A KALMAN FILTER BASED RESTORATION METHOD FOR IN-VEHICLE CAMERA IMAGES IN FOGGY CONDITIONS

Tomoki HIRAMATSU, Takahiro OGAWA, Miki HASEYAMA

Graduate School of Information Science and Technology, Hokkaido University
N14-W9, Kita-ku, Sapporo, 060-0814 JAPAN

ABSTRACT

This paper proposes a Kalman filter based restoration method for images obtained by in-vehicle camera in foggy conditions. The proposed method introduces two novel approaches into the Kalman filter based restoration. The first one is an automatic determination of a fog deterioration model. A vanishing point in the foggy image is estimated by using cross ratio of lane marking, and automatic determination of all parameters of the fog deterioration model is realized. Furthermore, the obtained model is introduced into the Kalman filter. Specifically, our method regards each frame as a state variable and its observation model is defined by the fog deterioration model. Then, since the correlation between successive frame can be effectively utilized by the Kalman filter, the accurate restoration of foggy images is achieved. Experimental results show that the proposed method achieves higher performance than the traditional method based on the fog deterioration model.

***Index Terms*—** Restoration, Kalman filter, In-vehicle camera, Foggy images

1. INTRODUCTION

A considerable number of vehicle accidents are caused by poor visibility in bad weather. This is mainly due to the presence of the considerable number of atmospheric particles with significant size and distributions in the participating media. Because of these particles, a light from the environment and a light reflected from objects are absorbed and scattered, making the visibility not as clear as if they are not present. Some techniques have been tackle the problem by using physics-based solutions. Specifically: first, methods that use polarizing filters[1, 2]; and second, methods that use multiple images taken from foggy scenes with different densities[3, 4]. However, both of the approaches require that the images are multiple and taken from exactly the same point of view, their requirement of the specific inputs makes them impractical, such as in-vehicle systems. On the other hand, the method in reference [5] has reported the in-vehicle camera images is restored by utilizing the deterioration model of the intensities by fog, if the parameters of this model can be obtained from a vanishing point based on a pinhole camera model. However, in order to estimate the vanishing point based on the pinhole camera model, the camera parameters are calibrated manually in advance. Furthermore, since the method in reference [5] performs the restoration of the foggy images for each frame, it cannot effectively utilize the correlation between the successive frames. Therefore, the traditional methods cannot achieve the accurate restoration.

In this paper, we propose an automatic and accurate restoration method of in-vehicle camera images in foggy conditions by using the Kalman filter. First, in order to set the parameters of the fog deterioration model automatically, we estimate the vanishing point using cross ratio of the lane marking. Then, the proposed method can estimate it insusceptible to the effect of roll and tilt in a road without using the camera calibration. Therefore, from the obtained result, we automatically determine the fog deterioration model. Secondly, in the proposed method, the obtained fog deterioration model is introduced into the observation model of the Kalman filter. Furthermore, the proposed method regards the elements of the state variable of the Kalman filter as the intensities in each frame, and models each frame of the original video image by using nonlinear state transition model. Consequently, since the correlation between the successive frames can be utilized effectively, our Kalman filter algorithm realizes the automatic and accurate restoration of the captured images.

The video images using in this paper are provided by DENSO Corporation. Furthermore, we wish to thank Yukimasa TAMATSU and Hiroaki KUMON of DENSO Corporation most sincerely for their invaluable help.

2. KALMAN FILTER

In this section, we explain the Kalman filter. The Kalman filter addresses a general problem of trying to estimate the state of a discrete-time controlled process governed by the linear stochastic difference equation. We consider the models given by the following two equations as a state transition model and an observation model, respectively.

