Vision-Based Train Position and Movement Estimation Using a Fuzzy Classifier

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퍼지 분류기를 이용한 비전 기반 열차 위치 및 움직임 추정

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Abstract We propose a vision-based method that estimates train position and movement for railway monitoring in which we use a fuzzy classifier to determine train states. The proposed method employs frame difference and background subtraction for estimating train motion and presence, respectively. These features are used as the linguistic variables of the fuzzy classifier. Experimental results show that the proposed method can correctly estimate train position and movement. Therefore the method can be used for railway monitoring systems which estimate crowd density or protect safety.

Key Words : Frame difference, Background subtraction, Fuzzy classifier, Image processing, Computer vision

요 약 본 논문에서는 열차 선로 모니터링을 위한 열차의 위치 및 이동을 추정하는 비전 기반 기법을 제안한다. 퍼지 분류기를 이용하여 열차의 상태를 판별하며, 프레임 차와 배경 감산을 각각 열차의 움직임과 존재를 판결하기 위해서 사용하고, 퍼지 분류기의 언어 변수로 사용된다. 실험 결과에서 제안하는 기법은 열차의 위치와 움직임을 정확히 추정하는 것을 볼 수 있다. 그러므로 제안하는 기법은 군중 밀도를 추정하거나 안전 감시를 수행하는 열차 모니터링 시스템에 활용될 수 있을 것이다.

주제어 : 프레임 차, 배경 감산, 퍼지 분류기, 영상 처리, 컴퓨터 비전

I. INTRODUCTION

CCTVs (closed circuit televisions) have been installed at many train stations to monitor safety on the tracks and platform. However, most CCTVs are watched by employees, and not used for automated monitoring. It is very inefficient to keep watch and monitor accidents and crowdedness manually. Therefore, this monitoring should be fully automatic.

A number of vision-based monitoring systems have been proposed to protect safety [3][5][6][8][9][11] or estimate crowd density [1][2][4]. Because both trains and fallen persons are observed on the tracks, train position estimation is quite important for safety systems. In crowdedness monitoring, the determination of train status is also important because train movements must not be regarded as persons' movements. This paper is aimed at developing automatic train state (position and movement) determining for railway monitoring systems. To

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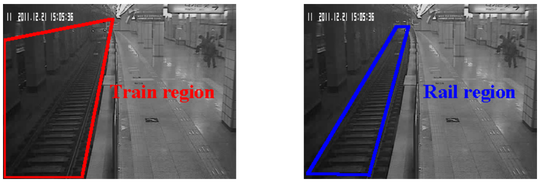
estimate the train state, train detection was used in Ref. [5], and Park and Lee [6] used edge information to determine a train's presence. However, it is very difficult to distinguish between person and train evidences owing to the perspective of the CCTV. To deal with this difficulty, we used frame difference and background subtraction in local regions. These methods are widely used for object detection [7][12][13]; however the detection performance is sensitive to their binary evidences and thus these evidences are so fuzzy. In the proposed method, motion of the train is estimated in the train region by frame difference, and the train's presence is estimated in the rail region by background subtraction. The train state is determined by a fuzzy classifier using these features.

II. FEATURE EXTRACTION

To determine the train state, two regions are used as shown in Fig. 1. If the train is coming towards (or going away from) the camera, motion may be observed in the train region (R_t), and if the train is present on the tracks, background subtraction reveals a large difference in the rail region (R_r). In other words, the motion of the train can be obtained R_t by the frame difference, and background subtraction can be utilized to determine the train's presence in R_r.



[Fig. 1] Train region and rail region.

The frame difference and the background subtraction are calculated by

$$F_t(x,y) = \begin{cases} 1 & |I_t(x,y) - I_{t-1}(x,y)| > \tau_f, \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

$$S_t(x,y) = \begin{cases} 1 & |I_t(x,y) - B_t(x,y)| > \tau_s, \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

where $F_t(x,y)$ and $S_t(x,y)$ denote the frame difference and the background subtraction at time t, respectively, $I_t(x,y)$ and $I_{t-1}(x,y)$ the input image at times t and $t-1$, respectively, $B_t(x,y)$ the background image at time t, and τ_f and τ_s the thresholds for $F_t(x,y)$ and $S_t(x,y)$, respectively. In (2), the background is updated by

$$B_t(x,y) = (1-\alpha)B_{t-1}(x,y) + \alpha I_t(x,y), \tag{3}$$

where α denotes the update gain.

