# A New Technique for Vehicle Tracking on the Assumption of Stratospheric Platforms

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**KEY WORDS:** Object Tracking, Movement Detection, High Resolution Data/Images, Image Sequence, Platforms, Algorithms, Stochastic.

## ABSTRACT

Traffic flow survey for traffic control and planning is usually conducted with traffic beacons set up at limited roadside points. Therefore, they cannot observe the exact dynamic movement of vehicles which is important information for sophisticated traffic policy. On the other hand, stratospheric platform system has been recently projected in Japan. One of the purposes of the stratospheric platform system is utilization for earth observation. The stratospheric platform is expected to result in high spatial and time resolution images at specific areas for continuous observations. These high resolution and continuous images certainly make observation of vehicle movement easier. In this paper, we explored the possibility of vehicle tracking with high resolution and time-serial aerial images, which are on the assumption of the use of stratospheric platforms. In estimation of displacement vectors of vehicles, the most characteristic problem is that appearance/disappearance of vehicles occur, when they are under overhead bridges or shadows of buildings, or going outside the image, or so on. We employed the probabilistic relaxation method for tracking vehicles. And then we improved the probabilistic relaxation method by introducing (1) the color information of vehicles , and (2) the displacement vectors of each other. We applied the proposed method to simulated data and sample images, which were on a one-way street. The time interval of successive images was 1.5 seconds. The proposed method yielded a better result than the original method, and the rate of correct correspondence is above 95%. Furthermore, we also applied to the various time interval images. When time interval was less than 1.5 seconds, the result was good for vehicle tracking in this case.

## 1. INTRODUCTION

Traffic flow survey for traffic control and planning is usually conducted with traffic beacons set up at limited roadside points. Therefore, they cannot observe the exact dynamic movement of each vehicle which is important information for policies decision for traffic problems. There have been a few attempts made to study the survey of dynamic movement of vehicles, for example, with aerial photographs. The results, however, were not sufficient for useful application to traffic engineering.

In recent years, a stratospheric platform system has been projected mainly by the Science and Technology Agency and the Ministry of Posts and Telecommunications in Japan. It is basically intended to contribute to telecommunication and the other different purposes. One of them is utilization for earth observation. The stratospheric platform is being supposed to be kept at a stratospheric altitude of about 20km, so it is expected to result in high spatial and time resolution images at specific areas for continuous observations. These high resolution and continuous images certainly make observation of vehicle movement easier. As a result, the stratospheric platform has a great potential with wider scope of utilization, for instance, survey for taking countermeasure against traffic jam, for taking origin-destination data, survey of rate of right and left turn in intersections for signal control, and so on.

In this paper, we explore the possibility of vehicle tracking with high resolution and time-serial aerial images, which are on the assumption of the use of stratospheric platforms. To be specific, we develop a new technique for vehicle tracking with high spatial and time resolution remotely sensed images. We propose improved probabilistic relaxation method as the new technique by introducing (1) the color information of vehicles, and (2) the displacement vectors of each other. And then, we confirm the effectiveness of the proposed method through applications to simulated data, sample images and different time interval successive images.

