Proposed Method for Estimating Traffic Accident Risk Factors Based on Object Tracking and Behavior Prediction Using Particle Filtering*

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Abstract

A traffic accident prediction method using a priori knowledge based on accident data is proposed for safe driving support. Implementation is achieved by an algorithm using particle filtering and fuzzy inference to estimate accident risk factors. With this method, the distance between the host vehicle and a vehicle ahead and their relative velocity and relative acceleration are obtained from the results of particle filtering of driving data and are used as attributes to build the relative driving state space. The attributes are evaluated as likelihoods and then consolidated as a risk level using fuzzy inference. Experimental validation was done using videos of general driving situations obtained with an on-vehicle CCD camera and one simulated accident situation created based on the video data. The results show that high risk levels were calculated with the proposed method in the early stages of the accident situations.

Key words: Driving Assistant System, Particle Filter, Likelihoods, Fuzzy Reasoning

1. Introduction

"Safe driving support" represents one of the areas in which work is under way to develop Intelligent Transport Systems (ITS). Various types of driver support systems are being developed in this field with the aim of building advanced safety vehicles, and many of the systems are reaching the stage of practical implementation (1). One key issue with regard to next-generation active safety technologies is to be able to collect and analyze data dynamically in order to warn drivers of the potential risk of an accident. This would help to reduce further the number of traffic accidents, which are tending to increase with every passing year (2),(3). Toward that end, it is necessary to incorporate knowledge of the accident process in active safety systems so that the system itself can evaluate traffic accident risk factors, based on an assessment of the potential for an accident, in the same way that experienced drivers do.
This paper proposes a traffic accident prediction method that incorporates a priori knowledge based on traffic accident data. An algorithm for evaluating traffic accident risk factors has been constructed by using particle filtering and fuzzy inference. Section 2 describes a method that uses a particle filter. Section 3 explains the construction of the relative driving state space. Section 4 presents the proposed traffic accident prediction method. Section 5 explains the experimental results.

2. Particle Filter for Vehicle Tracking in Video Images

The wheels and license plates of vehicles ahead of the host vehicle are tracked in an effort to monitor their behavior from video images captured with an on-vehicle camera. Because the color, shape and size of the wheels and the license plate are standardized, they offer the following tracking advantages: (1) detection by image processing is easy; (2) compact shape descriptions are possible using a small number of parameters; (3) estimation of space information obtained with a monocular camera is possible; and (4) feature fluctuation is stable in relation to disturbances in an outdoor environment.

However, despite these advantages, it is not such an easy task to track these vehicle parts robustly with an on-vehicle camera in a dynamic outdoor environment. One reason is that spurious tracking errors can occur no matter how carefully one selects image features for expressing wheel likeness. Such errors are caused by the presence of multiple tracking candidates in the form of shadows and similar-looking objects. Once a system loses sight of an object or objects being tracked and begins spurious tracking, error accumulates with elapsed time to reach a critical level that can cause the system to operate incorrectly. To avoid that sort of situation, it is necessary to have a robust method that can retain and track multiple target candidates simultaneously. For that reason, objects were tracked in this study using particle filtering, which is a quantitative Bayesian sequential estimation method.

A particle filter can express the position and shape of an object in a diverse state distribution and is capable of retaining multiple candidate objects. In this work, objects were tracked using a particle filter in order to monitor the behavior of target objects that might become accident risk factors, based on video images captured with an on-vehicle camera. In addition, the density gradient and color information were combined, rather than processing these feature quantities individually, in order to achieve efficient and accurate tracking.

2.1 State estimation using a particle filter

A tracking problem can be formulated as a problem of estimating at time $t$ the prediction distribution

$$
p(x_t | z_{1:t-1}) = \int p(x_t | x_{t-1}) p(x_{t-1} | z_{1:t-1}) \, dx_{t-1}
$$

and the filtering distribution

$$
p(x_t | z_{1:t}) = \frac{p(z_t | x_t) p(x_t | z_{1:t-1})}{\int p(z_t | x_t) p(x_t | z_{1:t-1}) \, dx_t}
$$

of the state variable vectors $x_{0:t}$ until time $t$, from the observed value vectors $z_{1:t}$ up to time $t$. In the framework of a particle filter, Eqs. (1) and (2) are calculated sequentially as numerical approximations by means of a finite set of discrete sample points $\{x_{t}^{(i)}, \tilde{\nu}_{i}^{(t)}\}, i = 1, \cdots, N$ composed of the state variable vectors.
\( \mathbf{x} \in \mathbb{R}^n \) and weights \( w \in \mathbb{R} \). These sample points are called particles. Here, \( \bar{w}_i = \frac{w_i}{\sum w_i} \). First of all, the state variable vectors \( \mathbf{x}_i \) are generated on the basis of the distribution \( f(\mathbf{x}\mid \mathbf{x}_{t-1}, z_{t-1}) \) at time \( t \). This function \( f \) is called the importance function.

