Vehicle infrastructure integration system using vision sensors to prevent accidents in traffic flow

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Abstract: This study describes the development of a vision sensor for detecting shock waves which is one of the main factors of accidents in highway traffic flow. The major contributions of this research are development of vehicle tracking and detection of shock wave in saturated traffic. Moreover, realisation of a vehicle infrastructure integration (VII) system for providing arrival information of such propagation to drivers is proposed. The experiment on the analysis of the propagation with the developed image sensor has shown that an error might occur in the arrival time information of the propagation provided to the driver. Therefore a prediction technique at the arrival time of the propagation is integrated in the authors’ system. By using this prediction technique and taking the error tolerance of drivers into account, the experimental results show that prediction success rates are improved by about 5%.

1 Introduction

Fatalities from traffic accidents in Japan are gradually decreasing owing to legal measures such as making the use of seat belts compulsory and the development of emergency medical care. On the other hand, the number of accidents has increased [1], and so the improvement of road safety is required to be considered with special attention. In this context, many incident detection systems have been developed [2–6]. Recently, many driver assistance systems for incident detection as well as prevention have been developed worldwide. These are mainly road and vehicle cooperated-type systems such as the vehicle infrastructure integration (VII) project in the USA, SARETEA project in Europe and advanced cruise assist highway system (AHS) project in Japan. Among them, in the California Path, field tests of collision warning systems in intersections [7, 8] and, in Japan, field tests of collision warning systems for obstacle forward in Tokyo metropolitan expressway [9] have been carried out. However, it is learnt that much research work remains to be done in these areas. So, this paper will explore, examine and extend the current VII systems.

Real-time traffic measurement systems are important for the driving assistance systems. Various sensors have been researched for the system [10–13]. Above all, a vision sensor is superior to other sensors especially from the viewpoint of cost effectiveness, because the surveillance camera that has already been set up by the monitoring purpose can be used together as a vision sensor for the traffic flow measurement.

In this way, the driver assistance systems and the traffic monitoring systems have been effective. However, research on such systems often fails to grasp the factorial analyses of traffic accidents. Especially in Japan, shock wave, caused by the repetition of a rapid acceleration and deceleration change, is paid attention to as a particular accident factor in the saturated traffic flow. The shock wave is a complicated phenomenon compared with the end-of-queue situation resulting from, for example, single-car accident or traffic jam that has been addressed by conventional driving assistance systems such as those described in [9]. Therefore we have analysed data of traffic accidents that occurred at the Akasaka tunnel in the Tokyo metropolitan expressway which is a typical famous point where the shock wave in saturated traffic occurs frequently [14]. For the analysis, the incident detection system, using both vision sensor and ultrasonic wave sensor that we have proposed, was employed [6]. As a result, it has been clearly found that the propagation of shock wave generated at downstream bottleneck is mainly the cause of accident. So, in this paper, a vision sensor that allows detection of the propagation of shock waves will be developed, and a detailed analysis of the propagation using these sensors will be presented. In addition, a VII system that informs the propagation to drivers will be proposed.

2 Relational works

2.1 Vehicle tracking algorithm

The number of approaches to vehicle tracking has recently grown at a tremendous rate. Among them, a vehicle shape model consisting of horizontal and vertical edges, by Kolling and Nagel [15, 16], is successful and widely used. A boundary extraction method by Peterfreund [17], Kass et al. [18], and statistical analysis and clustering of optical flows and vector quantisation algorithms by Smith and Brady [19] and Stauffer and Grimson [20] also have significant contributions to vehicle tracking research.
However, these approaches have not taken the occlusion cases into account. In this aspect, Leuck and Nagel [21] and Gardner and Lawton [22] employed 3D models of vehicle shape and developed a dedicated pattern matching algorithm for vehicle images. This method requires various kinds of vehicle models. So it does not have much impact on applications to a scene containing various kinds of vehicle models. On the other hand, a dedicated reasoning method of Weber and Malik [23] achieved good performance in a sparse traffic with only simple motion.