$$\boldsymbol{X}(n) = \boldsymbol{A}(n)\boldsymbol{X}(n-1) + \boldsymbol{U}(n), \tag{1}$$
$$\boldsymbol{Z}(n) = \boldsymbol{H}(n)\boldsymbol{X}(n) + \boldsymbol{V}(n), \tag{2}$$

where $\boldsymbol{X}(n)$ is a state vector at the time of n, $\boldsymbol{A}(n)$ is a state transition matrix, and $\boldsymbol{U}(n)$ is a zero-mean system noise vector. Further, $\boldsymbol{Z}(n)$ is an observation vector whose elements are observed values, $\boldsymbol{H}(n)$ is an observation matrix, and $\boldsymbol{V}(n)$ is an observation noise vector. Then, the Kalman filter algorithm is represented as follows:

$$\begin{aligned}
\boldsymbol{P_b}(n) &= \boldsymbol{A}(n)\boldsymbol{P_a}(n-1)\boldsymbol{A}^T(n) + \boldsymbol{Q}_U(n),\\
\boldsymbol{K}(n) &= \boldsymbol{P_b}(n)\boldsymbol{H}^T(n)\left[\boldsymbol{H}(n)\boldsymbol{P_b}(n)\boldsymbol{H}^T(n) + \boldsymbol{Q}_V(n)\right]^{-1},\\
\bar{\boldsymbol{X}}(n) &= \boldsymbol{A}(n)\hat{\boldsymbol{X}}(n-1),\\
\hat{\boldsymbol{X}}(n) &= \bar{\boldsymbol{X}}(n) + \boldsymbol{K}(n)\left[\boldsymbol{Z}(n) - \boldsymbol{H}(n)\bar{\boldsymbol{X}}(n)\right],\\
\boldsymbol{P_a}(n) &= \boldsymbol{P_b}(n) - \boldsymbol{K}(n)\boldsymbol{H}(n)\boldsymbol{P_b}(n),
\end{aligned} \tag{3}$$

where $\boldsymbol{P_b}(n)$ and $\boldsymbol{P_a}(n)$ are error covariance matrices given by the following equations:

$$\boldsymbol{P_b}(n) = E\left[\left(\boldsymbol{X}(n) - \bar{\boldsymbol{X}}(n)\right)\left(\boldsymbol{X}(n) - \bar{\boldsymbol{X}}(n)\right)^T\right], \tag{4}$$

$$\boldsymbol{P_a}(n) = E\left[\left(\boldsymbol{X}(n) - \hat{\boldsymbol{X}}(n)\right)\left(\boldsymbol{X}(n) - \hat{\boldsymbol{X}}(n)\right)^T\right]. \tag{5}$$

In the Kalman filter algorithm, $\boldsymbol{K}(n)$ is called a Kalman gain matrix. Further, $\boldsymbol{Q_U}(n)$ and $\boldsymbol{Q_V}(n)$ are covariance matrices of $\boldsymbol{U}(n)$ and

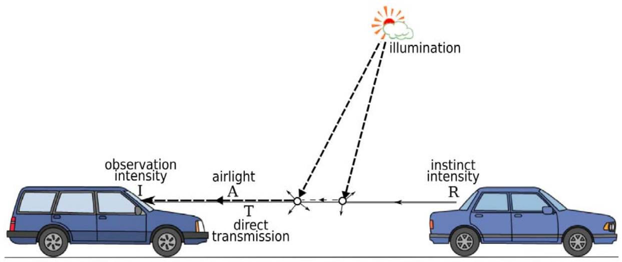

Fig. 1. Fog deterioration model.

$\boldsymbol{V}(n)$, respectively. $\bar{\boldsymbol{X}}(n)$ and $\hat{\boldsymbol{X}}(n)$ denote the estimation vectors of $\boldsymbol{X}(n)$ at the time of $n-1$ and n. By using the Kalman filter, $\bar{\boldsymbol{X}}(n)$ is compensated by the Kalman gain $\boldsymbol{K}(n)$ and the noisy observation vector $\boldsymbol{Z}(n)$ at the time of n to obtain the final estimation result $\hat{\boldsymbol{X}}(n)$. Consequently, the Kalman filter can accurately estimate the state iterating the state transitions.

