INFORMATION EXTRACTION
ABOUT TRAFFIC SITUATION OF RAILWAY
WITH WEB CAMERA IMAGES

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ABSTRACT

To improve convenience of public transportation, we propose a system that extracts and visualizes information about traffic situation of railway by using web camera images. In our method, we extract train information by existing moving object detection method and restriction about running position of trains. Then, passing time and direction of actual trains are visualized with scheduled time. This system enables users to obtain the accurate information about traffic situation in real time. Our experiment shows that the detection method works well in daytime. The proposed system can effectively provide real-time train frequency at a specific station.

1. INTRODUCTION

Recently, increase of carbon dioxide has become a serious problem. As a countermeasure, there is the promotion of utilization of public transportation such as trains and buses. Therefore, improvement of convenience of public transportation is required more than ever. As an example, traffic situation of public transportation, such as delay of trains, should be informed rapidly and precisely to users for better convenience. Such information is managed in the company of public transportation. However, the information provided to us is only a small fraction of managed information.

In this study, we intend to extract information about traffic situation of public condition from images taken by a web camera and provide the information to users of public transportation. In this paper, we select trains as target public transportation and extract the information such as time of passage, direction of movement and difference between actual running situation and railway schedule. By using image information, we can obtain accurate information about traffic situation, such as the actual train frequency at a specific station, in real time without going to the station.

2. TRAIN DETECTION

2.1. Gaussian Mixture Model Method

In this study, we extract information about traffic situation of train from web camera images. When we extract information about moving objects from images, we first need to identify the intended region in images (foreground). As basic techniques for this, there are background subtraction [1] and frame differencing are well known. However, these methods have the problem that it is difficult to keep pace changes of lighting or appearance with time. Since the target situation of our study is outdoor scene, such change of lighting always occurs. To solve this problem, posteriori probability method [2] and statistical background subtraction method has been proposed. In statistical background subtraction method, we make and update background model with past frames and identify if each pixel is foreground or background by getting subtracted image of input image and background model. We use this as a method to extract the region of train in images.

In statistical background subtraction methods, various modelization method of background has been proposed. Among them, there is Gaussian Mixture Model Method (GMM) [3-5] as most general method. GMM is based on Gaussian mixture distribution for
each pixel in order to extract moving object region. By modeling background with multiple Gaussian distributions, this method can keep pace even for sudden changes of background. In addition, this method can also treat the case that moving object stops and changes from foreground to background.

However, in basic GMM, each pixel is treated independently. Therefore, Quast et al. [6] proposed “temporal dependency” and “spatial dependency”. We use this method to detect moving object.

2.1. Gaussian mixture model method (GMM)

GMM is explained in this section. Pixel values \{X_1, ..., X_t\} obtained up to time \(t\) are modeled using \(K\) Gaussian distributions. Each Gaussian distribution is represented using following parameter.

- \(\omega_{i,t}\): weight of the \(i\)-th distribution at time \(t\)
- \(\mu_{i,t}\): mean value of the \(i\)-th distribution at time \(t\)
- \(\sigma^2_{i,t}\): variance of the \(i\)-th distribution at time \(t\)

Estimation of each background pixel is composed of the following five steps.

Step 1.
For newly obtained pixel value \(X_t\), search the matched distribution from \(K\) Gaussian distributions. Decide that \(X_t\) matches the distribution if:

\[
|X_t - \mu_{i,t}| < k_1 \sigma_{i,t},
\]

where \(k_1\) is an appropriate constant.

Step 2.
Update the parameter of \(K\) Gaussian distributions. Here, \(\mu_{i,t}\) and \(\sigma^2_{i,t}\) is updated only matched distribution.

Step 3.
If no distribution is matched, add new distribution based on \(X_t\). Then, if \(K\) Gaussian distributions exist, delete the distribution that has the lowest degree of collation \(\omega / \sigma^2\) and add new distribution.

Step 4.
Sort \(K\) Gaussian distributions in descending order by value of \(\omega / \sigma^2\).

Step 5.
Decide that \(B\) distribution(s) is background model if:

\[
B = \arg \min_{b} \left( \sum_{k=1}^{K} \omega_k > \text{thr} \right),
\]

where \(\text{thr}\) is an appropriate threshold.

Background in a series of images typically comes in more frequently than foreground. In other words, from this premise, distribution of high incidence means a high probability of belonging to background model. From here onwards, we arrange \(K\) Gaussian distributions by value of \(\omega / \sigma^2\) and update background model by some distributions of high degree of collation. In our method, if the matched distribution of \(X_t\) belongs to background model, the pixel is classified into background, otherwise, into foreground.

2.1.2. Spatial dependency

In basic GMM, each pixel is treated independently and spatial dependency between neighboring pixels is not taken account. This has the potential of causing noise and false-positive error by small changes of lighting. In case of false-positive error, pixel value of intended pixel become near to average value of a Gaussian distribution of background model. On the other hand, typically this does not apply true foreground pixels. Quast et al. [6] use this fact to remove false-positive error. They define the following mask,

\[
M(X) = \min_{i \in [1, ..., B]} \left| \left| X - \mu_i \right| \right| + \left( \sum_{k=1}^{K} \omega_k > \text{thr} \right)
\]

where \(c\) is pixel value. The value of mask is distance from background model. They calculate sum of mask each window of \(3 \times 3\) and determine if pixel is background or foreground by the value of sum.