2.2 Traffic monitoring system using vision sensors

There are substantial amounts of recognised image sensor-based incident detection systems. The most widely deployed one is that of the successfully integrating vision sensors and reasoning components into a well known prototype for California Roads [24]. In similar fashion, Cucchara et al. [25] applied traffic rule-based reasoning to images for simple traffic conditions on a single-lane straight road. Jung et al. [26] tracked vehicle from traffic images for precise traffic monitoring. Zhang and Taylor [27], Srinivasan et al. [28], and Byun et al. [29] employed Bayesian network and neural network to differentiate incidents from ordinary traffic. However, because of the lack of consideration on occlusion cases, these systems have difficulties in being applied to complicated traffic situations such as congestion.

3 Overview of the VII system by vision sensor network

In this section, a result of a factor analysis for traffic accidents in the Akasaka tunnel is represented. This becomes a motivation of our research.

3.1 Factor analysis of traffic accidents in the Akasaka tunnel

We have circumstantially analysed traffic accidents in the Akasaka tunnel by data from both ultrasonic wave sensors and video cameras installed in the tunnel. They are practically used for surveillance by the traffic management officers. According to the results, these traffic accidents can clearly be categorised into the following two types:

- **In the boundary of shock waves**: In saturated traffic, vehicles do not move at constant speed. They repeat high and low speed over a period of time. When the traffic density is low, vehicles run at 40 km/h. In contrast, when the traffic density is high, vehicles are almost stalled. In this situation, rapid speed difference is caused between low- and high-density parts. Therefore rear-end accidents caused by speed differential are more likely to occur.
- **In traffic jam**: In this situation, incidents occur at a low speed about 10 km/h. It would appear that the driver’s carelessness causes these incidents.

From the analysis, it was clear that 70% of these accidents originates in the speed differential in saturated traffic, and the remaining 30% occurs when a driver goes at a low speed without attention. In this paper, the system to prevent the accident of the former type with high possibility of causing a serious accident is constructed. It is mentioned that such a situation is not typical only in the Akasaka tunnel, but is also noticed as a common factor of traffic accidents in some places [30]. Therefore this solution is thought to be effective on any road where saturated traffic occurs. Also note that this analysis is biased towards shock wave detection. In general, there are many other factors leading to traffic accidents [31, 32].

3.2 Proposal of the VII system to prevent accidents occurring in saturated traffic

Fig. 1 is an illustration of Shinjuku Route of Tokyo Metropolitan Expressway. Fig. 1a indicates the installation of ultrasonic wave sensors and Fig. 1b represents the surveillance video cameras that are installed in the Akasaka tunnel every 70–80 m. Then we use these surveillance cameras as vision sensors, and propose a VII system that detects shock waves in saturated traffic and provides warning information to drivers if necessary. This system, however, works not only in tunnels but also in any roadway where saturated traffic occurs.

An overview of the VII system that we propose is shown in Fig. 2. The system consists of three parts: vehicle tracking part, detection part and information providing part. First, an average velocity of traffic flow is calculated from a result of the vehicle tracking part in a vision sensor. Second, in the detection part, the incoming shock wave is detected in each vision sensor by an algorithm based on the calculated average velocity. Finally, if the shock wave is detected, a warning information is provided by dedicated short-range communications (DSRC) placed at downstream point of the traffic flow. The information is related to the amount of time that drivers take for encountering the shock wave. This time is calculated from the position where the shock wave exists at the time the drivers goes through the DSRC spot. The calculation is described in a later section. By this information, drivers are called to attention, and traffic safety will be improved. In addition, if the shock wave has already come in the downstream point of traffic flow, the information is constrained.