## 2. VEHICLE TRACKING PROBLEM

The vehicle tracking problem basically consists of two components. The first is how to detect vehicles automatically in each image. The next is how to estimate displacement vectors of vehicles in successive images. Though sensors on the stratospheric platforms are not decided yet, taking account of altitude of about 20km, it is expected to result in high spatial resolution images. We can fairly expect the spatial resolution to be in the range of 20cm-50cm. Figure 1 compares between a high resolution image (a), which expected to be produced by stratospheric platforms, and a usual satellite's image (b). High resolution image (a) has resolution of 30cm and usual satellite's image (b) has resolution of 30m. It is obvious that vehicles can be recognized easily in the high resolution image. Using such high resolution images, it is expected to be comparatively easier to detect vehicles accurately. In this paper, we were concerned with the second component of the problem, that is estimation of displacement vectors.
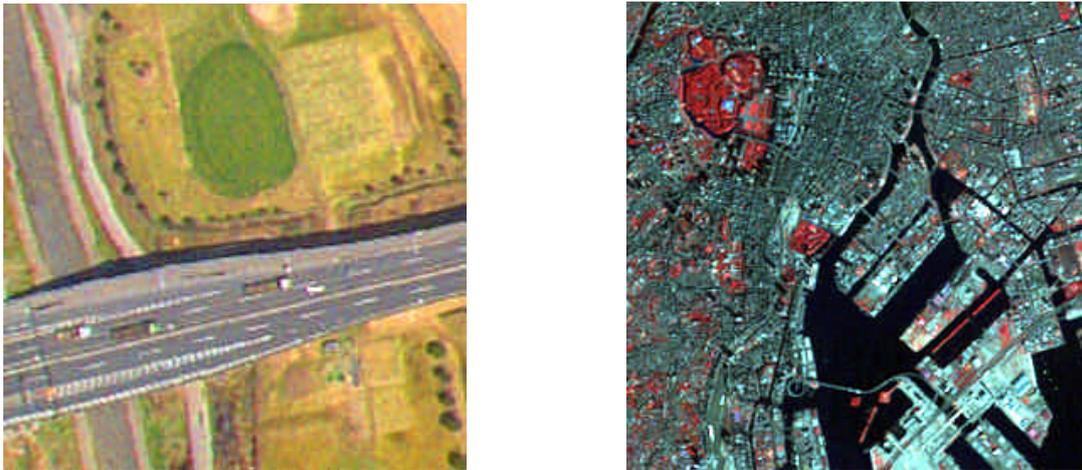


(a) High Resolution Image (Aerial HDTV Image, 30cm)   (b) Usual Satellite's Image (LANDSAT TM, 30m)
Figure 1: Comparison of High Resolution Image with Ordinary Satellite's Image.

The estimation of displacement vector specifies the origins and destinations of all vehicles in successive images. When the vehicles are detected as in Figure 2, the vehicle A in the image 1 can move to C, D or E in the image 2 or disappear. The most characteristic problem for the vehicle tracking is that appearance/disappearance of vehicles occur, when they are under overhead bridges or shadows of buildings, or going outside the image, or so on. The existence of the appearance/disappearance make the task of vehicle tracking challenging.
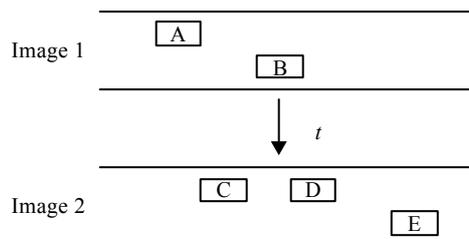


Figure 2: Vehicle Tracking Problem.

## 3. PROBABILISTIC RELAXATION METHOD AND IMPROVEMENT OF THE METHOD

The relaxation method was originally developed as an algorithm for numerical calculation (Takagi and Shimoda, 1991). The relaxation method has been widely employed for image matching techniques (Zucker, Hummel and Rosenfeld, 1977, Barnard and Thompson, 1980, Peleg, 1980, Ohmi and Yu, 1998, Sakamoto, Uchida and Wang, 1998). In the image matching, sets of candidate matching points are first selected independently in each image. An initial network of possible matches between the two sets of candidates is then constructed. An initial estimate of the probability of each possible match is made equally. Finally, these estimates are iteratively improved by a relaxation labeling technique making use of the local consistency property of displacement vectors, that is similarity between the displacement vectors of near candidate points.

