SEQUENTIAL IMAGE ANALYSIS OF VEHICLE MANEUVERS : EVALUATION OF VEHICLE POSITION ACCURACY AND ITS APPLICATIONS

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Abstract: Sequential images from high altitude platforms are suitable for traffic flow surveillance, which requires fixed-point continuous observation of vehicle movements over a wide area. The authors have developed a vehicle maneuver recognition method using these images, and confirmed its effectiveness. The method, however, required adjustments to some parameters, depending on the images. In addition, the results were given in image coordinates (pixels) instead of real world coordinates. This paper describes a method to adjust the parameters and a framework to evaluate the vehicle positioning accuracy using real distances. The proposed framework is applied to real sequential images obtained from a helicopter, and the vehicle positioning accuracy is estimated. The sequential images have 30 cm spatial resolution and 1/30 s time resolution. The framework provides exact and efficient vehicle recognition. The positioning accuracy of the recognized vehicles is better than 1.92m.

Key Words: vehicle maneuver recognition, sequential images, high altitude platforms, positioning accuracy

1. INTRODUCTION

Vehicle behavior models based on trajectories of each vehicle have been developed to analyze traffic congestion, traffic accidents, and environmental emissions in detail. These models require fixed-point continuous observation of the exact dynamic vehicle movements.

Images from video cameras are the most suitable sets of data that meet the model requirements. There have been some attempts to study the measurements of vehicle movement with fixed video cameras (*e.g.*, Kamijo *et al.*, 2000). The applications, however, were limited because of the narrow field of view, inaccurate trajectories caused by occlusion and laborious manual work. On the other hand, images from high altitude platforms, such as helicopters, have great potential for providing exact and efficient observations of vehicle maneuvers over wide areas. In addition, a stratospheric platform is currently being developed that will be maintained at a stratospheric altitude of 20 km. A test airship will be launched in 2004, equipped with an optical sensor that will have 4,000 x 4,000 pixels in the visible range. Images obtained with this sensor are supposed to have a 30 cm spatial resolution. Thus, these high altitude platforms are expected to provide high spatial and time resolution images of specific areas for continuous observations. These images will certainly make the observation of vehicle maneuvers easier.

The authors have developed a vehicle recognition method using images from high altitude platforms and confirmed its effectiveness using real sequential images (Fuse *et al.*, 2002). The method, however, requires adjustments to various parameters, which entails laborious work. In addition, the vehicle positions obtained using this method are in image coordinates (pixels), whereas the positioning accuracy is required in real distances.

In this paper, we develop a parameter adjustment method and a framework for evaluating the vehicle positioning accuracy using real distances.

2. VEHICLE RECOGNITION METHOD

The authors have previously developed a spatio-temporal clustering vehicle recognition method (Fuse *et al.*, 2002). The method uses a combination of geometric corrections, background subtractions, shadow detections, optical flow estimations, clustering, and labeling (Figure 1). The background subtraction value and optical flow are set as features of each pixel. The background subtraction value is the difference between the input and background images. The optical flow is the distribution of apparent velocities of movements of brightness patterns in the images. By using these two features, adjacent pixels in a spatio-temporal image that have similar features are grouped together, forming clusters in the image. Each cluster is then labeled as a vehicle if it matches known vehicle characteristics (Figure 2).

We applied this method to sequential images obtained from a helicopter. The spatial resolution was 10 cm, the time interval of successive images was 1/30 s, and the number of frames was 600. The method yielded positive results, and the rate of vehicle recognition was 100%.