2.2. Train Detection Method

Train is typically larger than other moving objects such as cars or people. In addition, train run on a fixed position. Therefore, in this study, we first select rectangular region and two lines as train run region in images. Only in intersection of the rectangular region between two lines is applied foreground extraction process. After selecting processing region, we apply foreground extraction process to the region and we define that train exists in image if:

\[
F > k_2 S,
\]

where \(F\) is foreground region, \(S\) is processing region and \(k_2\) is a threshold value. An example of result of above-described processing is shown as Figure 2.
3. TRAIN STATUS ESTIMATION

We explain the method of train status estimation in this section.

3.1. Time of Passage Extraction

Information about time of passage is one of basic and very important information about traffic situation. In this study, the information is identified by shooting time of frame that train exists.

3.2. Direction of Movement Extraction

To extract time of passage, we use center of gravity of the foreground train region. When train moves in images, the center of gravity also moves. Therefore, we divide the train region into rows with 1 pixel width, and define each row as foreground if the number $N$ of pixel fill up the following equation (5):

$$N > k_3 \times H,$$

where $H$ is the number of pixel in the row and $k_3$ is a threshold value. The $x$-coordinate of the center of gravity can be approximated as the average $x$-position of the foreground rows. Then we extract information about direction of train’s movement by observing the center of gravity.

4. VISUALIZATION

In this section, we show the method of visualization of results. We project the extracted information, time of passage and direction of train movement, and time on railway schedule to one-dimensional time axis. Figure 3 shows an example visualization result. The horizontal axis means time, and trains going right hand direction are visualized above the axis, where trains going left hand direction are below the axis. Green bars indicate scheduled time of trains with $\pm 30[s]$ error bound. Red and blue points represent actual time that trains passed. User can easily obtain rough information of train situation by seeing visualized result.

5. EVALUATION AND DISCUSSION

5.1. Evaluation of Train Detection

We show results of evaluation experiment and considerations. We take four types of image group under different lighting conditions, apply our method with $K = 3$, $k_1 = 2.5$, $k_2 = 0.25$, $k_3 = 0.2$, $thr = 0.7$ to each a series of images and compare these results. Each lighting conditions is shown in Table 1. We compare these results with attention to following two points.

- Train detection
  How much rate does this system detect trains for actual number?

- Direction of movement
  Can this system accurately detect direction of movement for actual direction?

We show the results of evaluation experiment in Table 2. In Table 2, “Left” and “Right” indicate the number of trains going left and right direction respectively, “Pass” indicates the number of sets of train passing each other. In other words, one “Pass” contains is one “Left” and one “Right” trains. In Pattern A and Pattern B, we comparatively obtain stable results. However, only in Pattern B, some false detection comes on ground of west sun. On the other hand, in Pattern C and Pattern D, the number of observed trains is more than that of actual trains. Train light is thought to be aftereffects of these false detections. We show precision and recall of the results in Figure 5.

<table>
<thead>
<tr>
<th>Pattern</th>
<th>Details</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pattern A</td>
<td>Daytime: sun light and skylight</td>
</tr>
<tr>
<td>Pattern B</td>
<td>Daytime: with backlight by west sun</td>
</tr>
<tr>
<td>Pattern C</td>
<td>Evening: twilight</td>
</tr>
<tr>
<td>Pattern D</td>
<td>Night: with various artificial lighting</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Pattern</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>Left</td>
<td>Right</td>
</tr>
<tr>
<td>Pattern A</td>
<td>16</td>
</tr>
<tr>
<td>Pattern B</td>
<td>12</td>
</tr>
<tr>
<td>Pattern C</td>
<td>12</td>
</tr>
<tr>
<td>Pattern D</td>
<td>20</td>
</tr>
</tbody>
</table>
5.2. Discussion

In this subsection, availability of the proposed methods is discussed.

If all of the actual train time agrees with scheduled time in the visualization result, it represents that the trains are on time. On the other hand, if the actual time partially agrees with the schedule, there are some possibilities: 1) some trains are on time and others delayed; 2) all trains are delayed and some of them agree with the scheduled time of different trains; 3) all trains are on time but the result has detection errors. In order to distinguish such situations, more attributes of each train, such as class (express / local / deadhead / ...) and destination, must be detected and visualized.

Although our detection and visualization methods only provide rough information of train situation, user can know actual frequency of trains in real time. When train operations are suspended or trains are heavily delayed, Railway companies announce such situation to users by web pages and cellular phones. However, user cannot know how frequently train runs at a specific station, which is often the most important information especially for short-distance users of urban trains. In such cases, our methods can effectively provide the information.

6. CONCLUSIONS

In this study, we propose a system that extract and visualize information about traffic situation of railway from web camera images. By using Gaussian mixture model method, passing time of actual trains and its direction is detected and visualized with the scheduled time. In our experiment, the detection method works well in daytime, but not accurate at night because of train’s light. The proposed system can effectively provide real-time train frequency at a specific station.

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REFERENCES