We employed the probabilistic relaxation method for tracking vehicles, because the similarity between the displacement vectors is appropriate to a characteristic of movement of vehicles. The probabilistic relaxation method is summarized

as follows in applying to vehicle tracking (Barnard and Thompson, 1980, Takagi and Shimoda, 1991). We used two successive images, Image 1 and Image 2. At first, we select candidates in Image 2 correspond to a vehicle in Image 1. The candidates are restricted by the velocity of the vehicle. These are referred to as possible correspondences. They include no correspondence due to the disappearance of the vehicle. And then, probabilities to the correspondences are set equally. The probabilities are improved successively by applying a consistency property, that is the similarity between displacement vectors of near vehicles. Finally, the most possible correspondence will have the highest probability.

However, the probabilistic relaxation method cannot take the color of vehicles into account, which is very significant information, and it cannot be applied to the appearance of vehicles. Taking countermeasure against these problems, we improve the probabilistic relaxation method by introducing:

(a) the color information of vehicles , and
(b) the displacement vectors of each other.

(1) Specifying Initial Probabilities

Color information is very significant for correspondence between vehicles. So the color information is introduced to specifying initial probabilities of the possible correspondences, namely the initial probabilities of correspondences are varied according to similarity of the colors.

From now, we introduce abbreviations as follows:
$r_1(x, y), g_1(x, y), b_1(x, y)$: Intensity of R, G, B (8bit) in Image 1,
$r_2(x, y), g_2(x, y), b_2(x, y)$: Intensity of R, G, B (8bit) in Image 2.
In both images, the value of intensity is

$$0 \le r, g, b \le 255 = C_{\max} . \tag{1}$$

$D$: Maximum of vehicles movement (pixels).
$a_i$: Vehicles detected in Image 1 locate $(x_i, y_i)$.   $i = 1, 2, \ldots, m.$
$b_k$: Vehicles detected in Image 2 locate $(x_k, y_k)$.   $k = 1, 2, \ldots, n.$
$\lambda$: Label of displacement vectors.

$$\lambda = \{ \lambda_1, \lambda_2, \ldots, \lambda_n, \lambda_p \} \tag{2}$$

$\lambda_p$: Label of no correspondence.

$$\lambda_k = (\Delta x_k, \Delta y_k), \quad -D \le \Delta x_k \le D, \quad -D \le \Delta y_k \le D \quad (k \ne p) \tag{3}$$

$P_i(\lambda_k)$: Probability that vehicle $a_i$ has label $\lambda_k$. We refer to label probability.

$$\sum_k P_i(\lambda_k) = 1, \quad 0 \le P_i(\lambda_k) \le 1 . \tag{4}$$

If $b_{kl}$ ($l = 1, 2, \ldots, L$) are candidates corresponding to $a_i$, $a_i$ has $L+1$ label.

$$L_i = \{ \lambda_{k1}, \lambda_{k2}, \ldots, \lambda_{kL}, \lambda_p \}, \tag{5}$$

where

$$\lambda_{kl} \in \lambda, \quad \lambda_{kl} = (x_{kl} - x_i, y_{kl} - y_i) = (\Delta x_{kl}, \Delta y_{kl}) . \tag{6}$$

The square of distance of vehicles' color in the RGB space is

$$C_i(\lambda_k) = (r_1(x_i, y_i) - r_2(x_k, y_k))^2 + (g_1(x_i, y_i) - g_2(x_k, y_k))^2 + (b_1(x_i, y_i) - b_2(x_k, y_k))^2. \tag{7}$$

At the no correspondence, the distance of color is defined by expectation of disparity of the color

$$C_i(\lambda_p) = 3 \cdot \left(\frac{1}{3} C_{\max}\right)^2. \tag{8}$$

Let

$$\hat{C}_i(\lambda_{kl}) = \frac{\sum_l^p C_i(\lambda_{kl}) - C_i(\lambda_{kl})}{\sum_l^p C_i(\lambda_{kl})}, \tag{9}$$

and then, the initial label probability is

$$P_i^{(0)}(\lambda_{kl}) = \frac{\hat{C}_i(\lambda_{kl})}{\sum_l^p \hat{C}_i(\lambda_{kl})}. \tag{10}$$