In our VII system, both a position detecting the shock wave and a position where drivers encounter the shock wave are important. To clear these positions, a detailed analysis of shock waves is required. However, it is difficult for ultrasonic wave sensors, because the granularity of sensing is rough. Even if surveillance video cameras are installed at many points in the Akasaka tunnel, it is also difficult to analyse the propagation of shock waves by visual check. Therefore in this paper, a vision sensor that automatically enables the detection of shock waves is presented in Section 5, by using the vehicle tracking algorithm presented in Section 4. By the developed vision sensor, the propagation of shock waves in the Akasaka tunnel is analysed in detail and our VII system is also discussed based on the result in Section 6.

4 Vehicle tracking algorithm

In our VII system, surveillance video cameras that have already been installed in the Akasaka tunnel are utilised for vision sensors to observe a condition of traffic flow. This section describes the detail of vehicle tracking by the Spatio-Temporal Markov Random Field model (the S-T MRF model) [33, 34].

4.1 S-T MRF model

The principal idea of the S-T MRF model is that segmentation of the object region in the spatio-temporal image is equivalent
to tracking the object against occlusions (see Fig. 3). Usually, the spatial MRF segments an image pixel by pixel. However, since the usual video cameras do not have such high frame rates, objects typically move ten or 20 pixels among consecutive image frames. Therefore neighbouring pixels within a cubic clique will never correlate in terms of intensities or labelling. Consequently, we defined our S-T MRF model so as to divide an image into blocks as a group of pixels, and to optimise the labelling of such blocks by referring to the texture and labelling correlations among them, in combination with their motion vectors. Combined with a stochastic relaxation method, our S-T MRF optimises object boundaries precisely, even when serious occlusions occur. Here, a block corresponds to a site in the S-T MRF, and only the blocks that have different textures from the background image are labelled as part of the

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**Fig. 1** Sensors on the Akasaka tunnel in Shinjuku route of the Tokyo Metropolitan Expressway

*a* Ultrasonic wave sensors  
*b* Vision sensors

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**Fig. 2** Flow of a driving assistance system for shock waves by the vision sensor

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**Fig. 3** Segmentation of spatio-temporal images
object regions. In this paper, an image consists of $640 \times 480$ pixels and a block consists of $8 \times 8$ pixels; such a distribution map of labels for blocks is referred to as an object-map.

4.1.1 \textbf{MAP estimation for segmentation:} Our S-T MRF estimates the current object-map (a distribution of labels for object regions) according to a previous object-map, and previous and current images. Here are the notations:

- $G(t - 1) = g$, $G(t) = h$: An image $G$ at time $t - 1$ has a value $g$, and $G$ at time $t$ has a value $h$. At each pixel, this condition is described as $G(t - 1; i, j) = g(i, j), G(t; i, j) = h(i, j)$.
- $X(t - 1) = x, X(t) = y$: An object-map $X$ at time $t - 1$ is estimated to have a label distribution as $x$, and $X$ at time $t$ is estimated to have a label distribution as $y$. At each block, this condition is described as $X_k(t - 1) = x_k, X_k(t) = y_k$, where $k$ is a block number.
- $V(t - 1; t) = v$: A motion-vector map $V$ from time $t - 1$ to $t$ is estimated with respect to each block. At each block, this condition is described as $V_k(t - 1; t) = v_k$, where $k$ is a block number.

By the S-T MRF model, we should simultaneously determine block number.

4.1.2 \textbf{Parameters for correlation function along the temporal axis:} In this subsection, we would like to define the probability $P(G(t - 1) = g, X(t - 1) = x, G(t) = h|X(t) = y, V(t - 1; t) = v)$ along the temporal axis as the following Boltzmann distribution

$$
P(G(t - 1) = g, X(t - 1) = x, G(t) = h; X(t) = y, V(t - 1; t) = v) = \prod_k \exp\left[-U_{\text{temp}}(D_{xyk} \cdot M_{xyk})/Z_{Dk}Mk\right]
$$

$$
= \prod_k \exp\left[-U_{\text{temp}}(D_{xyk} \cdot M_{xyk})/Z_{Dk}Mk\right]
$$

$$
\times \prod_k \exp\left[-1/2\sigma^2_{Dk}(D_{xyk} - \mu_{Dk})^2/Z_{Dk}Mk\right]
$$