In other words, it is assumed that \( \chi_i \sim f(\mathbf{x}\mid \mathbf{x}_{t-1}, z_{t-1}) \). The weight of the particles is updated as

\[
w_i = \frac{w_i}{\sum w_i} \frac{p(z_i\mid \mathbf{x}_i)}{f(\mathbf{x}_i\mid \mathbf{x}_{t-1}, z_{t-1})} \quad (3)
\]

Furthermore, the particles are again sampled based on this weight so as to avoid degeneracy to a distribution in which most of the particles would have a weight of zero. In this paper, we assume that \( f(\mathbf{x}\mid \mathbf{x}_{t-1}, z_{t-1}) = p(\mathbf{x}\mid z_{t-1}) \), and use this to abbreviate Eq. (3) as

\[
w_i = w_i p(z_i\mid \mathbf{x}_i) \quad (3)
\]

### 2.2 Target object tracking from video images taken with an on-vehicle camera

The wheels and license plates projected in the images are described as ellipses and rectangles, respectively. Their state transition is modeled under the assumption that these shapes change smoothly in relation to time. For example, the state variable vector of the wheels is expressed as

\[
\mathbf{x}_i = \left( r_1, r_2, x_{i-1}, y_{i-1}, r_{i-1}, r_{2i-1} \right)^T \quad (4)
\]

and the state transition model as

\[
\mathbf{x}_t = \mathbf{A} \mathbf{x}_{t-1} + \mathbf{B} \mathbf{v} \quad (5) \quad \mathbf{A} = \begin{bmatrix} 2I_{2x2} & -I_{2x2} \\ I_{2x2} & 0_{2x2} \end{bmatrix}, \quad \mathbf{B} = \begin{bmatrix} I_{2x2} \\ 0_{2x2} \end{bmatrix} \quad (6)
\]

where \( (x_i, y_i) \) and \( a_i, b_i \) are the center of the ellipses and the first radius and second radius at time \( t \), respectively, \( I_{2x2} \) is a unit matrix of 2x2, and \( \mathbf{v} = \left( v_x, v_y, v_x, v_y \right)^T \) is the normalized white noise of a covariance matrix \( \text{diag}\left( \sigma_{v_x}^2, \sigma_{v_y}^2, \sigma_{v_x}^2, \sigma_{v_y}^2 \right) \), with each of the covariances being mutually independent and having a mean value of zero.

In accordance with this model, the particles \( \mathbf{x}_i, i = 1, \ldots, N \) are propagated in the time direction and undergo a likelihood evaluation based on the observed values in the image. The observed values used are the points expressed by each particle in the normal direction of the profile of the shape model \(^{(7)}\) and the color histogram of the interior region \(^{(8,9)}\).

First, sampling points \( \mathbf{c}_j, j = 1, \ldots, M_s \), are selected at a suitable interval on the shape model and the density gradient of the pixels in the normal direction of the points is found. Then, letting \( \mathbf{z}_j, j = 1, \ldots, M_s \), denote the observed value at the point where the normal and the direction of the gradient are minimum, the likelihood is found as

\[
L_{\text{edge}}^{(i)} = \prod_{j=1}^{M_s} \frac{1}{\sqrt{2\pi \sigma_{\text{edge}}}} \exp \left( -\frac{(\mathbf{z}_j - \mathbf{c}_j)^2}{2\sigma_{\text{edge}}^2} \right) \quad (7)
\]
This is then normalized as \( \tilde{\mathcal{L}}_{\text{edge}}^{(i)} = \mathcal{L}_{\text{edge}}^{(i)} / \sum_{i=1}^{N} \mathcal{L}_{\text{edge}}^{(i)} \), where \( \sigma_{\text{edge}}^2 \) is the variance of the observed noise. Next, the color histogram for the interior region of the shape model corresponding to each particle is calculated as

