Novel Thresholding Algorithm for Change Detection in Video Sequence

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SUMMARY A novel thresholding algorithm for change detection in video sequences is proposed. The method is based on image differencing and the intensity distribution of a difference image. With a difference image between two consecutive images, we prepare a new image model for the distribution of stationary pixels. The distribution of moving pixels is then separated by extracting the distribution of stationary pixels from the overall distribution of the difference image. Pixels that exhibit a significant change in intensity are classified using a likelihood criterion. The proposed algorithm is tested on the standard MPEG sequences and verified to have reliable performance.

key words: image difference, change detection, adaptive thresholding, image model

1. Introduction

In various video processing and computer vision applications, change detection techniques based on frame differences are widely used for motion estimation and video compression due to simplicity. Difference values are computed for corresponding pixels between two consecutive frames. Pixels that have large values in a difference map are then labeled as representing a changed region. Otherwise, they are assigned to a stationary region.

To partition the difference map into changed and unchanged regions, we consider an adaptive thresholding scheme for selection of proper threshold values. The size and the shape of the moving part of an object can be dramatically changed based on these threshold values. Therefore, it is important to select proper threshold values for detection of the changed region for each frame.

Many change detection algorithms focus on selection of proper thresholds for extraction of the changed region based on object motion[1]–[6]. The best threshold values based on absolute pixel frame difference values are then determined experimentally[1]. More systematic schemes for automatic threshold selection have also been reported[2]–[6]. They used suitable image models for a difference image assuming for a stationary background or a moving (or changed) region. Park and Hush proposed a statistical method assuming a Gaussian distribution[2]. Several methods based on either spatial or intensity distribution characteristics have been suggested by Rosin and Ellis[3],[6] using a Gaussian distribution for modeling a frame difference intensity signal. The spatial properties of noise are modeled with a Poisson distribution. In [4], a probabilistic model of the displacement frame difference (dfd) within a region based on symmetric alpha-stable distribution was suggested. This model was set to detect outliers after global or local motion compensation. Nariman et al. provided a difference approach based on three Gaussian distributions[5] assuming that a histogram generated from the intensity difference between two successive frames contains three values combined with an additive Gaussian noise. The drawback of this method is a requirement for extensive computation because of a fitting procedure to search for suitable Gaussian parameters.

Based on the motions of the background and objects, video sequences can be categorized into two classes as follows: 1) moving background and moving objects and 2) stationary background and moving objects. In the cases including the motion of a tracking camera, the changed regions or moving edges are generated at the entire difference image. If we assume that object’s motion is continuous throughout the frames, then the stationary region occupies the most of the difference image. For obtaining the changed region in the difference image, we should determine proper tail regions (relatively large responses) of the histogram of the difference image. In the general video object tracking system, all moving regions in the image frame must be efficiently separated to analyze the motion of regions in the time domain.

For the second case of sequence, the change detection techniques are very useful to identify an object or object regions since the background is stationary. To extract the changed regions from the frame difference image, it is necessary to classify the pixels having large difference values, too. In this paper, we deal with a new change detection algorithm that is valuable to both the video sequences of the moving background/moving objects and the stationary background/moving objects.

We investigate an optimum change detection algorithm based on frame difference and a new image model of the intensity distribution of the stationary region without any motion compensation. Using the proposed image model of the stationary region, the changed regions or moving edges are adaptively separated in the frame difference image.

2. The Proposed Algorithm for Change Detection

Many kinds of scene change detection algorithms that use
a frame difference image have used the absolute difference between corresponding pixels to generate a frame difference image. We use the signed difference values between corresponding pixels to construct the frame difference image.

With the generated frame difference image, we can deduce the probability distribution of the signed difference value in a manner similar to the gray level histogram. The probability distribution of the signed difference value can be characterized as having a zero mean and variation of the signed difference value in both tails (positive and negative directions) if the motion of the regions is continuous between the successive frames. This means that the stationary part of a given frame difference image is dominant and concentrates near zero value in the frame difference image.