At first, a motion vector with respect to each block is estimated between the previous image and current image by the block matching technique. By referring to the motion vector, the two S-T MRF energies should be evaluated as shown in function (3)

$$
U_{\text{temp}}(D_{xyk} \cdot M_{xyk}) = b(M_{xyk} - \mu_{Mk}) + c(D_{xyk} - \mu_{Dk})^2
$$

$$
D_{xyk} = \sum_{0 \leq d_i < 8, 0 \leq d_j < 8} |G(t; i + d_i, j + d_j) - G(t - 1; i + d_i - v_{mi}, j + d_j - v_{mj})|
$$

The first parameter $D_{xyk}$ represents texture correlation between $G(t - 1)$ and $G(t)$. Suppose $C_k$ is translated backwards in the image $G(t - 1)$ referring to the estimated motion vector $-V_{O_m} = (-v_{mi}, -v_{mj})$. The texture correlation at block $C_k$ is evaluated as (see Fig. 4b) follows: $U_{\text{temp}}(D_{xyk})$ takes maximum value at $D_{xyk} = 0$. The smaller the $D_{xyk}$, the more likely that $C_k$ belongs to the object. That is, the smaller the $U_{\text{temp}}(D_{xyk})$, the more likely that $C_k$ belongs to the object.

The second parameter $M_{xyk}$ is a goodness measure of the previous object-map $X(t - 1) = x$ under a currently assumed object-map $X(t) = y$. Assume that block $C_k$ has an object label $O_m$ in the current object-map $X(t)$, and $C_k$ is shifted backwards in the amount of estimated motion vector, $-V_{O_m} = (-v_{mi}, -v_{mj})$ of the object $O_m$, in the previous image (Fig. 4a). Then the degree of overlapping is estimated as $M_{xyk}$; the number of overlapping pixels of the blocks labelled as the same object. The more the overlapping pixels, the more likely a block $C_k$ belongs to the object. The maximum number is $\mu_{Mk} = 64$, and the energy function $U_{\text{M}}(M_{xyk})$ takes a minimum value at $M_{xyk} = 64$ and a maximum value at $M_{xyk} = 0$.

4.1.3 \textbf{Parameters for correlation function on the spatial plane:} In this subsection, we would like to define the probability $P(X(t) = y, V(t - 1; t) = v)$ on the spatial
The third parameter of S-T MRF energy is of the neighbour condition about the object-map of the current spatial plane as shown in function (6)

\[ U_{N}(N_{y_k}) = a(N_{y_k} - \mu_{N_k})^2 \]  

(6)

Here, \( N_{y_k} \) is the number of neighbour blocks of block \( C_k \) that belongs to the same object as \( C_k \), as shown in Fig. 4c. Namely, the more neighbour blocks that have the same object label, the more likely the block is to have the object label. Currently, it is assumed that \( \mu_{N_k} = 8 \), because \( U_{N}(N_{y_k}) \) should have minimum value when block \( C_k \) and all its neighbours have the same object label. Therefore the energy function \( U_{N}(N_{y_k}) \) takes a minimum value at \( N_{y_k} = 8 \) and a maximum value at \( N_{y_k} = 0 \).