\[
\mathcal{P}^{(i)} = \left\{ p^{(i)}_g = \frac{1}{f^{(i)}} \sum_{q=1}^{f^{(i)}} \delta\left( \mathcal{H}(p_q^{(i)}) - g \right) \right\}, \quad g = 1, \ldots, U
\]

where \( f^{(i)} \) is the number of pixels \( P_q \) included in the region, \( \mathcal{H}(p_q^{(i)}) \) is the histogram creation function, \( \delta(\cdot) \) is Kronecker's delta function, and \( U \) is the number of gradations of the histogram. In the experiments, the HSV color space with 256 gradations (\( U=256 \)) was used as the color space. The difference between this color histogram \( \mathcal{P}^{(i)} \) and the color histogram of the template \( \mathcal{P}_{\text{template}} \) was evaluated using the Bhattacharyya Metric \((10)-(12)\). In other words, based on the Bhattacharyya coefficient

\[
\rho[\mathcal{P}_{\text{target}}, \mathcal{P}^{(i)}] = \sum_{g=1}^{U} \sqrt{\mathcal{P}_{\text{target},g} \mathcal{P}^{(i)}_g}, \quad i = 1, \ldots, N
\]

the likelihood is found as

\[
\mathcal{L}_{\text{color}}^{(i)} = \frac{1}{\sqrt{2 \pi \sigma_{\text{color}}}} \exp \left\{ -\frac{1}{2 \sigma_{\text{color}}} \left[ \rho[\mathcal{P}_{\text{target}}, \mathcal{P}^{(i)}] - 1 \right]^2 \right\}, \quad i = 1, \ldots, N
\]

This is normalized as \( \tilde{\mathcal{L}}_{\text{color}}^{(i)} = \mathcal{L}_{\text{color}}^{(i)} / \sum_{i=1}^{N} \mathcal{L}_{\text{color}}^{(i)} \). The color histogram of the template \( \mathcal{P}_{\text{template}} \) is updated as

\[
\mathcal{P}_{\text{target},t} = (1 - \varepsilon) \mathcal{P}_{\text{target},t-1} + \varepsilon \mathcal{P}_t
\]

where \( \mathcal{P}_t = \sum_{i=1}^{N} \mathcal{P}^{(i)}_t \). In the experiments, it was assumed that \( \varepsilon = 0.15 \). Finally, the two likelihoods are consolidated as

\[
\mathcal{L}_t^{(i)} = (1 - \lambda) \mathcal{L}_{\text{edge},t}^{(i)} + \lambda \mathcal{L}_{\text{color},t}^{(i)}
\]

assuming that the weight of the particles is \( w_t^{(i)} = \mathcal{L}_t^{(i)} \), where \( \lambda \) is the weight of the consolidation.

Figure 1 shows the wheel tracking results obtained from video images taken with an on-vehicle camera. The results were obtained with the method based on the consolidated likelihood given in Eq. (12). The results in Fig. 1 were obtained for 200 particles.
Accordingly, combining the shape and color information in images makes it possible to track objects efficiently with a small number of particles. Moreover, it is especially noteworthy that this approach facilitates accurate tracking of changes that cannot be captured on the basis of individual features. White circles are extracted as tires in figure 1.

Attention is paid to vehicle-to-vehicle crashes in creating the relative driving state space using the headway distance between the host vehicle and a vehicle ahead and their relative velocity and relative acceleration. For that purpose, the headway distance $d_i$, relative velocity vector $\mathbf{v}_i$, and relative acceleration vector $\mathbf{a}_i$ are found from the estimated value $\mathbf{X}_i$ of the state variable. The space composed of these states is called the relative driving state space. Because the sizes of the wheels and license plates are standardized, it is possible to find these values from images taken with a calibrated monocular camera.