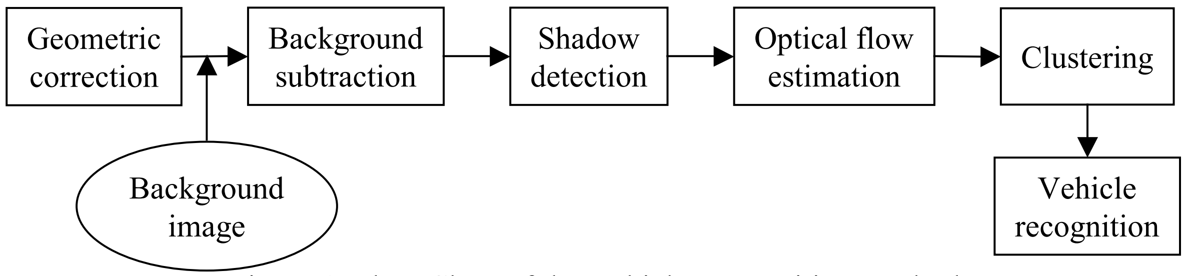

Figure 1. Flow Chart of the Vehicle Recognition Method

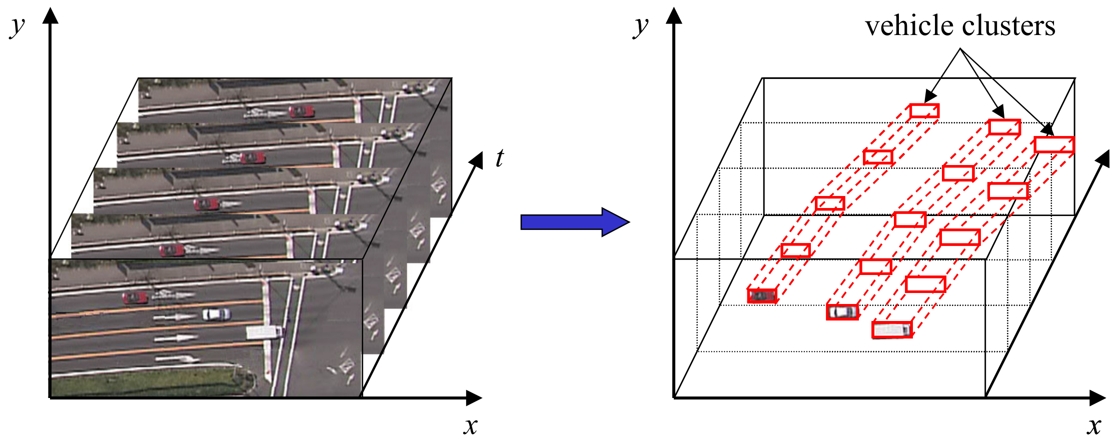

Figure 2. Concept of the Vehicle Recognition Method

3. PARAMETER ADJUSTMENT METHOD

3.1 Parameters in the Spatio-Temporal Clustering Method

The spatio-temporal clustering method has 13 parameters that must be adjusted. We performed a sensitivity analysis and confirmed that the parameters in the clustering procedure have the largest effects on the results. Furthermore, these clustering parameters depend on the image quality, such as the spatial or temporal resolution. The other parameters can be easily specified according to the vehicle characteristics.

The term "spatio-temporal clustering" means unifying pixels that have homogeneous properties or similar features. In the clustering procedure, adjacent pixels that have similar features (background subtraction value b_i, optical flow (u_i, v_i)) are grouped together in a spatio-temporal image. We adopt the weighted Euclidian distance measure as the similarity metric. To perform this operation, we simply compute the distance d between adjacent pixels in the feature space:

$$d^2\left(\boldsymbol{f}_i, \boldsymbol{f}_j\right) = w_b\left(b_i - b_j\right)^2 + w_{of} R\left\{\left(u_i - u_j\right)^2 + \left(v_i - v_j\right)^2\right\} \quad (1)$$

$$b^2\left(x, y\right) = \left(I_r\left(x, y\right) - B_r\left(x, y\right)\right)^2 + \left(I_g\left(x, y\right) - B_g\left(x, y\right)\right)^2 + \left(I_b\left(x, y\right) - B_b\left(x, y\right)\right)^2 \quad (2)$$

where

d: similarity measure,
f_i: feature of pixel i,
b: normalized background subtraction value,
u, v: x- and y- components of the normalized optical flow,
R: reliability of the optical flow,
w_b, w_{of}, weighting parameters for the background subtraction value and optical flow,
I_c, B_c: intensity of the input and background images ($c = r$ (red), g (green), b (blue)).

The similarity measure ($d(f_i, f_j)$) between two pixels (i, j) is defined according to equation (1), and the background value is defined as the distance in RGB color space (equation (2)). When the similarity is less than a threshold T_{sim}, those two pixels are merged into one cluster. The parameters are therefore the weighting parameters for the background subtraction value (w_b) and optical flow (w_{of}), and the threshold (T_{sim}).