At the no correspondence, the initial label probability is

$$P_i^{(0)}(\lambda_p) = \frac{\hat{C}_i(\lambda_p)}{\sum_l^p \hat{C}_i(\lambda_{kl})}. \tag{11}$$

(2)Improvement of Label Probability

In the process of improving probabilities, the displacement vectors from Image 1 to Image 2 and from Image 2 to Image 1 are used.  We refer the displacement vectors from Image 2 to Image 1 to opposite displacement vectors.  This method can be applied to the appearance of vehicles using the displacement vectors of each other.

We also introduce the additional abbreviations as follows:
   $\lambda'$: Label for opposite displacement vectors.

$$\lambda' = \{\lambda'_1, \lambda'_2, \ldots\ldots, \lambda'_m, \lambda'_p\}. \tag{12}$$

$\lambda'_p$: Label of no correspondence, and

$$\lambda'_k = (\Delta x_k, \Delta y_k), \quad -D \leq \Delta x_k \leq D, \quad -D \leq \Delta y_k \leq D \quad (k \neq p). \tag{13}$$

$Q_i(\lambda'_k)$: Probability that vehicle $b_i$ has label $\lambda'_k$.  We refer to opposite label probability.

$$\sum_k Q_i(\lambda'_k) = 1, \quad 0 \leq Q_i(\lambda'_k) \leq 1 \tag{14}$$

A vehicle $a_j$ locates $(x_j, y_j)$ near a vehicle $a_i$.  When vehicle $a_j$, which has high label probability $P_j(\lambda_{kl})$, exists near vehicle $a_i$, it is consistent that vehicle $a_i$ has label $\lambda_{kl}$.  This property is called as consistency property.  In this case, the label probability is increased.  Degree of consistency are defined as follows

$$\hat{P}_i(\lambda_{kl}) = \sum_j \sum_{l' \in L''} P_j(\lambda_{kl'}), \quad (l=1,2,\ldots\ldots,L), \tag{15}$$

$$\hat{Q}_j(\lambda'_{kl}) = \sum_i \sum_{l' \in L''} Q_i(\lambda'_{kl'}), \quad (l=1,2,\ldots\ldots,L). \tag{16}$$

Labels are considered to be consistent if they represent nearly the same displacements,

$$\sqrt{(\Delta x_{kl} - \Delta x_{kl'})^2 + (\Delta y_{kl} - \Delta y_{kl'})^2} \le T .$$  (17)

$L''$ in the equations (15) and (16) is a set of labels which satisfy equation (17). When vehicle $a_j$ does not have the label $_{kl'}$ which satisfy equation (17), degree of consistency is $\hat{P}_i(\lambda_{kl})$ =0, otherwise $\hat{P}_i(\lambda_{kl})$ >0. Vehicle $a_j$ are selected by satisfying equation (18).

$$\sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \le R .$$  (18)

For opposite label $'_{kl}$, degree of consistency is defined by (16).

Improvement of label probabilities is accomplished by applying following equation,

$$P_i^{(\text{new})}(\lambda_{kl}) = \frac{P_i'^{(\text{new})}(\lambda_{kl})}{\sum_{l' \in L_i} P_i^{(\text{new})}(\lambda_{kl'})} \quad (l=1,2,\ldots\ldots, L, p),$$  (19)

where

$$P_i'^{(\text{new})}(\lambda_p) = P_i^{(\text{old})}(\lambda_p) ,$$  (20)

and

$$P_i'^{(\text{new})}(\lambda_{kl}) = P_i^{(\text{old})}(\lambda_{kl})(A + B\hat{P}_i^{(\text{old})}(\lambda_{kl}) + CQ_i^{(\text{old})}(\lambda_{kl})) , (l=1,2,\ldots\ldots,L).$$  (21)