3. DETERMINATION OF FOG DETERIORATION MODEL

In this section, in order to restore foggy images by using a fog deterioration model, we set its parameters, which determine a degradation character. As shown in Fig. 1, since the light, which is scattered and absorbed by atmospheric particles, is added to an instinct intensity, the fog deterioration model [5] is defined as follows:

$$I = Re^{-\beta d} + A_\infty(1 - e^{-\beta d}), \tag{6}$$

where I is an observation intensity, R is the instinct intensity, and A_∞ is an intensity coming from the sun and scattered by atmospheric particles. Further, β is an extinction coefficient of the atmosphere equal to the sum of the absorption and diffusion coefficients, and d is a distance from the object. Then, Eq. (6) is rewritten as follows:

$$R = Ie^{\beta d} + A_\infty(1 - e^{\beta d}). \tag{7}$$

Note that, in order to calculate R, the values βd and A_∞ must be determined. In the traditional method [5], these values βd and A_∞ can be calculated, if the position of a vanishing point is determined. Specifically, based on pinhole camera model, the traditional method uses the vanishing point v_h to calculate βd and A_∞ as follows:

$$\begin{cases} \beta d = 2\frac{v_i - v_h}{v - v_h}, \\ A_\infty = I_i - \frac{v_i - v_h}{2} \frac{dI}{dv}_{|v=v_i}, \end{cases} \tag{8}$$

where v_i is the point of the inflection point and I_i is the observation intensity at v_i. Thus, the parameters of the fog deterioration model are calculated in Eq. (8). However, in this method, camera parameters must be manually calibrated in advance.

In order to solve the above problem, we estimate the vanishing point from only foggy images, and set the parameters of the fog deterioration model automatically. Specifically, the proposed method calculates edges of the lane marking in the foggy image and regards the intersection of the lines including these edges as the vanishing point. In order to realize more stable estimation of the vanishing point, we perform its estimation for the image simply restored by the fog deterioration model.

In this way, the proposed method achieves accurate estimation of the vanishing point. Therefore, utilizing the vanishing point estimated from the foggy image, the automatic setting of the parameters βd and A_∞ in Eq. (6) can be realized[1].

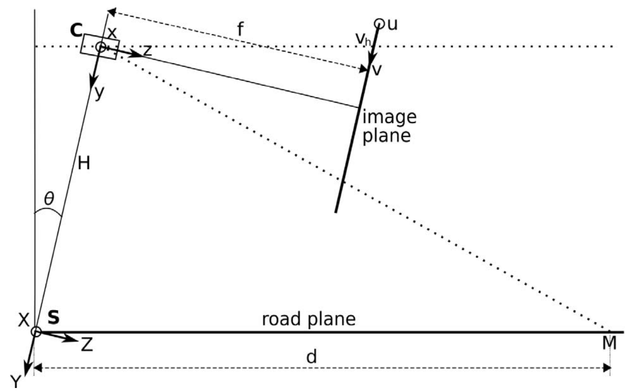

Fig. 2. Pinhole camera model.

4. KALMAN FILTER BASED RESTORATION OF FOGGY IMAGES

In this section, we propose a new restoration method of the foggy images by introducing the fog deterioration model into the Kalman filter. In the proposed method, the target image is restored by block-based procedures. Further, the original image model and the fog deterioration model are respectively introduced into the state transition model and the observation model as follows:

[**state transition model**]

$$\boldsymbol{X}_{x,y}(n) = A_n(\boldsymbol{X}(n-1)) + \boldsymbol{W}_{x,y}(n) + \boldsymbol{U}(n). \tag{9}$$

[**observation model**]

$$\boldsymbol{Z}_{x,y}(n) = \boldsymbol{H}_{x,y}(n)\boldsymbol{X}_{x,y}(n) + \boldsymbol{F}_{x,y}(n) + \boldsymbol{V}(n). \tag{10}$$

where $\boldsymbol{X}_{x,y}(n)$ and $\boldsymbol{Z}_{x,y}(n)$ are the vectors of raster scanned intensities of the target $N \times N$ blocks $B^o_{x,y}(n)$ and $B^f_{x,y}(n)$. Note that these blocks $B^o_{x,y}(n)$ and $B^f_{x,y}(n)$ are centered at (x, y) in the frame n of the original image and the foggy image, respectively. Moreover, A_n is a function, which performs a pixel-wise matching between pixels within $B^o_{x,y}(n)$ and those within the previous frame based on the motion vector. The other matrices and vectors of the Kalman filter are defined as follows:

