

Extended fuzzy background modeling for moving vehicle detection using infrared vision

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Abstract: Running average is a simple and effective background modeling method that generates adaptive background image for moving object detection. Fuzzy Running Average (FRA) improves the selectivity of Standard Running Average (SRA). However, its background restoration rate is slow. This leads to false object detection when a static object becomes dynamic. To overcome this problem, an Extended Fuzzy Running Average (EFRA) is proposed. The results show that the EFRA not only retains the selectivity benefit of FRA, but also improves the restoration rate significantly.

Keywords: fuzzy background modeling, vehicle detection, thermograph

Classification: Science and engineering for electronics

References

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1 Introduction

Vision-based vehicle detection system detects moving vehicles by comparing the captured image frames to a referenced image called background. The background image is a collection of static objects in the background scene, whereas the captured images consist of both static and dynamic (or moving) objects. Dynamic objects correspond to regions of pixels which are significantly different from the background. Most exterior surveillance systems need to cope with varying background scene, especially when the illumination is different in the morning, evening, and night. Therefore, background image generation must be adaptive and free from foreground object pollution. Some examples of background modeling methods are: running average [1], Mixture of Gaussian (MOG) [2], eigen-background [3], and Support Vector Data Description (SVDD) [4]. Compared to the other three methods, running average has the lowest computational complexity and memory requirement. Most statistical methods such as MOG employs running average to update the relative parameters in real-time.

For real-time video surveillance system, the captured video or the train of image frames is processed in sequence to generate the background frames. The captured image frames and the corresponding generated background frames are presented by $I_t(x, y)$ and $B_t(x, y)$ respectively, where t is a temporal parameter numbering the image sequences. x and y denote the pixel's spatial coordinates. To simplify the conceptual description for the algorithms in this paper, grayscale color format is used for all images, unless otherwise specified. The color intensity is a real number in the range of 0 to 1.

1.1 Standard running average

Standard Running Average (SRA) generates the background $B_t(x, y)$ by averaging the incoming image sequence $I_t(x, y)$ with the following equation.

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

where α ($0 \leq \alpha \leq 1$) is the update rate. The background $B_t(x, y)$ is updated using the old background $B_{t-1}(x, y)$ and the input $I_t(x, y)$. Since a moving object normally exists in the captured video for a short time duration, sufficiently low update rate ensures only small portion of the moving object is included into the background. When the moving object becomes static for a long period, it is eventually registered into the background and become a background object.

1.2 Moving object detection

The moving objects can be recognized using background subtraction, based on the difference between the incoming images $I_t(x, y)$ and the referenced background $B_{t-1}(x, y)$, i.e.,

$$S_t(x, y) = \begin{cases} 1 & \text{if } |D_t(x, y)| = |I_t(x, y) - B_{t-1}(x, y)| > th_s \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

$S_t(x, y)$ is a binary image and th_s is the threshold parameter. The pixels with difference $|D_t(x, y)|$ greater than the threshold are classified as foreground pixels.

2 Fuzzy running average

SRA is a simple background modeling method since the entire background frame shares a common update rate. Consequently, it has poor selectivity. SRA updates the pixels from the input image $I_t(x, y)$ into the background $B_t(x, y)$ even when the difference $|D_t(x, y)|$ is high. This leads to heavy foreground object pollution to the background $B_t(x, y)$. A fuzzy approach was proposed to improve the selectivity in [1]. A dynamic update rate $\alpha_t(x, y)$ was used to selectively and individually update each background pixel. The Fuzzy Running Average (FRA) can be written as:

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

where $\alpha_t(x, y)$ dynamically changes between 0 and α_{max} . Based on the fuzzy approach, high difference $|D_t(x, y)|$ drives $\alpha_t(x, y)$ towards 0 and low difference $|D_t(x, y)|$ drives $\alpha_t(x, y)$ towards α_{max} . This significantly slows down the rate of updating the foreground objects into the background $B_t(x, y)$. Therefore, more accurate object detection is achieved through background subtraction.

The selectivity of the FRA is good, but it fails to restore the background immediately when a background object becomes dynamic. The weakness of FRA is illustrated in second and third rows of Fig. 2. Two cars are initially registered into the background $B_t(x, y)$ due to long parking duration, making them transparent with background subtraction $S_t(x, y)$. Later, the cars still remain in the background $B_t(x, y)$ even though they have moved away from the original locations, resulting false vehicle detection.

2.1 Extended fuzzy running average

SRA and FRA do not distinguish background update from restoration. Background update is defined as the action of including the background objects into the background $B_t(x, y)$, and background restoration is defined as the action of removing the objects from the background $B_t(x, y)$ when the objects are no longer static. By generating the update rate $\alpha_t(x, y)$ based on only the difference $|D_t(x, y)|$, FRA performs background update and restoration to an object at the same rate. In this paper, FRA is extended to speed up the rate for background restoration by measuring the color similarity between neighboring pixels.