For opposite label probabilities,

$$Q_j^{(\text{new})}(\lambda'_{kl}) = \frac{Q_j'^{(\text{new})}(\lambda'_{kl})}{\sum_{l' \in L_i} Q_j^{(\text{new})}(\lambda'_{kl'})} , (l=1,2,\ldots\ldots, L, p),$$  (22)

where

$$Q_i'^{(\text{new})}(\lambda'_p) = Q_i^{(\text{old})}(\lambda'_p) ,$$  (23)

and

$$Q_i'^{(\text{new})}(\lambda'_{kl}) = Q_i^{(\text{old})}(\lambda'_{kl})(A + B\hat{Q}_i^{(\text{old})}(\lambda'_{kl}) + CP_i^{(\text{old})}(\lambda'_{kl})) , (l=1,2,\ldots\ldots,L).$$  (24)

Parameters $A$, $B$ and $C$ in equation (21) and (24) are positive constants which influence the convergence characteristics of the model. The role of $A$ is to delay the total suppression of unlikely labels. The role of $B$ and $C$ is to determine the rate of convergence. The larger the value of $B$ and $C$ relative to $A$, the faster will be the convergence of similarity assignments.

The complete procedure to estimate the most likely correspondence for each vehicle can be summarized as follows. Each possible correspondence is assigned an initial probability. These probabilities are iteratively refined using equation from (19) to (24). This procedure is repeated until the probabilities reach steady states, but in practice we may need to arbitrarily stop it at 50 iterations (Barnard and Thompson, 1980, Takagi and Shimoda, 1991).

## 4. EXPERIMENTS

### 4.1 Confirmation of Effectiveness of Proposed Method

We applied the original probabilistic relaxation method and the proposed method to simulated data. We employed traffic micro simulator PARAMICS (PARAMICS TRAFIIC SIMULATION LTD.) for producing the simulated data. The data were on a one-way and two-lane road. The time interval of successive images was 1.5 seconds. Detected vehicles are 52 in Image 1 and 51 (one vehicle disappeared) in Image 2, respectively.

We applied the following method:

(a) Original probabilistic relaxation method (original method);
   The initial probabilities are specified equally, and only one direction label probabilities are considered.
(b) Probabilistic relaxation method with color information (with color information);
   The initial probabilities are specified by taking account of color information, and only one direction label probabilities are considered.
(c) Probabilistic relaxation method with opposite label (with opposite label);
   The initial probabilities are specified equally, and two direction label probabilities are considered.
(d) Proposed method;
   The initial probabilities are specified by taking account of color information, and two direction label probabilities are considered.

Parameter $A$, $B$ and $C$ in (21) and (24) were specified based on results.

We applied these methods to two types of images. In the first, all vehicles were detected ( (1) without appearance and disappearance: Without), in second, 10% of vehicles were not detected intentionally ( (2) with appearance and disappearance: With). Table 1 shows the results.

Table 1: Correct Rates to Simulated Data.

|  | (1) Without | (2) With |
|---|---|---|
| (a) Original method | 82.7% | 80.1% |
| (b) With color information | 88.5% | 91.5% |
| (c) With opposite label | 98.1% | 97.8% |
| (d) Proposed method | 100.0% | 100.0% |

The correct rate by the proposed method are 100.0% in the both cases, that are without appearance/disappearance, and with appearance/disappearance. These results verify the effectiveness of the proposed method and robustness to appearance/disappearance problem.

### 4.2 Application to Sample Images

### 4.2.1 Specification of Parameters with Simulated Data

When the proposed method are applied to real image, some parameters must be specified. Parameters $T$, $R$ and $D$ ($T$: threshold for consistency, $R$: threshold for neighborhood, $D$: maximum of vehicles movement) can be specified easily by considering the limit of vehicle velocity in the road of interest, and so on.