- $\boldsymbol{W}_{x,y}(n)$: an error vector estimated between $\boldsymbol{X}_{x,y}(n)$ and $A_n(\boldsymbol{X}(n-1))$.
- $\boldsymbol{U}(n)$: an error vector representing $\boldsymbol{X}_{x,y}(n) - \left(A_n(\boldsymbol{X}(n-1)) + \boldsymbol{W}_{x,y}(n)\right)$.
- $\boldsymbol{H}_{x,y}(n)$: a diagonal matrix whose elements are $e^{-\beta d}$ in Eq. (6).
- $\boldsymbol{F}_{x,y}(n)$: a vector whose elements are the constant term $A_\infty(1 - e^{-\beta d})$ in Eq. (6).
- $\boldsymbol{V}(n)$: a vector whose elements are the observation noise added by in-vehicle camera.

Based on the above definitions, we can estimate $\boldsymbol{X}_{x,y}(n)$ from frame

[1]We should note the following two points.

- In the traditional method, the distance d becomes infinity in the region above the vertical line on the vanishing point. In the proposed method, the distance d is finite, and βd is a constant value in this region.
- In the traditional method, each frame of the foggy images includes only one inflection point. The inflection point is the one whose Laplacian value of intensities becomes zero. In the proposed method, each local block in the foggy images includes one inflection point.

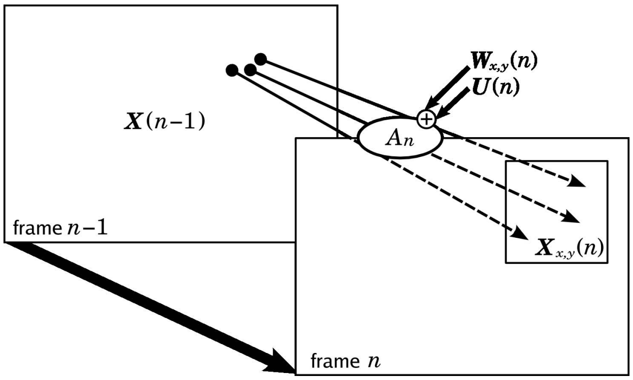

Fig. 3. State transition model in the proposed method.

$n-1$. Thus, in order to restore the foggy images using the Kalman filter, we need to calculate these vectors and matrices of the state transition and observation models. In this section, we respectively explain the details of each model and the calculation of its vectors and matrices in 4.1 and 4.2. Next, we propose the Kalman filter based restoration method of the foggy images in 4.3.

4.1. Proposed state transition model

In the proposed method, Eq. (9) models a target frame n from the previous frame $n-1$ based on the motion vectors. In this equation, $A_n(\boldsymbol{X}(n-1))$ is an estimation result of $\boldsymbol{X}_{x,y}(n)$ from $\boldsymbol{X}(n-1)$. Note that, in order to realize the estimation, we select the pixel in the frame $n-1$, which is best matched to each pixel within $B^o_{x,y}(n)$. Therefore, we need to calculate the motion vectors for each pixel within $B^o_{x,y}(n)$ and determine A_n. Note that, since the original image is not given, we need to calculate the motion vectors from only the foggy image. Therefore, the proposed method regards the image restored by using the fog deterioration model as a virtual original image, and calculates the reliable motion vectors. Specifically, by using a block matching algorithm, we calculate the motion vectors $(v_{x'}, v_{y'})$ for each pixel within $B^m_{x,y}(n)$ from $\hat{\boldsymbol{X}}(n-1)$. Note that $B^m_{x,y}(n)$ is the block centered at (x, y) in the frame n of the virtual original image, and $\hat{\boldsymbol{X}}(n-1)$ is the estimation vector which is calculated in the frame $n-1$ by the Kalman filter. Then, the function A_n is determined, and the intensities in the frame n are estimated from the frame $n-1$. In this estimation method, the errors may be caused between $\boldsymbol{X}_{x,y}(n)$ and $A_n(\boldsymbol{X}(n-1))$. Therefore, in the proposed method, the errors $\boldsymbol{W}_{x,y}(n)$ are estimated as follows:

