation and partial autocorrelation coefficients of difference sequences of \( X_t \) and \( X_t \) are listed respectively:

![Figure 7. Autocorrelation and partial autocorrelation coefficients of the original visibility sequence MOR.](image-url)
Figure 8. Autocorrelation and partial autocorrelation coefficients of differential visibility series MOR.

It can be seen that the original estimation series is not stable and the autocorrelation and partial autocorrelation functions are tailed, which is not suitable for the time series prediction model [9-10]. The sequence after the difference is stable and the autocorrelation function is truncated. We perform the regression on the sequence after the difference process and eliminate the insignificant coefficients so as to get the fitting model, which is as follows:

\[ \text{diff}(X_t) = \epsilon_t + 0.1296\epsilon_{t-1} \]  \hspace{1cm} (22)

\[ \delta^2 = 1.152 \] \hspace{1cm} (23)

The standard error of coefficient estimation is 0.111, and all the coefficients are significant, which shows that the model is sufficient, and AIC is 298.99. After getting the estimated values of the model coefficients, the ARIMA model is to be further predicted. The model has a limited memory, and the predicted visibility values are shown in the figure.

![Figure 9. Forecast results based on ARIMA model.](image)

We have carried out 50 periods of forecast, the changing trend of the fog is dissipating gradually, and the visibility value is constantly improving. At the 37th frame of the forecast (the 137th frame in total), the visibility MOR value is more than 150 meters, dedicating that the fog has dissipated.

6. Conclusion

The visibility model based on lane detection ignores the influence of camera angle, which leads to low accuracy of estimation results. In this paper, on this basis, a visibility detection model based on dark channel prior and image entropy is proposed. This model is based on Koschmieder law and dark channel prior theory, which is not affected by camera calibration parameters and position. The visibility calculation problem can be transformed into atmospheric transmittance calculation one, and the obtained results are processed elaborately by guided filter. In this way we can get more accurate and stable visibility estimation results. On the basis of this model, then we put forward a visibility prediction model——ARIMA. We perform the ADF test on the visibility data obtained from the visibility detection model, and calculate the autocorrelation and partial autocorrelation functions. It is found that the original series is non-stationary. After the difference, it is incorporated into the ARIMA
model for fitting, and all non-significant factors are eliminated. Finally, the fitting and prediction results are obtained. By applying the above model to deal with the video capture of a section of expressway, we finally get more accurate and stable visibility estimation results and accurate prediction results which verifies the optimization of the detection model and the effectiveness of the prediction model.

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