Adjacent pixels in the spatio-temporal domain are added to the region as long as they satisfied the desired homogeneity property. The number of reference pixels in the spatio-temporal domain is 26. This procedure result in many regions in the spatio-temporal image.

It is laborious to specify all of the parameters simultaneously. In the next section, a convenient parameter adjustment method will be described.

3.2 Hierarchical Parameter Adjustment

The three parameters w_b, w_{of} and T_{sim} in the clustering procedure are related to each other. The main purpose of the parameter adjustment method is to specify the parameters separately.

Histograms provide a convenient means of identifying thresholds (Nixon and Aguado, 2002; Pratt, 1978). Therefore, histograms of the difference between the features of adjacent pixels are plotted to examine the similarity. Figures 3 and 4 show histograms of the background subtraction value and optical flow, respectively. In general, the histogram of the optical flow is more discrete than the histogram of the background subtraction value. The optical flow histogram has a single-peaked pattern while the background subtraction value histogram has a double-peaked pattern. We can use vehicle characteristics, such as the maximum velocity, to identify a threshold in the optical flow histogram.

We developed a hierarchical parameter adjustment procedure as follows.

(1) Histograms of the difference between features (the background subtraction value and magnitude of the optical flow) of adjacent pixels are plotted.
(2) The weighting parameters for the optical flow and background value are set to w_{of}=1 and w_b=0, respectively.
(3) A tentative threshold T_{of} is determined from the optical flow histogram based on the vehicle characteristics. The threshold is set to T_{of}=0.04 in Figure 4.

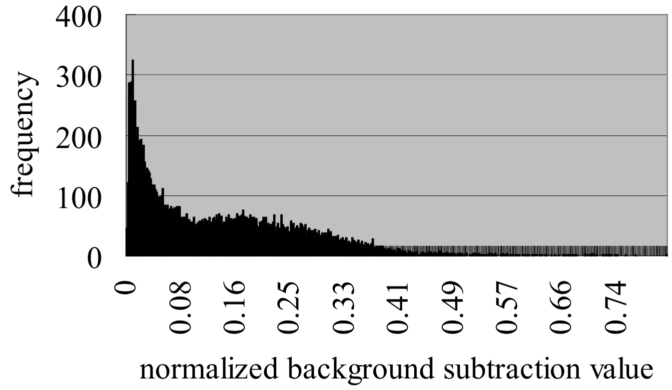

Figure 3. Difference between the Background Subtraction Value of Neighboring Pixels

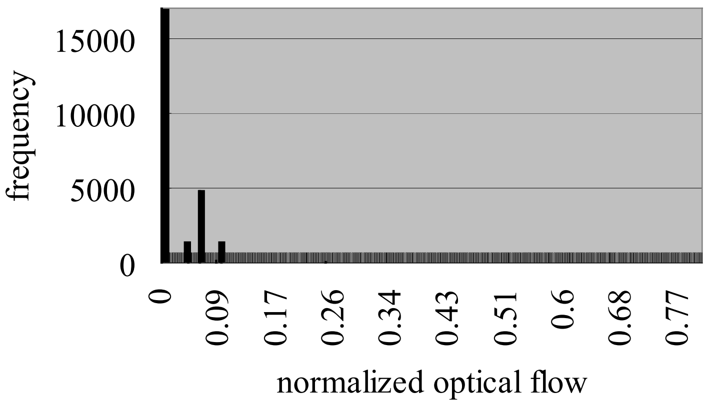

Figure 4. Difference between the Optical Flow Value of Neighboring Pixels

(4) The weighting parameters for the optical flow and background subtraction value are then set to w_{of}=0 and w_b=1, respectively.
(5) Another tentative threshold T_b is determined from the background subtraction value histogram using the mode method, which seeks the local minimal value between two peaks (Castleman, 1996). The threshold is set to T_b=0.09 in Figure 3.
(6) The weighting parameter for the background subtraction value is adjusted to equalize the two tentative thresholds, *i.e.*, w_b is calculated using

$$w_b = \frac{T_{of}}{T_b} \tag{3}$$

In the case of Figure 3 and 4, the parameter is calculated as $w_b=T_{of}/T_b$= 0.04/0.09=0.44.
(7) The threshold T_{sim} is set to T_{of}. The threshold is set to $T_{sim}=T_{of}$=0.04 in this case.