Since $F_t(x,y)$ and $S_t(x,y)$ should be observed in the train region and the rail region, respectively, we use the ratios of the regions,

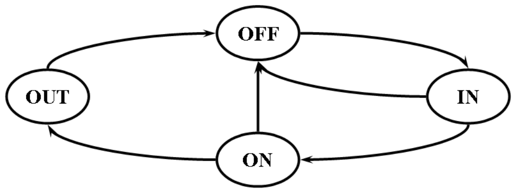
$$\gamma_f = \frac{1}{N_{R_t}} \sum_{(x,y)\in R_t} F_t(x,y), \tag{4}$$

$$\gamma_s = \frac{1}{N_{R_r}} \sum_{(x,y)\in R_r} S_t(x,y), \tag{5}$$

where N_{R_t} and N_{R_r} denote the number of pixels in R_t and R_r, respectively.

III. FUZZY CLASSIFIER

In the train station, we classify the train's position and movement condition into four states: OFF, IN, ON and OUT [5]. OFF is the state when the train is not at the station, IN is the state when the train is approaching to the station, ON is the state when the train is stopped, and OUT is the state when the train is leaving the station. Transitions between these states are shown in the state diagram in Fig. 2. In this figure, the transition to OFF is possible from anywhere. This transition is used for modifying false states since OFF is characterized by a clear distinction from other states.

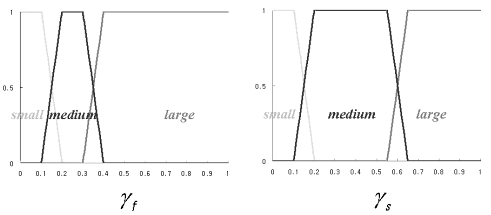


[Fig. 2] Train state diagram.

When the train is not in the station, both γ_f and γ_s are small since motion cannot be observed. When the train is stopped, γ_f is small since motion cannot be observed, and γ_s is large since the rail region is hidden by the train. When the train is coming (or going), γ_f is large since motion may be observed, and γ_s is large since the rail region is hidden by the train. With this knowledge, we use four following fuzzy rules for determining the train states:

R1 : IF γ_f is small AND γ_s is small, THEN the train state is class 1 (OFF).
R2 : IF γ_f is small AND γ_s is large, THEN the train state is class 2 (ON).
R3 : IF γ_f is large AND γ_s is large, THEN the train state is class 3 (IN or OUT).
R4 : OTHERWISE, THEN the train state is class 4 (N/A, Not applicable).

The membership functions of the input linguistic variables and their associated linguistic terms are defined as shown in Fig. 3. In these linguistic terms, medium is defined for N/A. Therefore, the cases of R4 consist of the six remaining conditions created by combinations of small, medium and large values for the linguistic variables.



[Fig. 3] Membership functions for the linguistic terms.

We use a fuzzy classifier based on the TS (Takagi-Sugeno) fuzzy system [10] and the maximum aggregation method. So the train state is classified by

$$C(i)=\frac{\sum_k \beta_{i,k}(\mu_k^1(\gamma_f)\wedge\mu_k^2(\gamma_s))}{\sum_k \mu_k^1(\gamma_f)\wedge\mu_k^2(\gamma_s)}, \quad (6)$$

$$\text{train state}=\arg_i \max C(i) \quad , \quad (7)$$

where $C(i)$ denotes the output of each class, $\beta_{i,k}$ the consequent constant for class i in rule k, and μ_k^1 and μ_k^2 the membership values of γ_f and γ_s, respectively.