Finally, some of such estimated motion vectors would have errors. Such errors sometimes occur in blocks where boundaries of objects exist, where very poor textures exist and where some periodical textures exist. Since those errors should lead to segmentation errors, it is necessary to correct errors in motion vectors. For that purpose, it would be effective to optimise motion vectors themselves by referring to motion vectors of their neighbour blocks on the current spatial plane as shown in Fig. 4d. Therefore as the fourth parameter, we would like to define the following energy function

\[ U_{V}(V_{xk}) = f \sum_{C_{\text{neighbours}}} \frac{|V_{C_k}(t-1) - V_{C_{\text{neighbours}}(t-1)}|^2}{N_{x_k}} \]  

(7)

Here, \( C_{\text{neighbours}} \) represents the neighbour blocks that have the same object label as the block \( C_k \), and \( N_{x_k} \) represents the number of blocks of \( C_{\text{neighbours}} \), same object label as the block \( C_k(t-1) \). Dividing by \( N_{x_k} \) means normalisation of the energy by the number of neighbour blocks belonging to the same object. The more a motion vector of a block \( C_k(t-1) \) becomes similar to the motion vectors of neighbour blocks \( C_{\text{neighbours}}(t-1) \), the more probable a motion vector of a block \( C_k(t-1) \) becomes.

5 Detection of shock waves by the vision sensor network

This section shows the development of a vision sensor based on the vehicle tracking mentioned in the foregoing section. First, the measurement of traffic flow is shown. Second, a detection algorithm based on the measurement is
5.1 Detection Algorithm

Detection is handled with the use of the average speed of vehicles that pass the vision sensor. The speed of vehicles is calculated by tracking the results of the S-T MRF model (Fig. 5). In this regard, the horizontal position of a vehicle is defined as the lower side of the frame of tracking results, and both the position on the image and the real position are coordinated by the calibration. An algorithm of the detection is presented below in detail. The value of $n$ is frame number per 0.1 s. In addition, the sensor range for tracking the vehicle is about 70 m towards the vanishing point of the image. However, the range of calculating the average speed in traffic flow is set to 30 m from the restriction of the resolution.

$$\text{score}_n = \begin{cases} 
1 & \text{average velocity} \geq V_{\text{flow}} \text{ (km/h)} \\
2 & V_{\text{cong}} < \text{average velocity} < V_{\text{flow}} \\
3 & \text{average velocity} \leq V_{\text{cong}}
\end{cases}$$

(8)

$$\text{average score} = \left( \frac{\sum_{i=n-128}^{n} \text{score}_i}{128} \right)$$

(9)

$$\text{condition}_n = \begin{cases} 
\text{flow} & \text{average score} \leq \text{Score}_{\text{flow}} \\
\text{critical} & \text{Score}_{\text{flow}} < \text{average score} < \text{Score}_{\text{cong}} \\
\text{congestion} & \text{average score} \geq \text{Score}_{\text{cong}}
\end{cases}$$

(10)

- **Step 1:** Score in each frame is decided by the average speed calculated by tracking results of S-T MRF model. The score is a value from 1 to 3.
- **Step 2:** The average score is calculated from scores of past 128 frames (12.8 s).
- **Step 3:** Traffic conditions in the present frame are estimated {flow, critical, congestion} by the average score.
- **Step 4:** The propagation of shock waves is detected if the current traffic condition is ‘congestion’ or ‘critical’, when the last traffic condition is ‘congestion’. In this algorithm, the ‘critical’ condition has a role of preventing unstable changing of traffic conditions.

5.2 Parameters setting of shock wave detection

The parameters such as $V_{\text{flow}}$ and $V_{\text{cong}}$ in the shock wave detection algorithm are decided based on the factorial analysis of incidents that occurred in the Akasaka tunnel. This area is one of the high-accident prone locations as mentioned in Section 2. Especially, accident by the shock wave in saturated traffic has become a huge issue. We have obtained about 150 incidents’ data in the past years and have analysed the traffic stream of the accidents by the shock wave with ultrasonic wave sensor data. From the results, the accident by shock waves occurs when the traffic flow changes from a critical to the congestion in saturated traffic. To be concrete, the accidents by shock waves occur when the velocity of traffic flow is transited from 30 or
40 km/h to around 20 or 10 km/h. From these results, the $V_{\text{flow}}$ and $V_{\text{cong}}$ in our algorithm are decided to be 40 and 20 km/h, respectively. Moreover, $\text{Score}_{\text{flow}}$ and $\text{Score}_{\text{cong}}$ are also decided to be 1.6 and 2.4, respectively. The detail of the traffic analysis of the shock wave is shown in [14, 30, 35].