$$\boldsymbol{W}_{x,y}(n) = \boldsymbol{X}^m_{x,y}(n) - A_n(\hat{\boldsymbol{X}}(n-1)), \tag{11}$$

where $\boldsymbol{X}^m_{x,y}(n)$ is the vector of raster scanned intensities of $B^m_{x,y}(n)$. Then, $\boldsymbol{W}_{x,y}(n)$ includes the estimation errors, since the errors may be caused between $\boldsymbol{X}^m_{x,y}(n)$ and $\boldsymbol{X}_{x,y}(n)$. Thus, we define the vector representing these errors as $\boldsymbol{U}(n)$. Additionally, it is assumed that each elements of $\boldsymbol{U}(n)$ is the white noise with the normal distribution $N(0, \sigma_U^2)$. In this way, the proposed method enables to model the frame of the original image by Eq. (9).

4.2. Proposed observation model

In the proposed method, the observation model represents the deterioration of the original image by the fog and the process of adding the observation noise to the deteriorated image. First, we assume that the parameters of the fog deterioration model are the same values in each pixel of $B^f_{x,y}(n)$. Therefore, the deterioration process of the original image by the fog is represented by $\boldsymbol{H}_{x,y}(n)\boldsymbol{X}_{x,y}(n) + \boldsymbol{F}_{x,y}(n)$. Consequently, $\boldsymbol{H}_{x,y}(n)$ is a diagonal matrix whose elements are $e^{-\beta d}$, and $\boldsymbol{F}_{x,y}(n)$ is a vector whose elements are $A_\infty(1 - e^{-\beta d})$. Note that $e^{-\beta d}$ and A_∞ are calculated in Eq. (8). Further, $\boldsymbol{V}(n)$ is the observation noise added by in-vehicle camera, and assumed to be a white noise with the normal distribution $N(0, \sigma_V^2)$.

4.3. Kalman filter based restoration method

From the definition of the state transition and the observation models in 4.1 and 4.2, the Kalman filter algorithm is shown as follows:

$$\begin{aligned}
\boldsymbol{P}_{\boldsymbol{b}\,x,y}(n) &= M^A_n(\boldsymbol{P}_{\boldsymbol{a}}(n-1)) + \boldsymbol{Q}_U(n), \\
\boldsymbol{K}_{x,y}(n) &= \boldsymbol{P}_{\boldsymbol{b}\,x,y}(n)\boldsymbol{H}^T_{x,y}(n)\left[\boldsymbol{H}_{x,y}(n)\boldsymbol{P}_{\boldsymbol{b}\,x,y}(n)\boldsymbol{H}^T_{x,y}(n)+\boldsymbol{Q}_V(n)\right]^{-1}, \\
\bar{\boldsymbol{X}}_{x,y}(n) &= A_n(\hat{\boldsymbol{X}}(n-1)) + \boldsymbol{W}_{x,y}(n), \\
\hat{\boldsymbol{X}}_{x,y}(n) &= \bar{\boldsymbol{X}}_{x,y}(n) + \boldsymbol{K}_{x,y}(n)\left[\boldsymbol{Z}_{x,y}(n)-\left(\boldsymbol{H}_{x,y}(n)\bar{\boldsymbol{X}}_{x,y}(n)+\boldsymbol{F}_{x,y}(n)\right)\right], \\
\boldsymbol{P}_{\boldsymbol{a}\,x,y}(n) &= \boldsymbol{P}_{\boldsymbol{b}\,x,y}(n) - \boldsymbol{K}_{x,y}(n)\boldsymbol{H}_{x,y}(n)\boldsymbol{P}_{\boldsymbol{b}\,x,y}(n),
\end{aligned} \tag{12}$$

where $\boldsymbol{P}_{\boldsymbol{b}\,x,y}(n)$ and $\boldsymbol{P}_{\boldsymbol{a}\,x,y}(n)$ are the error covariance matrices given by the following equations:

$$\boldsymbol{P}_{\boldsymbol{b}\,x,y}(n) = E\left[\left(\boldsymbol{X}_{x,y}(n) - \bar{\boldsymbol{X}}_{x,y}(n)\right)\left(\boldsymbol{X}_{x,y}(n) - \bar{\boldsymbol{X}}_{x,y}(n)\right)^T\right], \tag{13}$$

$$\boldsymbol{P}_{\boldsymbol{a}\,x,y}(n) = E\left[\left(\boldsymbol{X}_{x,y}(n) - \hat{\boldsymbol{X}}_{x,y}(n)\right)\left(\boldsymbol{X}_{x,y}(n) - \hat{\boldsymbol{X}}_{x,y}(n)\right)^T\right]. \tag{14}$$