3. Construction of relative driving state space from image information

As noted previously, specific attention is paid here to vehicle-to-vehicle crashes among the information based on accident data, and use is made of the headway distance between the host vehicle and a vehicle ahead and their relative velocity and relative acceleration. For that reason, the headway distance vector $D_i$, relative velocity vector $\mathbf{v}_i$, and relative acceleration vector $\mathbf{a}_i$ are found from the state variable vector in Eq. (4). The resultant state space, called the relative driving state space, is found from the right-hand system pinhole camera model shown in Fig. 2 using the two components $x_i, y_i$. Here, the notation $(X, Y, Z)^T$ denotes the camera coordinates, and the $Z$-axis coincides with the direction of the optical axis. The notation $(x, y)^T$ denotes the image coordinates, $L = (X_L, Y_L, Z_L)^T$ denotes the central (focal) coordinates of the camera lens, $o$ is the origin of the image, $l = (x_l, y_l)^T$ denotes the coordinates of the optical axis point in the image, and $f$ is the focal distance of the camera. From this pinhole camera model, the relationship between the spatial coordinates and 2D image coordinates can be expressed as

$$ x = \frac{e_x}{m_x} \cdot \frac{X}{Z} + x_i $$
$$ y = \frac{e_y}{m_y} \cdot \frac{Y}{Z} + y_i $$

where $m_x \times m_y$ denotes the overall size of a pixel and $e_x \times e_y$ is the number of pixels.

Fig. 2  Pinhole camera model
As illustrated in Fig. 3, the distance from the on-vehicle CCD camera to the ground $Y_i$ is projected in the Y-axis direction in relation to the wheel radius $R$ in the perpendicular direction in space as expressed by the estimated value $\hat{x}_i$ in the posterior distribution at time $t$.

$$y_{1,t} = \frac{e_{y_i}}{m_{y_i}} \cdot f \cdot \frac{Y_i}{Z_i} + y_i, \quad (15)$$

$$y_{2,t} = \frac{e_{x_i}}{m_{x_i}} \cdot f \cdot \frac{Y_i - R}{Z_i} + y_i, \quad (16)$$

In other words,

$$y_{1,t} - y_{2,t} = r_i = \frac{e_{x_i}}{m_{x_i}} \cdot f \cdot \frac{Y_i - Y_{\hat{x}_i}}{Z_i} = \frac{e_{x_i}}{m_{x_i}} \cdot f \cdot \frac{R}{Z_i}, \quad (17)$$

Hence,

$$Z_i = \frac{e_{x_i}}{m_{x_i}} \cdot f \cdot \frac{R}{r_i}, \quad (18)$$

Furthermore, in the X-axis direction

$$X_i = \frac{e_{x_i}}{m_{x_i}} \cdot Z_i \cdot \frac{x_i - x_{\hat{x}_i}}{f}, \quad (19)$$

As a result, the headway distance becomes

$$D_i = \sqrt{(X_i)^2 + (Z_i)^2}, \quad (20)$$

where it is assumed that the wheel is perpendicular to the ground. The wheel radius $R$ in the perpendicular direction in space can be found from the tire size description as

$$R = \text{rim diameter}/2 + \text{wheel width}/\text{aspect ratio} \quad (21)$$

The reason why the Y-axis component is not considered in Eq. (20) is that it can be assumed that the Z-axis of the camera coordinate system is virtually parallel to the ground. The relative velocity of the host vehicle and the vehicle ahead can be calculated from Eqs. (18) and (19) as

$$V_{R,i} = \|D_i - D_{i-1}\| = \sqrt{(Z_i - Z_{i-1})^2 + (X_i - X_{i-1})^2}, \quad (22)$$

where $D_i = (X_i, Z_i)^T$. 

Table 1 Parameters used in constructing the relative driving state space and overhead CG images

<table>
<thead>
<tr>
<th>(a) Camera parameters</th>
<th>(b) Vehicle parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pixel size</td>
<td>1/3 inch, CCD camera image</td>
</tr>
<tr>
<td>Number of pixels</td>
<td>310 (H) x 1051 (V)</td>
</tr>
<tr>
<td>Frame rate</td>
<td>50 fps</td>
</tr>
<tr>
<td>Focal distance</td>
<td>8.96 mm</td>
</tr>
<tr>
<td>Optical axis coordinates in the image</td>
<td>(x,y) = (120, 86)</td>
</tr>
<tr>
<td>Camera height from the ground</td>
<td>0.7 m</td>
</tr>
<tr>
<td>Overall vehicle width</td>
<td>3 m</td>
</tr>
<tr>
<td>Overall vehicle length</td>
<td>1.5 m</td>
</tr>
<tr>
<td>Wheel rim diameter</td>
<td>15 inch</td>
</tr>
<tr>
<td>Wheel width</td>
<td>195 mm</td>
</tr>
<tr>
<td>Aspect ratio</td>
<td>0.6</td>
</tr>
<tr>
<td>Road width</td>
<td>2.5 m</td>
</tr>
<tr>
<td>Road median width</td>
<td>1.5 m</td>
</tr>
<tr>
<td>White line width</td>
<td>0.1 m</td>
</tr>
<tr>
<td>White line length</td>
<td>5 m</td>
</tr>
</tbody>
</table>
The various parameters used in constructing the relative driving state space and in creating the overhead CG images are listed in Table 1. The road structure parameters were determined largely on the basis of the Road Structure Law of Japan.