2.1 Statistical Image Model for Stationary Region

Usually, the overall probability distribution contains the distributions of the stationary part and moving part in the frame difference image. Let \( x \) be a signed difference value in the frame difference image. If \( p_0(x) \) is the overall probability distribution, then \( p_0(x) \) can be written as:

\[
p_0(x) = p_M(x) + p_S(x),
\]

where \( p_M(x) \) is the probability distribution of the moving part and \( p_S(x) \) is that of the stationary part. In Eq. (1), we can determine the probability distribution of the corresponding part if either the probability distribution of the moving part or the probability distribution of the stationary part is first computed. We assume that the probability distribution of the stationary part follows an asymmetric Laplacian distribution as follows:

\[
p_S(x) = \begin{cases} \frac{\alpha}{2} e^{\frac{x - E[X]}{\beta^S}}, & x \leq m, \\ \frac{\alpha}{2} e^{-\frac{x - E[X]}{\beta^S}}, & x > m, \end{cases}
\]

where \( E[X] = m \) (the maximum peak value) and \( Var[X] = \frac{\alpha}{a} \). To minimize the modeling error, it is requested to optimize the slope parameters \( \beta^S_{left} \) and \( \beta^S_{right} \), respectively. We optimize the slope parameters by employing the steepest descent method with the following error function and updating equation:

\[E^k(n) = \frac{1}{2} \sum_{x \in [a, b]} |p_0(x) - p_S(x)|^2 \]

\[
\beta_0^S \text{(or right)} = \alpha \text{ (Initial conditions)},
\]

\[
\beta_{k+1}^S \text{(or right)} = \beta_k^S \text{(or right)} + \eta \nabla \beta_k^S \text{(or right)},
\]

where \( k \) is iteration time, \( p_0(x) \) is the overall or real probability density function, \( p_S(x) \) is the modeled probability density function of the stationary part, \( \eta \) is the step size or learning rate and \( \nabla \beta_1^S \text{(or right)} = \frac{\partial E}{\partial \beta_1^S \text{(or right)}} \) in the modeling interval \( [a, b] \). The iteration stops when \( |E^{k+1}(n) - E^k(n)| < \varepsilon \), where \( \varepsilon \) is a small positive real number.

We constrained the difference values as \( a = p(0.01m) \) and \( b = p(m) \) to give the learning samples. As shown in the above, the error was defined as \( |p_0(x)_{\in [a,b]} - p_S(x)_{\in [a,b]}|^2 \).

That is, data samples within \( [a, b] \) are employed to fit the true probability distribution. The number of iterations for optimization of slope parameters was within 10 iterations for each parameter in this study. If \( \beta^S_{left} = \beta^S_{right} \), Eq. (2) becomes a symmetric Laplacian distribution.

2.2 Optimum Threshold Values for Change Detection

The probability distribution of the changed intensity part can be easily separated from the overall distribution by using the modeled distribution of the stationary region because the overall distribution is composed of the sum of the probability distributions of the stationary and the changed part as expressed in Eq. (1). Let \( p_M(x) \) be the separated distribution for the moving part. Then, the probability distribution function of the changed part can be given as

\[
p_M(x) = p_O(x) - p_S(x).
\]

After separating the distributions, it is easy to select the optimal threshold to analyze the foreground moving part. Let \( T_{opt} \) be the optimum threshold values of the positive gray level and the negative gray level, respectively, to distinguish between two classes. \( T_{opt} \) can be selected by the following likelihood criterion:

\[
T_{pos \ (or \ neg)}^{opt} = \text{Arg}_{x \in [-L_{limit}, L_{limit}]} \{p_M(x) = p_S(x)\},
\]

where \( [-L_{limit}, L_{limit}] \) is the range which the signed gray levels exist.

With two optimal values, \( T_{pos}^{opt} \) and \( T_{neg}^{opt} \), a pixel which has a gray level \( x \) in the signed frame difference is classified into a stationary or changed partition as following:

\[
c(m, n) = \begin{cases} 1, & \text{if } x \geq T_{pos}^{opt} \lor x \leq T_{neg}^{opt}, \\ 0, & \text{otherwise}, \end{cases}
\]

where \( (m, n) \) denotes a pixel position in the image plane and \( x \) is a signed difference value of its position. Also, 1 denotes the moving region and 0 denotes the stationary region, respectively.

3. Simulation Results

To demonstrate the performance of change detection from the frame difference image, the Foreman, Tabletennis, Susi, Akiyo and Football sequences were tested using the proposed scheme.