5.3 Shock wave detection by the vision sensor network

Both the vehicle tracking technique and the shock wave detection algorithm mentioned above allow the realization of the vision sensor. In the VII system, this vision sensor is implemented to eight industrial television (ITV) surveillance cameras in the Akasaka tunnel, and a vision sensor network is constructed. The vision sensor network can detect the shock wave that occurred in the Akasaka tunnel. Then, the result of the detection from eight vision sensors is converted to time information defined as $t_{\text{information}}$, that is, the time until the shock wave arrives, by expression (12)

$$t_{\text{information}} = \frac{x_{\text{distance}}}{V_{\text{tunnel}}} + t_{\text{correction}}$$ (12)

In the expression, $x_{\text{distance}}$ is a distance from the DSRC point where information is provided to the vision sensor point where the shock wave is detected. As for the distance value, the distance from the DSRC point to the entrance of the Akasaka tunnel is 260 m, as shown in Fig. 3b, and the vision sensors are arranged at equal intervals in the Akasaka tunnel whose length is 560 m. In addition, the average velocity of traffic flow in the Akasaka tunnel defined as $V_{\text{tunnel}}$ is assumed to be 60 km/h. This is obtained from real traffic flow data in the Akasaka tunnel. Then the information is provided to the drivers going in the DSRC spot. $t_{\text{correction}}$ is a value to correct the value of $t_{\text{information}}$. In our system, if drivers do not think $t_{\text{information}}$ to be accurate, the reliability of the system to the driver might decrease remarkably. Therefore the important point to note is that how accurate time is provided to the driver. The $t_{\text{correction}}$ is the value that determines the reliability of the system. The $t_{\text{correction}}$ is discussed in detail in the latter section.

6 Experimental results

To show the effectiveness of our VII system mentioned above, experiments performed on vehicle tracking precision, shock wave detection precision and optimization of the system are discussed in this section.

6.1 Vehicle tracking

Experiments were performed by using images from surveillance video cameras that are installed in the Akasaka tunnel. They consist of straight, separating and merging
traffic. Performance for vehicle tracking was evaluated by using 40 min images at each location by applying the S-T MRF model.

Fig. 6 shows an example of vehicle tracking results in each vision sensors. In these images, the number of areas including only one vehicle is 4185 and these areas were tracked successfully. On the other hand, as for the performance for vehicle segmentation, the number of areas containing more than one vehicle is 1266 in total. Among them, the number of areas that were correctly segmented by the S-T MRF model is 1181 (about 93% of areas were divided precisely and tracked successfully). As a result, the vehicle tracking success rate on the whole became 91%. This is the value that can be worthy of practical use.

6.2 Detection of shock wave

To evaluate the performance of the developed vision sensor mentioned above, experiment of the detection algorithm is conducted. Image data used in experiment are selected randomly, but these are in specific conditions as shown in Table 1. The correct answer for the shock wave is obtained by visual observation. Evaluation indexes in the table are defined as follows:

- The number of shock waves: count of shock waves by visual observation.
- Correct: count of shock waves observed both in visual and the system.
- Lack: count of shock waves not observed in the system, whereas it was observed in visual.
- False: count of shock waves observed wrong in the system, whereas it was not observed in visual.

As a result of experiment, there are no recall reports in any condition. Moreover, false reports were not looked even in both midnight and rainy conditions. The cause of false report in fine condition is a failure of cancelling the report when two shock waves are concatenated.

6.3 Optimisation of the proposed VII system

In the VII system to suggest, precision of the prediction time is important from the viewpoint of reliability. In this section, experimental result of the prediction precision of this time is represented.