4. Estimation of Accident Risks Using Accident Prediction Method

The risk level in the present driving situation is estimated by evaluating the accident potential based on the behavior of a potentially dangerous target object (vehicle) in video images captured with an on-vehicle CCD camera. Beginning drivers generally tend to have a higher possibility of causing an accident owing to their misjudgment of the behavior of potentially dangerous target objects. Such misjudgment stems from their limited a priori knowledge of accidents that might occur on the road ahead, driving inexperience and other factors. Owing to the decline in their physical capabilities with aging, older drivers also have a higher possibility of being involved in an accident because they are apt to misjudge the behavior of potentially dangerous target objects. On the other hand, veteran drivers determine the behavior of their own vehicle after assessing and predicting on the basis of their ample experience the possibility of an accident occurring in the immediate future, based on their recognition of the driving environment and the behavior of potentially dangerous target objects. Even unexpected accidents always have premonitory signs, and because veteran drivers do not overlook such signs, they are less likely to be involved in an accident. An accident prediction method that takes this behavior of veteran drivers into account is proposed in the following discussion. This method is designed to be a means of detecting the signs of an impending accident by assessing and predicting the potential for an accident.

4.1 Accident distributions

The a priori knowledge used by the proposed method consists of state distributions of the headway distance to a vehicle ahead, relative velocity and relative acceleration in the process leading to an accident, as shown in Fig. 4. These distributions are referred to here as accident distributions, which are created on the basis of statistical analyses of accident analysis reports. The distributions used in this study assume an unsignalized segment of a two-lane road where traffic is relatively light and the speed limit is 40 km/h.

![Fig. 4 Typical examples of accident distributions](image)

Accident analysis reports give a detailed account of the circumstances of an accident based on the statements of the principals involved and witnesses and the police investigation of the accident scene. The abbreviation TTC in Fig. 4 expresses the time to collision in seconds. For example, TTC = 1 means one second before a crash. In Fig. 4(a), the distribution for TTC = 1 shows the probability of the headway distance values obtainable at one second prior to a crash. The distributions used in the accident prediction
method are those of the headway distance, relative velocity and relative acceleration in the relative driving state space at TTC = 1, 2 and 3, as shown in Fig 4.

4.2 Likelihood calculation based on accident distributions

The proposed accident prediction method consists of a state space expression using a particle filter and an evaluation that takes into account ambiguity by means of fuzzy reasoning. It incorporates the accident data described in the preceding subsection as a priori knowledge. Particle filtering is performed on the accident distributions in Fig. 4, and a likelihood evaluation is made of the observed values obtained from the estimated results. A high likelihood value means there is a strong possibility that the present situation shows the premonitory signs of an accident, the occurrence of which is close at hand. The observed value considered here is the value of $X_t = (D_t, V_{R,t}, a_{R,t})^T$ in the relative driving state space. Accordingly, the respective likelihood is found at TTC = 1, 2 and 3 with respect to the headway distance, relative velocity and relative acceleration:

$$L_{TTC,s,t} = s = D_t, V_{R,t}, a_{R,t}$$

Finally, the likelihood for the headway distance, relative velocity and relative acceleration at each TTC is found as

$$L_{TTC} = \ln \prod_{s} L_{TTC,s,t}$$

The values thus obtained are called the TTC likelihoods.

Fuzzy reasoning is applied to the TTC likelihoods calculated with Eq. (24) to estimate the accident risk level of the present circumstances. Because an evaluation of the risk level is strongly dependent on individual drivers, it is suitable to use a model that includes ambiguity, instead of a mathematical model that can make objective evaluations. With the fuzzy reasoning method, this type of information can be expressed as fuzzy sets, and their output information, including ambiguities, can be estimated on the basis of fuzzy rules. Because fuzzy rules can be created on the basis of human sensibilities, the output information can be obtained in the form of results close to human sensibilities.