The parameters can be adjusted using this procedure, which increases the versatility of the vehicle recognition method.

4. VEHICLE POSITIONING IN REAL THREE-DIMENSIONAL COORDINATES

4.1 Moving Object Positioning in Real Three-Dimensional Coordinates

The vehicle recognition method gives vehicle trajectories. The vehicle positioning accuracy will influence the analysis of vehicle maneuvers as well as vehicle recognition. However, the vehicle positioning accuracy is evaluated in image coordinates (pixels) whereas the accuracy is required in real distances. In this section, we develop a framework to evaluate the vehicle positioning accuracy in the real three-dimensional world.

When real space coordinates of a point in an image are computed, one of the following two approaches may be used (Kraus, 2000):

(1) stereo imaging,
(2) single imaging

Two video cameras must be synchronized to perform a three-dimensional reconstruction of moving objects using stereo images. Remote synchronizing systems, however, are still very expensive. In addition, it is assumed that high altitude platforms will be equipped with single video cameras. Thus, the stereo imaging approach is not feasible.

In case of single imaging, a geometric constraint must be introduced. Normally, the constraint is that the scene must be a planar surface without any depth variations, which leads to a projective transformation (Mikhail *et al.*, 2001),

$$u = \frac{ax + by + c}{px + qy + 1}, \quad v = \frac{dx + ey + f}{px + qy + 1} \tag{4}$$

where, x and y are image coordinates, u and v are real space coordinates.

This assumption is reasonable if and only if the field-of-view (FOV) of the camera is sufficiently narrow, typically 5 degrees or less (Irani and Anandan, 1998). Furthermore, the constraint does not apply when the area of vehicle monitoring has depth variations (*e.g.* sag). Therefore, it is also difficult to apply this approach to our problem.

However, the road is a static area and vehicles move on the road. It is not necessary to synchronize the stereo pair when using a stereo image to create a three-dimensional reconstruction of a static object. Therefore, we can create a three-dimensional road model, and then identify the vehicle position on that model.

Accordingly, we developed a framework to track vehicles using real three-dimensional coordinate positioning as follows:

(1) Reconstruct a real three-dimensional model of a road using stereo images.
(2) Geometrically correct all of the frames to a reference frame.
(3) Identify the vehicle position on the three-dimensional road model.

Each step is explained in detail in following sections.

4.2 Three-Dimensional Road Model Obtained Using Stereo Image

First, a “reference frame” and an “image for camera orientation” are obtained. The two images are taken from different viewpoints. Because high altitude platforms can move arbitrarily, the image for camera orientation can be acquired in advance.

Given two images (the reference frame and the image for camera orientation) of a road, we can create a stereo model that can be viewed to obtain a three-dimensional impression of the road (Cooper and Robson, 2001). In Figure 5, suppose that the image coordinate axes (x_1,y_1,z_1) of the reference frame with a perspective center at O_1 are the primary coordinates, and we wish to evaluate the camera position and rotation (exterior orientation elements) of the image for camera orientation with its perspective center at O_2. Target A is imaged at a_1 and a_2. Vector $\mathbf{a}_1$, $\mathbf{a}_2$ and $\mathbf{b}$ are coplanar. In other words, target A and the two perspective centers lie in the same plane. Relative to the primary axes, these vectors are:

$$\mathbf{a}_1 = -\lambda\left[x_1, y_1, -c_1\right]^T, \quad \mathbf{a}_2 = -\mu\mathbf{R}^T\left[x_2, y_2, -c_2\right]^T, \quad \mathbf{b} = \left[b_x, b_y, b_z\right]^T \tag{5}$$