3.1 Statistical Probability Model for Frame Difference Image

Results of the segmented distributions by using the proposed statistical probability model of a signed frame difference in the Foreman and Susi sequences are shown in Figs. 1 and 2. Optimum threshold values were determined as \( T_{neg}^{opt} = -20 \) and \( T_{pos}^{opt} = 18 \) with computed \( \beta^S_{left} = 0.19709 \).
and $\beta_{\text{right}} = 0.20824$ for the Foreman difference image. Figure 2 displays the modeled results of the frame difference image between frame 2 and frame 3 in the Susi sequence. In this case, $T_{\text{neg}}^{\text{opt}} = -16$ and $T_{\text{pos}}^{\text{opt}} = 18$.

### 3.2 Detection of Changed Region

Figures 3 through 7 illustrate results of change detection by the proposed method and some other methods [5], [6]. Figures 3 (d), (e) and (f) are the detection results of the frame difference image between frame 5 and frame 6 in the Foreman sequence by the Gaussian noise model with the error probability $P_F = 0.01$ [6], Nariman’s model [5] and the proposed distribution model, respectively. We can see that the proposed algorithm yields a better visual result in comparison with the frame difference image.

Similarly, the result of the proposed change detection method in the Tabletennis is more reliable than the results for other methods (Fig. 4) for the Gaussian noise model with the error probability $P_F = 0.01$ (Fig. 4 (d)), Nariman’s model (Fig. 4 (e)) and the proposed model (Fig. 4 (f)). In this result, it seems that the method using the Gaussian noise model gives very small detected region, visually. But, the proposed algorithm provides a credible region for change detection and has reliability to detect the changed region.

Figures 5, 6 and 7 show the change detection results for the Football, Akiyo and Susi sequences. Moving objects with fast motion are contained in the Football sequence. Therefore, there exists a large changed region in the frame difference image. Unlike this, the Akiyo and Susi sequences have small change between two successive frames. As shown in the results, we can make out that the proposed algorithm (Figs. 6 (d) and 7 (d)) gives better results for change detection in comparison with the results of others (Figs. 6 (b) ~ (c) and 7 (b) ~ (c)).

To analyze the detection performance quantitatively, our algorithm is compared with others [5], [6]. We measure the total variance (intra-class variance) to do this as following:

$$v = v_s + v_m,$$

where $v_s$ and $v_m$ denote the variances of the separated stationary region and moving region, respectively. Smaller values of $v$ result in better detection from the viewpoint of image thresholding.

Table 1 displays the total variance for change detection methods. From this result, it can be seen that the proposed change detection method gives more credible results than others.
Fig. 3 The detection results of the changed region in the *Foreman* sequence by the proposed algorithm: (f) and other methods [5]: (d), [6]: (e).

Table 1 Performance comparison: Total variance (intra-class variance).

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<tr>
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<tbody>
<tr>
<td>Foreman</td>
<td>7.232</td>
<td>5.629</td>
<td>3.550</td>
</tr>
<tr>
<td>Tabletennis</td>
<td>9.213</td>
<td>8.482</td>
<td>7.356</td>
</tr>
<tr>
<td>Football</td>
<td>10.254</td>
<td>9.688</td>
<td>7.077</td>
</tr>
<tr>
<td>Susi</td>
<td>2.566</td>
<td>2.207</td>
<td>2.140</td>
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4. Conclusion

In this paper, the optimal scene change detection algorithm is provided to generate the change detection mask from the frame difference image. In most sequences, the stationary part is dominant in the frame difference image. Under this fact, a new probability model for the stationary part is set as an asymmetric Laplacian model to separate the moving part. Based on a new image model of the stationary part, the threshold values are optimally selected by the likelihood criterion.

To validate the algorithm performance for detecting the changed region, a comparative analysis was performed. Results of the proposed algorithm were very reliable in the standard tested sequences.
Fig. 6  The detection results of the changed region between frames 27 and 28 in the Akiyo sequence by the proposed algorithm: (f) and other methods [5]: (d), [6]: (e).

Fig. 7  The detection results of the changed region between frames 3 and 4 in the Susi sequence by the proposed algorithm: (f) and other methods [5]: (d), [6]: (e).

References