A COLOR-BASED GRAY-LEVEL COMPENSATION ALGORITHM FOR FAST CHANGE DETECTION

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ABSTRACT

Gray-level based change detection is effective but suffers when gray-levels of objects are similar to backgrounds. A color-based gray-level compensation algorithm for fast change detection is proposed in this paper. Based on the object scatter estimation in difference frames, the gray-levels of the non-significant pixels in object regions are compensated according to their significance probabilities in color channels. Experimental results show that the proposed method significantly improve the quality of difference frames.

***Index Terms*—** Image processing, image segmentation, object detection, image color analysis

1. INTRODUCTION

Change detection (CD) is widely used in video processing. It can be used to segment objects [1] to reduce noise [2] or to compress videos [3]. Gray-level based CD is popular due to its efficiency, but it suffers when the foreground (objects) has similar gray-levels as the background. For accurate CD, color becomes more and more used [4, 5, 6, 7]. However, color-based CD methods are, in general, computational expensive. Most color-based CD are statistical based.

Durucan *et al.* [4] detect moving objects based on color Gramian matrix, yet the Gramian-matrix based method is computationally expensive and sensitive to artifacts. Stefano *et al.* [5] propose a content-adaptive CD using image structure and color. Since a hierarchical CD method is applied in all color channels, the method is computationally expensive, and any failures of CD in a color channel may affect the final output. Hwang *et al.* [6] model the noise in color channels as a generalized exponential model (GEM), then they deduce a statistical model of the Euclidean distance for unchanged regions in a video. Change detection is performed based on an energy minimization graph cuts methods. The method is also computational expensive due to considerable iterative computation in image spaces. Although Alexandropoulos *et al.* [7] propose a statistic-based CD method for real-time applications, the method is based on RGB color model, which does not perform well for CD [8].

In this paper, we propose a color-based gray-level compensation algorithm for fast CD using the YUV color model that overcome the difficulties of both the gray-level based CD (accuracy) and the color-based CD (efficiency). Section 2 describes the proposed algorithm. Experimental results are given in Section 3, and Section 4 concludes this paper.

This work is supported, in part, by the Natural Science and Engineering Research Council (NSERC) of Canada.

2. PROPOSED ALGORITHM

The proposed algorithm is based on the observation that a recognizable object in a color video sequence is different from the background in at least one of the color channels Y, U, and V. The YUV color model is applied for effective CD [8]. Fig.1 shows the block diagram of the proposed algorithm. First, three difference frames D_n^Y, D_n^U and D_n^V are obtained by CD (e.g., [1]) between the current frame F_n at time instant n and its reference frame R_n in the Y, U and V channels, respectively. Second, a regions of change (ROC) scatter estimation method [9] is applied to D_n^Y to indicate the blocks in D_n^Y that contain ROC. (The ROC scatter estimation is based on the first moment of block histogram.) Then, based on the statistical model of the gray-level distribution of D_n^Y under no-change hypothesis $\mathcal{H}_0$, a pixel-based significance test (Sec.2.2) is used to test if a pixel $\mathbf{i}$ in ROC blocks is significantly different from background in D_n^Y. Based on the significance test with a statistical model of the maximum-intensity (MI) distribution between D_n^U and D_n^V under $\mathcal{H}_0$ (Sec.2.1), a gray-level compensation algorithm (Sec.2.3) is applied to the pixels which are non-significant in ROC blocks of D_n^Y but significant in D_n^U or D_n^V to generate gray-level compensated difference frame $D_n^{Y_c}$.

As shown in [10], the gray-level distribution of D_n^Y under $\mathcal{H}_0$ can be modeled as a Gaussian random variable (RV) Y with zero mean and variance $2\sigma_\nu^2$ due to frame differencing followed by taking absolute value, where σ_ν^2 is the noise variance in F_n. The pdf of Y is then,

$$Y \sim 2N(0, 2\sigma_\nu^2), \quad Y \geq 0. \tag{1}$$

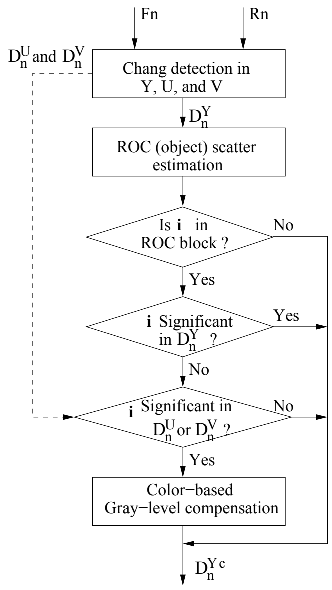


Fig. 1. Block diagram of the proposed algorithm.