In the above equations, $\boldsymbol{Q}_U(n)$ and $\boldsymbol{Q}_V(n)$ are diagonal matrices whose diagonal elements are σ_U^2 and σ_V^2, respectively. Further, M^A_n is a function, which selects the best matched covariance matrix of previous frame based on the motion vector. Specifically, given the the motion vector (v_x, v_y) of the target block centered at (x, y), $M^A_n(\boldsymbol{P}_{\boldsymbol{a}}(n-1))$ outputs $\boldsymbol{P}_{\boldsymbol{b}\,x+v_x,y+v_y}(n)$. As mentioned in section 2, the Kalman filter compensates $\bar{\boldsymbol{X}}_{x,y}(n)$ by the Kalman gain $\boldsymbol{K}_{x,y}(n)$ and the noisy observation $\boldsymbol{Z}_{x,y}(n)$. Therefore, the Kalman filter enables to estimate the state accurately by iterating the state transitions. Consequently, using the Kalman filter algorithm, an accurate restoration, which uses the correlation between the successive frames, can be achieved.

5. EXPERIMENTAL RESULTS

The performance of the proposed method is verified in this section. We use in-vehicle camera video images in foggy conditions (220×160 pixels, 8-bit gray levels, 15 fps, 600 frames). Figs. 4(a-1)–(a-3) show its 233–235 frames. Figs. 4(b-1)–(b-3) and Figs. 4(c-1)–(c-3) respectively show the results of the proposed method and the traditional method [5].

As shown in Figs. 4(b-1)–(b-3), the proposed method enables to recognize a forward vehicle, an iron railing, and the lane marking. Therefore, since the state transition model of the original image based on the motion vectors and the fog deterioration model set its parameters automatically are introduced into the Kalman filter respectively, we have achieved the accurate restoration of the foggy images. Then, the effectiveness of the proposed method can be verified in this experiment.

Fig. 4. Experimental results:(a-1)–(a-3) 233–235 frames of foggy images, (b-1)–(b-3) restoration results of the proposed method, (c-1)–(c-3) restoration results of the traditional method

6. CONCLUSIONS

This paper proposes the Kalman filter based restoration method for images obtained by the in-vehicle camera in the foggy conditions. Regarding the elements in the state variable of the Kalman filter as the intensities in each frame, the proposed method models the target frame from the previous frame by using non-linear state transition model based on the motion vectors. Further, the fog deterioration model is introduced into the observation model of the Kalman filter. Consequently, utilizing this Kalman filter, the proposed method realizes the accurate restoration of the foggy images.

7. REFERENCES

[1] L. J. Denes, M. Gottlieb, B. Kaminsky, and P. Metes, "Aotf Polarization Difference Imaging," in *Proc. SPIE*, vol. 3584, 1998.

[2] Y. Y. Schechner, S. G. Narasimhan, and S. K. Nayar, "Instant Dehazing of Images Using Polarization," in *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, 2001.

[3] S. G. Narasimhan and S. K. Nayar, "Contrast Restoration of Weather Degraded Images," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 25, June. 2003.

[4] S. G. Narasimhan and S. K. Nayar, "Interactive Deweathering of An Image Using Physical Model," in *IEEE Workshop on Color and Photometric Methods in Computer Vision*, 2003.

[5] N. Hautiere and D. Aubert, "Contrast Restoration of Foggy Images through use of an Onboard Camera," in *Proc. IEEE Conf. Intelligent Transportation Systems*, Sept. 2005.

[6] M. Kazui, M. Haseyama, H. Kitajima, "The Estimation of the Vanishing Point for Automatic Driving Systems," *IEICE Trans. Information and Systems*, vol. J84-D-II, no. 7, July. 2001.