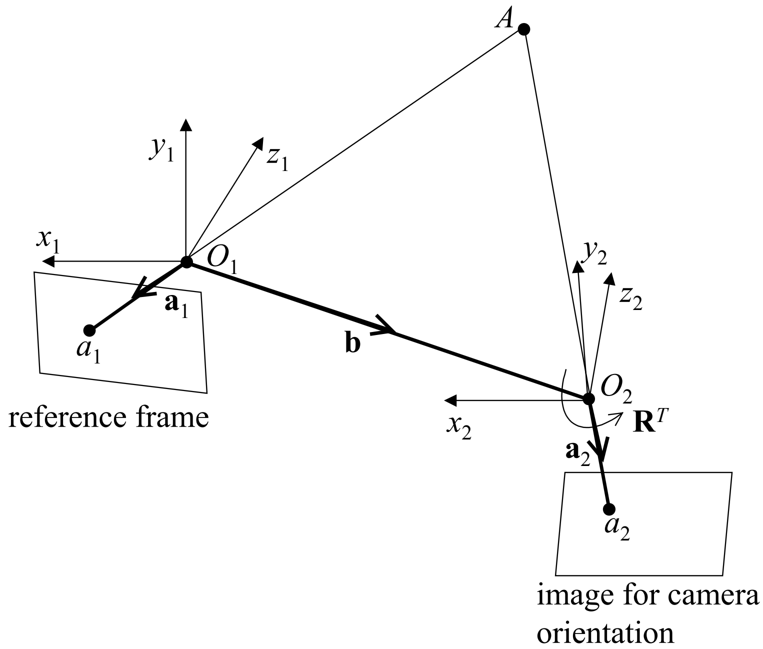

Figure 5. Geometry of the Stereo Model

$$\mathbf{R} = \begin{bmatrix} r_{11} & r_{12} & r_{13} \\ r_{21} & r_{22} & r_{23} \\ r_{31} & r_{32} & r_{33} \end{bmatrix} \tag{6}$$

where $\mathbf{b}$ is the camera base, $\mathbf{R}^T$ is a rotation matrix relative to the primary axes, μ is a scale factor and c_1, c_2 (known parameters) are the focal lengths of the cameras. The degree of freedom (number of parameters to be estimated) of the rotation matrix is three (ω, φ and κ). The triple scalar product of three vectors is zero, so $\mathbf{b} \cdot \mathbf{a}_1 \times \mathbf{a}_2 = 0$, or

$$\det \begin{bmatrix} b_x & x_1 & r_{11}x_2 + r_{21}y_2 - r_{31}c_2 \\ b_y & y_1 & r_{12}x_2 + r_{22}y_2 - r_{32}c_2 \\ b_z & -c_1 & r_{13}x_2 + r_{23}y_2 - r_{33}c_2 \end{bmatrix} = 0. \tag{7}$$

Assuming that at least one of the components (say b_x) of the base vector $\mathbf{b}$ is non-zero, and setting $\mathbf{R}^T \mathbf{a}_2 = \mathbf{a}_2{}' = \left[x_2{}', y_2{}', z_2{}' \right]^T$ gives

$$\det \begin{bmatrix} 1 & x_1 & x_2{}' \\ b_y/b_x & y_1 & y_2{}' \\ b_z/b_x & -c_1 & z_2{}' \end{bmatrix} = 0. \tag{8}$$

This equation is the coplanarity equation for target A. Since there are five parameters

(b_y/b_x, b_z/b_x, ω, φ and κ), at least five measured image coordinates of the targets will be required. This process is called relative orientation.

After a relatively oriented stereo model is obtained, the relationship between the model space of the relative orientation (**X**) and the real space (**Y**) coordinate systems must be established. This is known as absolute orientation. Seven parameters are involved: a uniform scale (μ), three translations (**T**) and three rotations (**M**):

$$\mathbf{Y} = \mu\mathbf{M}\mathbf{X} + \mathbf{T} \tag{9}$$

We employ reference points as targets whose image coordinates and real space coordinates are known.

4.3 Geometric Correction

Although this is a laborious process, the frames of the image sequence must be aligned in the same coordinates. We geometrically correct all frames to the coordinates of the reference frame and the image for camera orientation. The most popular method for geometric correction is to match Ground Control Points (GCPs). The geometric correction process can be summarized as follows:

(1) Specify GCPs as reference points. These points should be clearly perceived and have known coordinates.
(2) Use the GCPs to determine the coordinate transformation using the least squares method.

In this study, we use the corners of the edge contours of the markers on the road, such as crossings and speed indicators, as the GCPs. Since the markers are restricted to specified colors and shapes, the SUSAN operator (Smith and Brady, 1997), which is restricted in color, is used to detect the edges. Then inappropriate edge contours are eliminated using shape constraints, such as the aspect ratio, number of pixels, and whether the object is closed or not.