**Fig. 5** Membership functions

**Table 2** Fuzzy rules (partial rules of 19 rules)

<table>
<thead>
<tr>
<th>Rule</th>
<th>Description</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>IF TTC1 is LOW and TTC2 is HIGH and TTC3 is LOW THEN D is MIDDLE</td>
<td></td>
<td></td>
</tr>
<tr>
<td>IF TTC1 is LOW and TTC2 is HIGH and TTC3 is MIDDLE THEN D is MIDDLE</td>
<td></td>
<td></td>
</tr>
<tr>
<td>IF TTC1 is LOW and TTC2 is HIGH and TTC3 is HIGH THEN D is HIGH</td>
<td></td>
<td></td>
</tr>
<tr>
<td>IF TTC1 is MIDDLE and TTC2 is LOW and TTC3 is LOW THEN D is HIGH</td>
<td></td>
<td></td>
</tr>
<tr>
<td>IF TTC1 is MIDDLE and TTC2 is LOW and TTC3 is MIDDLE THEN D is MIDDLE</td>
<td></td>
<td></td>
</tr>
<tr>
<td>IF TTC1 is MIDDLE and TTC2 is LOW and TTC3 is HIGH THEN D is MIDDLE</td>
<td></td>
<td></td>
</tr>
<tr>
<td>IF TTC1 is MIDDLE and TTC2 is MIDDLE and TTC3 is LOW THEN D is MIDDLE</td>
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</tr>
<tr>
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<td></td>
<td></td>
</tr>
</tbody>
</table>

Furthermore, the fuzzy rules and membership functions can be varied to match different individuals, making this approach suitable for information that is strongly driver-dependent.
The risk level is condensed to values of [0, 1] by fuzzy reasoning. The membership functions and fuzzy rules used here are shown in Fig. 5 and Table 2, respectively. Defuzzification of the inference results is accomplished by using the integrated min-max center of gravity method (12). A standard algorithm for fuzzy reasoning using the integrated min-max center of gravity method is shown below.

5. Validation Experiments

Experiments were conducted to verify the effectiveness of the proposed method by demonstrating that it can detect and advise the driver in advance of the potential for an accident. The ordinary driving situation without an accident was a video tape of actual city driving recorded with an on-vehicle camera. The accident situations were simulated collisions created on the basis of videos of ordinary driving scenes. Simulated data were used here because of the difficulty of filming actual accident scenes.

Virtual collision scenes of about four seconds in duration were created from accident distributions of three seconds in length just prior to an accident. The simulated accident situations were created according to the following procedure. In the process of creating the overhead CG video images explained in section III, the host vehicle’s velocity and the other vehicle’s velocity are varied as follows:

\[ V'_{\text{self}} = \zeta_{\text{self}} \times V_{\text{self}}, \quad V'_{\text{other}} = V_{\text{other}} + \zeta_{\text{other}} \]

where \( \zeta_{\text{self}} \) is the rate of change in the host vehicle’s velocity and \( \zeta_{\text{other}} = (\zeta_{\text{other}, x}, \zeta_{\text{other}, z}) \) is the change in the other vehicle’s velocity at each point in time. The velocities are adjusted such that a collision will occur in approximately four seconds. Whether a collision actually occurs or not can be confirmed in overhead CG images, like those shown in Fig. 6.

In order to process the simulated accident situations under the same conditions as the ordinary driving situation, video images are created for input to the particle filter. That is done by transforming the data obtained with Eq. (25) to the three components \( x, y, r_{x,z} \) among the state values expressed in the images by Eq. (4). The transformation is accomplished with Eqs. (13), (14) and (17).

Fig. 6  Simulated collision situation (Overhead CG images) Numbers indicate the frame numbers

To validate the effectiveness of the proposed method, it was applied to the video of ordinary city driving recorded with the on-vehicle camera and to the simulated accident situations explained above. The accident situation considered here is a rear-end collision with a vehicle that cuts in front of the host vehicle. In this situation, the license plate is the object tracked because the wheels cannot be seen. The tracking algorithm used in particle filtering is the same as the one for tracking the wheels, but a rectangular model is used in place of the ellipse model. Like the ellipse model, the rectangular model can also be described in state space using Eq. (4).