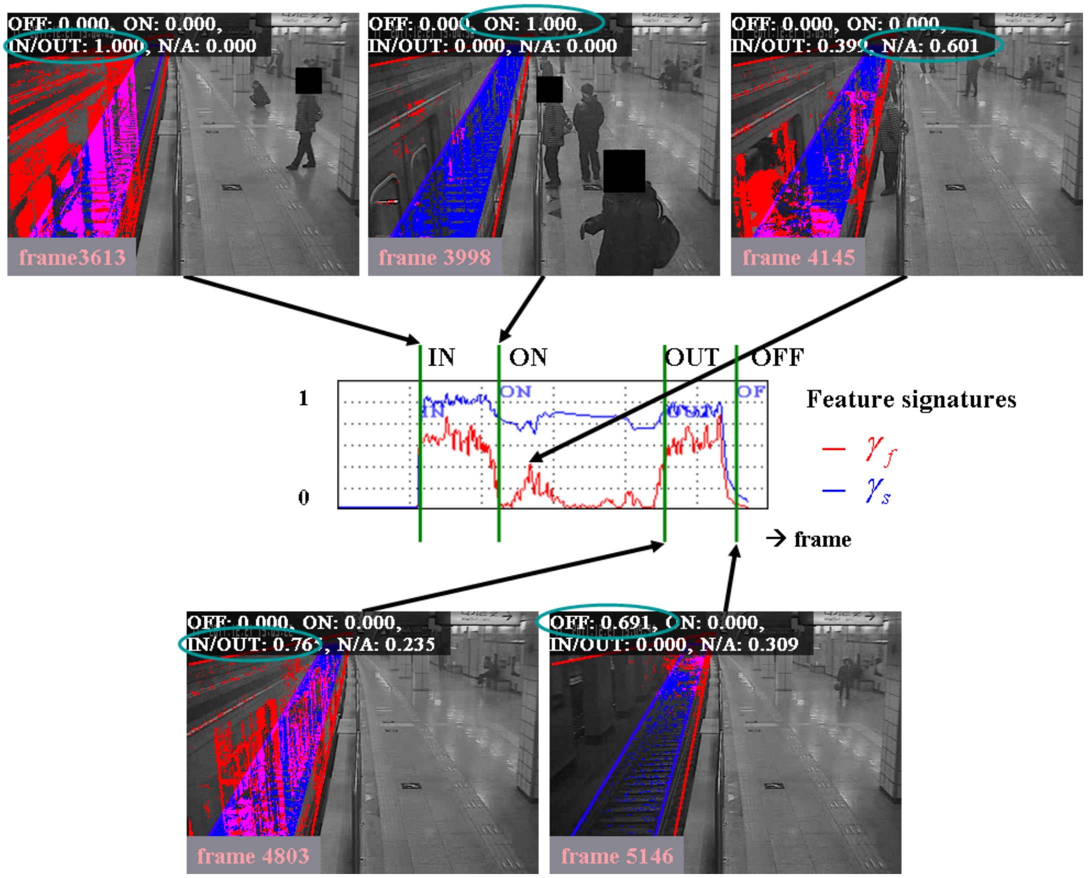
In every frame, the train state is classified by (7), and the state is then changed so that the current state satisfies the state diagram (Fig. 2).

IV. EXPERIMENTAL RESULTS

The proposed method has been tested on five underground station image sequences to evaluate its performance. Three image sequences were acquired from a camera turned toward the head of a train with a 200 ms duration, whereas the others turning toward the tail of a train in Korea. The image resolution is 320×240 (8 bit grayscale).

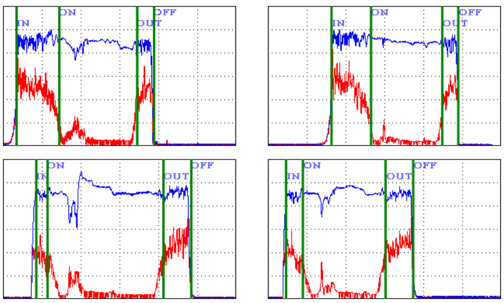
The method was tested on a Pentium PC (Core™ 2 Duo, 3.0GHz). Results of one sequence are shown in Fig. 4, where the red region shows F_t, the blue region shows S_t, and each $C(i)$ is shown on the top. The train state is correctly classified, as shown in the feature signature image. At frame 4145, γ_f is medium because some moving persons are observed, and the state is determined to N/A.

Figure 5 shows several examples of feature signature images and results of the state transition associated with various image sequences. In all of the test image sequences, false status transition did not occur in this test. While, several false estimation



[Fig. 4] Train state determination results.

results were observed by the train detection method [5] owing to split movements. The average processing time of a single frame is about 12.5 ms, so this method can be used at determining the train states for railway monitoring systems.



[Fig. 5] Various feature signature images and results of the state transition.

V. CONCLUSIONS

We have proposed a method to estimate a train position and movement for railway monitoring in which we use a fuzzy classifier to determine train states. The train movement is obtained in the train region by the frame difference, and background subtraction is utilized to determine the train's presence in the rail region. In the experimental results, the train state is correctly determined in all of the test image sequences. The proposed method may play a very important role in railway monitoring systems. Therefore, it is expected that this study will significantly contribute to the performance of these systems.

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