Because the extracted GCPs are essentially static area points, the displacement vectors of the GCPs between adjacent images are very small. Therefore the searching window used to identify corresponding points is limited to points within a few pixels.

Using the specified GCPs, a coordinate transformation is determined. In general, affine or projective transformations are selected for the coordinate transformation. The transformations assume that the scene is a planar surface without depth variation. This assumption, however, may not be appropriate, as describe previously. Furthermore, the coordinate transformations must coincide with the GCPs, which are the corners of markers on the road, because the markers affect the results of the background subtraction. We utilize Kriging interpolation for the geometric correction so that the GCPs coincide in all of the images. Kriging denotes a body of techniques to predict data at arbitrary locations using the structuring error covariance matrix, provided that some observations are recorded at a set of known locations. The details can be found in Cressie (1993).

4.4 Vehicle Positioning in Real Space Coordinates

Since the exterior orientation (position and rotation) of the reference frame and the image for camera orientation are known (**4.2**), their coordinates, (x_1, y_1) and (x_2, y_2) respectively, are used to evaluate the real space coordinates (X, Y, Z) of the road area. In addition, all of the image sequence frames are transformed to the (x_1, y_1) and (x_2, y_2) coordinates using the geometric correction (**4.3**).

Vehicles move on the road. We can identify the position of any vehicle if we estimate the real space coordinates of all of the positions on the road. Vehicle positioning in real space coordinates can be accomplished in following manner:

(1) Recognize each vehicle using the spatio-temporal clustering method.
(2) Transform the position of each vehicle in each frame to the coordinates of the reference image and the image for camera orientation.
(3) Evaluate the real space coordinates of each vehicle using the 3D road model.

5. APPLICATIONS

5.1 High Definition Television Images

We applied the proposed framework to aerial High Definition Television (HDTV) images. Two image resolutions were used to evaluate the parameter adjustment method, as shown in Figures 6 and 7.

Figure 6. Aerial HDTV Image (Spatial Resolution: 10 cm)

Figure 7. Aerial HDTV Image (Spatial Resolution: 30 cm)

The details of these images are as follows:

Platform:	Helicopter;
Spatial resolution:	10 cm, 30 cm;
Altitude of platform:	300 m (10 cm), 900 m (30 cm);
Time interval of successive image:	1/30 s;
Number of frames:	600 frames (10 cm), 300 frames (30 cm);
Number of channels:	3 (R, G and B, 8bit);
Size of image:	1920 by 1080 pixels.

The accuracy of the vehicle position was evaluated using the 30 cm resolution image.

In the 10 cm image, the traffic situation varies from waiting at stoplights to free flowing into an intersection. The velocities of the vehicles range from 0 to approximately 50 km/h, and the traffic density is approximately 60 veh/km. In the 30 cm image, the area of interest is a sag in a highway. The velocities of the vehicles range from approximately 70 to 90 km/h, and the density of the lane of interest is approximately 45 veh/km.

5.2 Vehicle Recognition Using the Parameter Adjustment Method

We applied the proposed parameter adjustment method to the spatio-temporal clustering technique. The parameters for the two spatial resolution images were adjusted as follows:

10 cm: $w_b = 0.5$, $w_{of} = 1.0$, $T_{sim} = 0.06$
30 cm: $w_b = 0.2$, $w_{of} = 1.0$, $T_{sim} = 0.05$

Figure 8 shows part of the results obtained using the proposed method with the 10 cm image. The recognized vehicles are outlined by rectangles. The road was set as the area of interest. In this experiment, 77 vehicles were recognized; their movements included direct advances, left and right-hand turns, lane changes and stopping (the recognition rate was 100%). This means that the proposed method can be corresponded to rapid and dynamic changes of traffic conditions.

Figure 9 shows part of the results obtained using the proposed method with the 30 cm image. In this case, 23 out of 24 vehicles were recognized (the recognition rate was 96%). At this scale, it was quite difficult to visually observe the vehicle that was not recognized by the algorithm.