Vehicle detection system differentiates the moving cars from the road. On the background $B_t(x, y)$, the road is represented with a region of pixels, which are similar in color. Therefore, the color of every background pixel can be predicted by averaging the colors of the neighboring pixels from the old background $B_{t-1}(x, y)$. The predicted background is:

$$N_t(x, y) = \frac{\sum_{\substack{m=x-1 \\ m \neq x}}^{x+1} \sum_{\substack{n=y-1 \\ n \neq y}}^{y+1} W_t(m, n) \cdot B_{t-1}(m, n)}{\sum_{\substack{m=x-1 \\ m \neq x}}^{x+1} \sum_{\substack{n=y-1 \\ n \neq y}}^{y+1} W_t(m, n)} \quad (4)$$

where

$$W_t(x, y) = \exp\left(\frac{-5|D_t(x, y)|}{th_s}\right)$$

The old background $B_{t-1}(x, y)$ is weighted by $W_t(x, y)$, according to the difference $|D_t(x, y)|$. The weight $W_t(x, y)$ is high when the difference $|D_t(x, y)|$ is low and vice versa. As a parameter for restoration, the difference $|E_t(x, y)|$ between the input $I_t(x, y)$ and the predicted background $N_t(x, y)$ can be calculated as:

$$|E_t(x, y)| = |I_t(x, y) - N_t(x, y)| \quad (5)$$

Fig. 1 shows the block diagram of the proposed Extended Fuzzy Running Average (EFRA) scheme. It generates new background $B_t(x, y)$ based on the input frame $I_t(x, y)$ and the old background $B_{t-1}(x, y)$. The background image $B_t(x, y)$ is updated once for every incoming input frame $I_t(x, y)$.

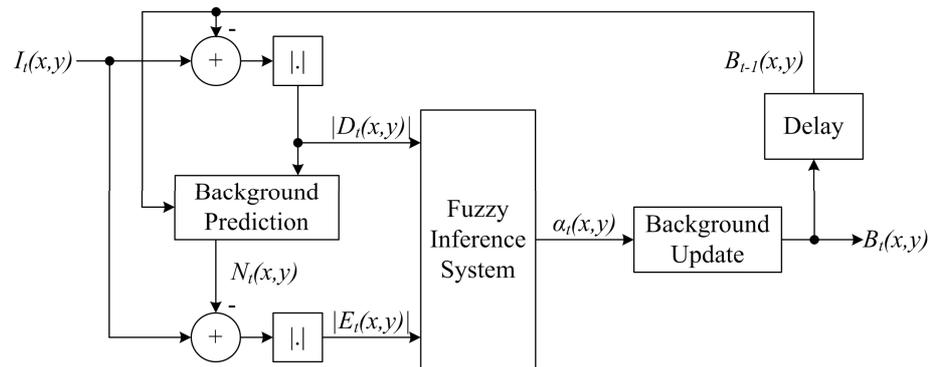


Fig. 1. Block Diagram of Extended Fuzzy Running Average Scheme

EFRA extends the capability of FRA with fast background restoration. EFRA's dynamic update rate $\alpha_t(x, y)$ changes not only according to $|D_t(x, y)|$, but also $|E_t(x, y)|$. To determine the update rate $\alpha_t(x, y)$, the following fuzzy rule set is used:

1. If $|D_t(x, y)|$ is high, and $|E_t(x, y)|$ is high, then $\alpha_t(x, y)$ is low.
2. If $|D_t(x, y)|$ is high, and $|E_t(x, y)|$ is low, then $\alpha_t(x, y)$ is high.
3. If $|D_t(x, y)|$ is low, then $\alpha_t(x, y)$ is medium.

Rule 1 and Rule 2 are designed to provide fast background restoration since the region with high background difference $|D_t(x, y)|$ but with low predicted difference $|E_t(x, y)|$ is the region requiring fast restoration. Rule 3 is designed for normal background update, adopted from FRA. Four exponential membership functions can be generated for high and low difference $|D_t(x, y)|$, and for high and low difference $|E_t(x, y)|$:

$$F_{t,D,low}(x, y) = \exp\left(\frac{-5|D_t(x, y)|}{th_s}\right) \quad (6)$$

$$F_{t,D,high}(x, y) = 1 - F_{t,D,low}(x, y) \quad (7)$$

$$F_{t,E,low}(x, y) = \exp\left(\frac{-5|E_t(x, y)|}{th_n}\right) \quad (8)$$

$$F_{t,E,high}(x, y) = 1 - F_{t,E,low}(x, y) \quad (9)$$

Finally, through defuzzification [5], the update rate $\alpha_t(x, y)$ can be determined as:

$$\alpha_t(x, y) = \frac{X_t(x, y) \cdot \alpha_{low} + Y_t(x, y) \cdot \alpha_{high} + Z_t(x, y) \cdot \alpha_{medium}}{X_t(x, y) + Y_t(x, y) + Z_t(x, y)} \quad (10)$$