The results obtained for the ordinary driving situation without an accident and for the
simulated cut-in accident situation are shown in Fig. 7. Time histories of each TTC likelihood in the ordinary driving situation and in the simulated accident situation are shown in Figs. 7(a) and (b), respectively. The likelihood values have been normalized so that their maximum value is one. Figures 7(c) and (d) show time histories of the risk level estimated by fuzzy reasoning from the TTC likelihood values in the ordinary situation and simulated accident situation, respectively. In addition, overhead CG images indicating the risk levels estimated from the TTC likelihood values are shown in Fig. 8 along with the particle filtering results. These results were obtained with a consolidation weight of $\lambda = 0.5$ in Eq. (12). It is clear from Figs. 7(a) and (b) that the changes in the likelihood values show substantial differences between the ordinary driving situation and the simulated accident situation. In the ordinary driving situation, the TTC likelihood curves are mixed in nearly every frame, and virtually no high likelihood value is seen that would clearly characterize these driving circumstances. In the final stage where the host vehicle closes on the other vehicle, the likelihood values for TTC=1 and TTC=2 increase and that of TTC=3 decreases gradually. As a result, the likelihood curves begin to be distinguishable, and the risk level starts to show a high value in Fig. 7(c). Even though this is the ordinary driving situation, a high risk value is seen here because there is a possibility that an accident might occur in this situation several seconds later. That possibility stems from the assumption made here that the host vehicle’s velocity is constant in the time direction.

For the simulated accident situation, all the TTC likelihood curves are separated and are not mixed. In the early stage, the likelihood curve for TTC=3 shows a high value, but in the final stage, the likelihood curves for TTC=1 and TTC=2 increase sharply, whereas that for TTC=3 declines sharply. These values signify the definite progression toward an accident from the state at three seconds before a collision to that at two seconds and then at one second. As seen in Fig. 7(d), the risk level is high from the relatively early stage of the simulated accident situation and the level is especially high at around the 80th frame. The time around the 80th frame corresponds to two seconds before a collision, and it is clear that the signs of an impending accident are detected.

The results of particle filtering are shown in Fig. 8. Without scrutinizing the results for the ordinary driving situation and the simulated accident situation closely, there does not appear to be much difference between them regarding the appearance of the other vehicle until around the 80th frame. However, it is observed that a high risk level is detected several times in an interval of about 1.5 seconds until around the 80th frame. The reason for that is the actual difference in the headway distance, as is clear from the overhead CG images, even though a large difference is not discernable to the eye in the images taken with the on-vehicle camera. In addition to the headway distance, there are also differences of course in the relative velocity and relative acceleration, and there are signs of an impending collision. Detecting such signs at a glance in a scene that does not differ very much from an ordinary driving situation is not a very easy thing to do. It would be all the more difficult for beginning drivers and older drivers to accomplish. The proposed method detects such signs, without overlooking them, in a manner similar to veteran drivers, and alerts the host vehicle driver to the risk of an accident at an early stage.

A pronounced change in the risk level is seen between Figs. 7(c) and (d). One presumable reason for that can be attributed to error in the estimation results of the particle filter. Error in estimating the wheel radius $r_2$, $t$ in the perpendicular direction in the image would have an especially large effect on the headway distance. As a result, it would also influence the relative velocity and relative acceleration. Owing to the robustness of particle filtering, sudden changes appear in the results here only discontinuously. Since the duration of one
frame is equal to 0.02 s, it is possible to compensate for a sudden decline in the risk level even if it appears in several consecutive frames. For example, the risk level at the previous time step in the past can be stored for comparison with each subsequent time step, making it possible to detect a sudden change. At that point, the number of particles can be increased to improve the tracking accuracy, which is one possible way of dealing with this issue.

![Graphs showing likelihood and risk level over frames for ordinary and simulated accident situations.](image)

**Fig. 7** Results obtained with the accident

6. **Conclusion**

This paper has proposed an accident prediction method that incorporates a priori knowledge based on accident data and has described an algorithm that uses particle filtering and fuzzy reasoning to evaluate traffic accident risk factors. The aim of this work is to
develop a next-generation safe driving support system for automobiles. This suggests that the proposed method could also be used as an active safety technology at places where accidents frequently occur such as at intersections with poor visibility. Therefore, the proposed method is seen as being a fundamental technology of next-generation safe driving support systems.

References