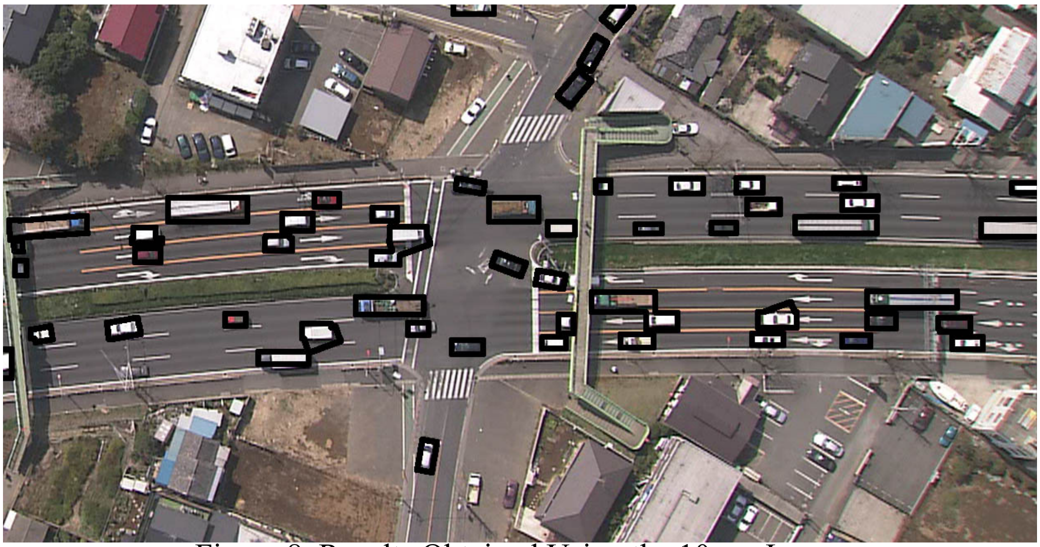

Figure 8. Results Obtained Using the 10 cm Image

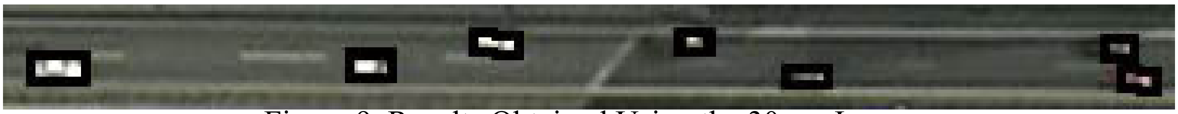

Figure 9. Results Obtained Using the 30 cm Image

These results confirm the effectiveness of the proposed method. It is necessary for applying the method to more frames to analyze traffic congestion or so on. The method can be also applied to many frames. If the observation time is very long, the sequential images are divided into some groups of successive frames, and then the method is applied to each group, respectively.

The effectiveness depends on weather. In the case of fair conditions, the shadows of vehicles affect the results. On the other hand, when it is cloudy or rainy, the difference of the colors in the whole image will become small (small dynamic range of the image). It makes the background subtraction difficult. Especially, vehicles that have similar color with the background (color of asphalt etc.) are affected.

5.3 Evaluation of the Vehicle Positioning Accuracy

We applied the framework of real space coordinate positioning to the 30 cm resolution image. The vehicle positioning accuracy was evaluated by comparing the results obtained using the proposed method with manual recognition using real distances. The centers of gravity of outlined rectangles were set as the vehicle positions. Figure 10 and 11 show comparisons of some of the trajectories after Kalman smoothing was applied (Catlin, 1989). In the figures, *x*- and *y*- axis represent horizontal coordinates in real world coordinate system (the longitude and latitude).