Parameters $A$, $B$ and $C$ in (21) and (24), however, cannot be specified easily. Because these parameters are affected by state of traffic flow, time interval of successive images, and so on. It is appropriate that these parameters are specified by applying to simulated data which assume the real traffic flow. To be specific, simulated data reproduce the real traffic flow of interest. The methods are applied to simulated data with the various value of parameters, and then the results are compared. Based on the comparison, the parameters will be specified.

In this paper, we used following value of parameters.

$A = 0.5$, $B = 1$, $C = 1$, $T = 20$, $R = 200$, $D = 150$.

Here, we varied value of $A$ from 0 to 1 at an interval of 0.1, values of $B$ and $C$ from 0 to 10 at an interval 0.2.

### 4.2.2 Application to a Sample Image

We also applied the above-mentioned four methods to a sample image produced from an aerial HDTV image (Figure 3). The data of this image are as follows:

Platform: Helicopter;
Time: 1996, March 16th;
Area: Yodogawa-River Area;
Length of the road: about 700m (one-way and two-lane);
Altitude of platform: about 500m;
Time interval of successive image: 1.5 seconds;
Spatial resolution: 0.33m ;
Number of channels: 3 (R, G and B, 8bit);
Size of image: 1920 by 650 pixels ;
Number of detected vehicles: 47 in Image 1,
                              48 in Image 2 (one vehicle appeared).



Figure 3: Sample Image.

We used the value of parameters specified in the Section **4.2.1**. We applied the four methods to both of types of images as mentioned in Section **4.1**.

Vehicle detection was accomplished manually. The coordinates of vehicles were the center of gravity, and the colors were the average of the each vehicle. For calculating the correct rate, accurate labeling were constructed with successive images at a short interval manually.

Table 2 shows the results with the sample image. The proposed method produced improved results than the original method, and the rate of correct correspondence is above 95%. In the case of (c) with opposite label, the results were better than (a) original method and (b) with color information. However, they were much worse than those by the proposed method, because there existed vehicles whose colors were not similar and displacement vectors were similar. The algorithm of relaxation method improves the probabilities using only consistency property. So, if these vehicles exist, the label probabilities cannot reach convergence. The proposed method has advantage over (c) with opposite label method due to use color information.

Table 2: Correct Rates to Sample Image.

|  | (1) Without | (2) With |
|---|---|---|
| (a) Original method | 78.7% | 75.6% |
| (b) With color information | 80.9% | 75.6% |
| (c) With opposite label | 83.2% | 78.9% |
| (d) Proposed method | 95.8% | 96.7% |

## 4.3 Application to Different Time Interval Successive Image

Furthermore, we also applied the proposed method to some successive images at different time intervals, which were 0.5s, 1.5s, 2.5s and 4.0s. The data of the images are same as those in Section **4.2**.

Table 3 shows the results. When the time intervals were less than 1.5 seconds, the correct rates were good. On the contrary, when the time intervals were over 2.5 seconds, the correct rates were less than 80%. When the time interval is less than 1.5 seconds, the accuracy of vehicle tracking is sufficient in this case. It is note that the relation between time interval and accuracy is much affected by states of traffic flow.

Table 3: Correct Rates to Different Time Interval Images.

| $t$ (seconds) | Correct rates |
|---------------|---------------|
| 0.5 | 100.0% |
| 1.5 | 97.9% |
| 2.5 | 78.9% |
| 4.0 | 70.5% |

For all the methods mentioned above (Section **4.1** to **4.3**), the processing time is about 60 seconds with a usual computer (CPU: Pentium 266MHz, RAM: 128MB).

## 5. CONCLUSION

The conclusions of this paper are as follows:

(1) We proposed a new method by improving probabilistic relaxation method;
(2) We confirmed the effectiveness of the proposed method through applications to simulated data, sample images and some different time interval successive images.

The future works are as follows:

(1) Application to more complex traffic flow;
(2) Comparison with other matching method;
(2) Development of automatic vehicle detection method;
(3) Unification of detection method and tracking method as vehicle tracking system.

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