where

$$X_t(x, y) = \text{Min}(F_{t,D,high}(x, y), F_{t,E,high}(x, y)); \quad (11)$$

$$Y_t(x, y) = \text{Min}(F_{t,D,high}(x, y), F_{t,E,low}(x, y)); \quad (12)$$

$$Z_t(x, y) = F_{t,D,low}(x, y) \quad (13)$$

2.2 Experimental setup

To experiment with the EFRA, a thermal camera is fixed at a distance away from the road surface and used to capture video of the moving vehicles on the road. The video is composed of sequential RGB image frames; however, only the red component of the images is used for the experiment since the cars are clearly differentiated from the road. In the video, two cars which were initially parked beside the road for a very long period had become background objects. Then, the cars moved away. The purpose of the experiment is to compare the background restoration rate of FRA and EFRA. For EFRA, α_{low} and α_{high} are set to 0 and 1 respectively, allowing the update rate $\alpha_t(x, y)$ to dynamically change in full scale. The parameter α_{medium} is equivalent to the maximum update rate in FRA for background update. It is set to 0.1. Meanwhile, the thresholds th_s and th_n are set to 0.15 and 0.05 respectively.

3 Results and discussion

The background $B_t(x, y)$ and the result of background subtraction $S_t(x, y)$ for FRA and EFRA are shown in Fig. 2. The input video is a train of 200 image frames. For Frame 1, the two cars are registered in the background $B_1(x, y)$ for both the methods. Thus, they are transparent in $S_1(x, y)$. After the cars move away, they are immediately detected in $S_{50}(x, y)$ at Frame 50. The background $B_{50}(x, y)$ of FRA still registers the cars as background objects. On the other hand, EFRA starts to restore the road as the background (the memory of cars start to fade). The EFRA then restored the background at Frame 200. The cars are completely removed from the background. Thus, only two cars are detected using background subtraction. FRA, on the other hand, has detected four cars at Frame 200 due to slow restoration rate.

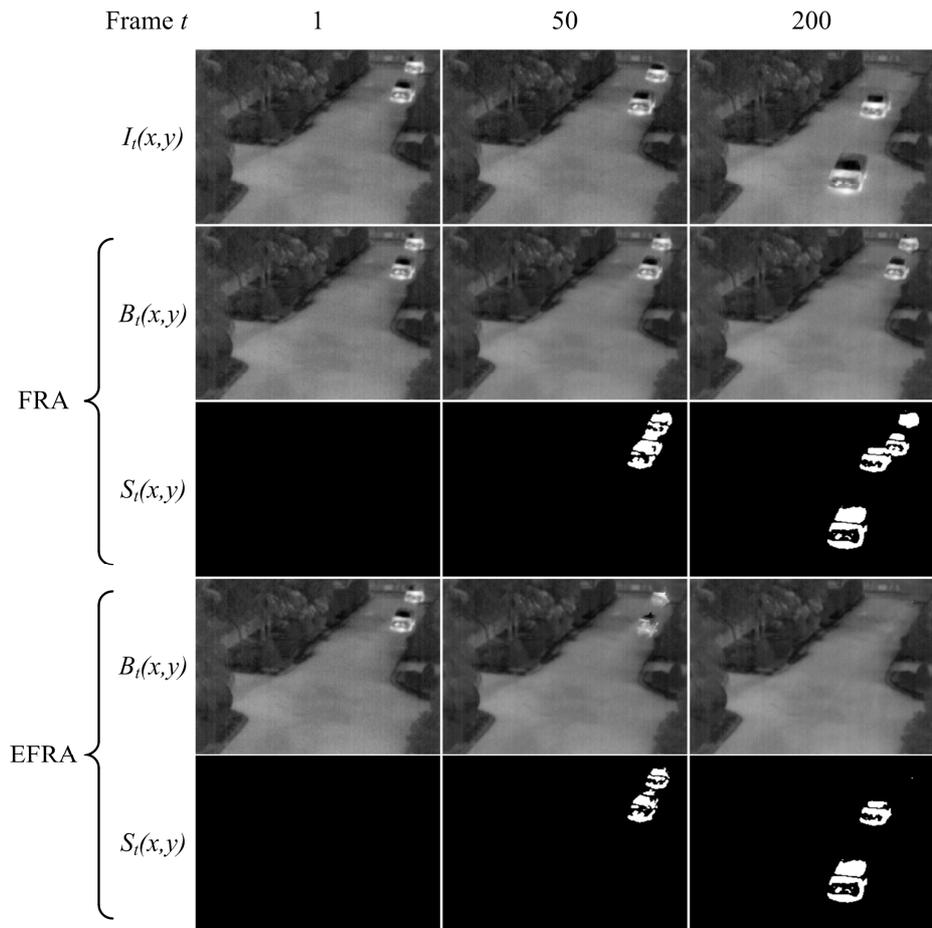


Fig. 2. Background Model and Background Subtraction with FRA and EFRA

4 Conclusion

Standard Running Average (SRA) is a simple and fast method for background modeling. Fuzzy Running Average (FRA) improves SRA selectivity for updating the referenced image frame, which is called background image. But, FRA is slow in background restoration, when a static object becomes dynamic. In this paper, the problem is overcome with an Extended Fuzzy Running Average (EFRA). EFRA not only retains the benefit of FRA on the selectivity, but also speeds up the background restoration. The generated background enables more accurate moving object detection.