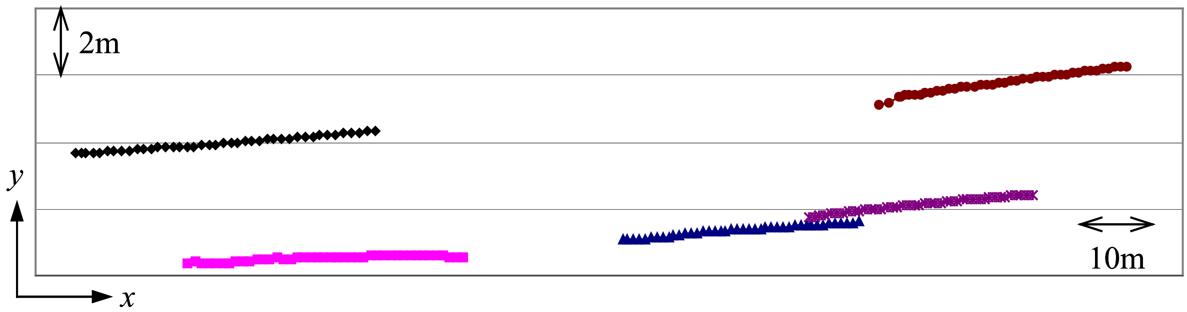

Figure 10. Vehicle Trajectories by the Proposed Method

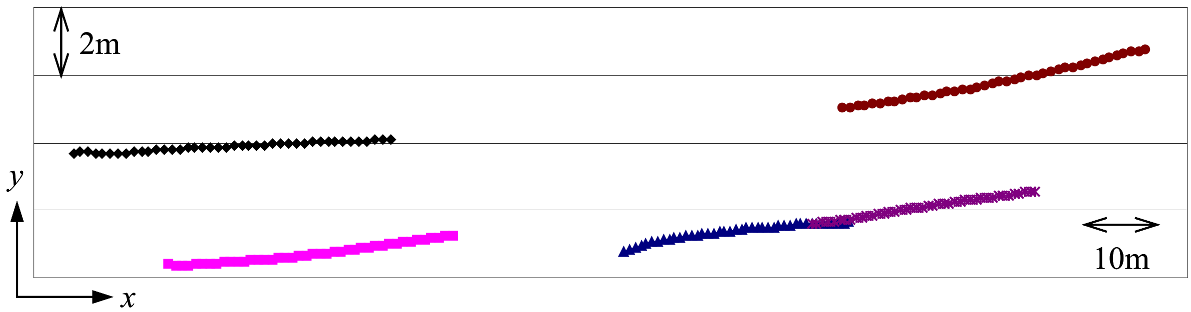

Figure 11. Vehicle Trajectories by Manual Recognition

The position accuracy of standard-sized vehicles and large-sized vehicles, such as trucks, was examined for 10 seconds. The average values and the variances of the horizontal differences are summarized in Table 1. Although it was difficult to identify the exact shape of black vehicles, the position accuracy was better than 2m. The accuracy of the results obtained using the proposed method was almost equivalent to those obtained manually. We examined two standard-sized black vehicles in this experiment. The variances in the result are extremely different. The shape of the standard-sized vehicle (1) was recognized uniformly. In other word, the same part of the vehicle was not recognized all the time. The color of the standard-sized black vehicle (2) was more similar to background color than the color of the vehicle (1), so that the vehicle shape varied from frame to frame.

Table 1. Horizontal Accuracy of Vehicle Positions

Vehicle type		Average (m)	Variance (m^2)
White	Standard-sized (1)	0.04	0.02
White	Standard-sized (2)	0	0.03
Black	Standard-sized (1)	1.73	0.04
Black	Standard-sized (2)	1.12	0.66
Black	Large-sized	1.92	0.75

6. CONCLUDING REMARKS

The conclusions of this paper are as follows:

(1) We confirmed the versatility of the spatio-temporal clustering method.
(2) We developed a parameter adjustment method for the spatio-temporal clustering method.
(3) We proposed a framework to evaluate the accuracy of the vehicle positioning technique.
(4) We confirmed the effectiveness of the proposed method by applying it to aerial HDTV images.

The future prospects for this research are related to:

(1) Application the proposed method to more frames.
(2) Analysis of traffic phenomenon based on the results obtained using the proposed method.
(3) Application of this work to sequential images obtained from a test airship of the Stratospheric Platform.
(4) Integration of the vehicle recognition and position/shape adjustment algorithm.
(5) Comparison of the position accuracy of the image measurement with GPS data.
(6) Obtaining observations from multiple high altitude platforms with video cameras.
(7) Combining the data obtained from various sensors, such as beacons, GPS, fixed and high altitude video cameras.

The results obtained form this study have the potential to improve many intelligent transportation system strategies.

ACKNOWLEDGEMENTS

We gratefully acknowledge the financial support obtained from Research Fellowships offered by the Japan Society for the Promotion of Science for Young Scientists (06958).

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