To investigate the arrival time to a shock wave, a detailed analysis of shock waves is performed with vision sensor network installed in the Akasaka tunnel. The analysed data relate to 7662 vehicles that passed a DSRC spot between 22:00 and 7:00 during 2 days in November 2007. The result of the analysis is shown in Fig. 7. Then the number of drivers who actually encountered a shock wave after each vision sensor detected the shock wave as shown in Fig. 8 according to a sensor position where drivers encountered shock waves. These results indicate that a difference may occur between the position where a shock wave exists when a driver passes a DSRC spot and the position where the driver encounters a shock wave. This is originated because a shock wave propagates from traffic flow of the upstream side to traffic flow of the downstream side. In addition, the degree of difference is increased in the condition that the position of the shock wave is far from the DSRC spot and a driver passes DSRC. In the VII system, an error in the calculation of the prediction time is caused by this difference of position. This time error tends to occur in the direction that the shock wave arrives earlier than a driver thought. Therefore it is considered that correction of this error is required when the system predicts the arrival time.

![Table 1 Shock wave detection success rate of the vision sensor](image-url)

<table>
<thead>
<tr>
<th>Number of shock wave</th>
<th>Result of detection</th>
<th>Vision condition</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Correct</td>
<td>Lack</td>
</tr>
<tr>
<td>10</td>
<td>10</td>
<td>0</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>61</td>
<td>61</td>
<td>0</td>
</tr>
<tr>
<td>7</td>
<td>7</td>
<td>0</td>
</tr>
<tr>
<td>10</td>
<td>10</td>
<td>0</td>
</tr>
</tbody>
</table>

Fig. 7 Shock wave propagation

![Shock wave propagation diagram](image-url)
So, let us attempt to correct an error by taking advantage of a correction straight line as shown in line (ii) of Fig. 7 in the prediction time of shock wave arrival. In this figure, line (i) represents the case where the prediction time of the arrival is not corrected.

To quantify the performance of the arrival time error correction, the prediction success rate is defined for an evaluation index as follows

\[
\text{prediction success rate} = \frac{N_{\text{success}}}{N_{\text{total}}} \tag{13}
\]

In the formulation, \(N_{\text{total}}\) is the number of all drivers (7662) and \(N_{\text{success}}\) is the number of drivers of the case that an error of arrival time is within an allowance (defined as \(t_{\text{tolerance}}\)). Fig. 9 shows the prediction success rate of case of both straight line (i) and straight line (ii) for different \(t_{\text{tolerance}}\). It is observed that the prediction success rate in case of line (ii) where error is corrected is higher than that of line (i). When \(t_{\text{tolerance}}\) is supposed to be degree for 5–10 s, it seems that there is effectiveness in the error correction using line (ii), because the difference of the prediction success rate becomes about 5%.

However, as for the assumption that the x is 5–10 seconds degree, an investigation from human-factors engineering is necessary for verification. We have experimentally examined the driver’s behaviour using a driving simulator for the optimisation of the VII system. Therefore as a future work, we are going to perform experiments related to how much an error will be tolerated by drivers.

7 Conclusions

In this paper, vehicle tracking and detecting shock waves in saturated traffic algorithms have been developed from the point of view that the propagation is caused by downstream bottleneck in traffic flow, which is one of main factors for traffic accident in the critical flow. In addition, a VII system that informs arrival of such shock waves to drivers has been investigated by the vision sensor network. To increase the reliability of the VII system, a technique to correct an error about a prediction of the shock wave arrival time has been proposed. By the detailed analysis of the propagation of shock waves by the vision sensor network in our system, this technique achieves around 5% prediction success rate improvement at the maximum compared to the case without error correction.

In our system, tolerance of prediction time error is an important factor in determining the prediction success rate. Therefore, we are going to evaluate the tolerance from the view of human-factors engineering in the future.

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