2.1. Maximum-intensity (MI) modeling in D_n^U and D_n^V

To avoid including the artifacts in color channels into the final difference frames, we take not only noise but also global (e.g., illumination changes) and local (e.g., shadows) artifacts into account when modeling the MI distributions between D_n^U and D_n^V under $\mathcal{H}_0$. First, we model the color intensity distribution in D_n^U and D_n^V under $\mathcal{H}_0$. Note that only positive values in D_n^U and D_n^V due to frame differencing followed by taking absolute value. For precise significance-test, the tail sections of the models must be consistent with the intensity distribution of D_n^U and D_n^V under $\mathcal{H}_0$. In this paper, we model the intensity distributions of D_n^U and D_n^V under $\mathcal{H}_0$ as two exponential RVs U and V, respectively, i.e.,

$$\begin{array}{rcl} U & \sim & \lambda_u e^{-\lambda_u u} \\ V & \sim & \lambda_v e^{-\lambda_v v}, \end{array} \tag{2}$$

where λ_u and λ_v are the mean of the U and V, respectively. Fig.2 shows an example of intensity modeling in D_n^U and D_n^V under $\mathcal{H}_0$. As can be seen, the tail sections of the exponential models are more consistent with the real intensity distribution than the Gaussian models does under $\mathcal{H}_0$.

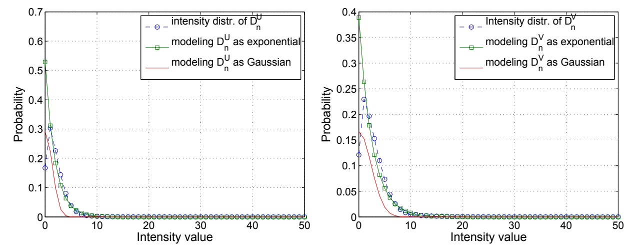
Let $Z = \max(U, V)$, then under $\mathcal{H}_0$, the cumulative distribution function (cdf) of Z is

$$\begin{array}{rcl} F_Z(z|\mathcal{H}_0) & = & P[Z \leq z|\mathcal{H}_0] \\ & = & P[\max(U,V) \leq z|\mathcal{H}_0]. \end{array} \tag{3}$$

Since U and V are independent, and $Z \geq 0$, we have

$$\begin{array}{rcl} F_Z(z|\mathcal{H}_0) & = & \iint\limits_{D(z)} p_U(u) p_V(v)\, du dv \\ & = & 1 - e^{-\lambda_u z} - e^{-\lambda_v z} + e^{-(\lambda_u+\lambda_v)z}, \end{array} \tag{4}$$

where $p_U(u)$ and $p_V(v)$ are pdf of U and V shown in (2), and $D(z)$ are integral region for the function $\max(U, V)$.



(a) Modeling in D_n^U (b) Modeling in D_n^V

Fig. 2. Intensity modeling under $\mathcal{H}_0$ (video "Hall").

2.2. Significance test

Significance test is firstly performed in the ROC blocks of D_n^Y. We regard a pixel $\mathbf{i}$ in D_n^Y with gray-level $g_\mathbf{i}$ a significant pixel if $g_\mathbf{i}$ is high probable greater than Y, i.e.,

$$P[Y \leq g_\mathbf{i}|\mathcal{H}_0] > p_h, \tag{5}$$

where p_h is a high probability. From (1), we get

$$P[Y \leq g_\mathbf{i}|\mathcal{H}_0] = \int_0^{g_\mathbf{i}} \frac{1}{\sqrt{2\pi}\sqrt{2}\sigma_\nu} e^{-\frac{y^2}{4\sigma_\nu^2}}\, dy < \frac{p_h}{2}. \tag{6}$$

(6) gives

$$Q\left(\frac{g_\mathbf{i}}{\sqrt{2}\sigma_\nu}\right) < \left(0.5 - \frac{p_h}{2}\right), \tag{7}$$

where $Q(\cdot) = 1 - \Phi(\cdot)$, and $\Phi(\cdot)$ is the standard Gaussian cdf. We can determine if $\mathbf{i}$ is significant by testing if $g_\mathbf{i}$ satisfies (7), e.g., for $p_h = 0.9975$, (7) gives that $\mathbf{i}$ is significant if $g_\mathbf{i} > 4.27\sigma_\nu$. (In this paper, σ_ν is estimated by the noise estimation method in [11].)

Similarly, significance test in D_n^U and D_n^V is performed by testing if $s_\mathbf{i} = \max(D_n^U(\mathbf{i}), D_n^V(\mathbf{i}))$ is high probable greater than Z, i.e.,

$$P[Z \leq s_\mathbf{i}|\mathcal{H}_0] > p_h. \tag{8}$$

From (4), we can determine if pixel $\mathbf{i}$ is significant in color channels by testing if (9) is satisfied.

$$e^{-\lambda_u s_\mathbf{i}} + e^{-\lambda_v s_\mathbf{i}} - e^{-(\lambda_u+\lambda_v)s_\mathbf{i}} < (1 - p_h). \tag{9}$$

2.3. Gray-level compensation

The pixels which are non-significant in ROC blocks of D_n^Y but significant in D_n^U and D_n^V, in general, belong to objects yet have similar gray-levels with background. We compensate the gray-levels of those pixels based on their significance probabilities p_s in color channels, where p_s is

$$p_s = F_Z(s_\mathbf{i}|\mathcal{H}_0), \tag{10}$$

and $s_\mathbf{i} = \max(D_n^U(\mathbf{i}), D_n^V(\mathbf{i}))$. Thus, we compensate the gray-level $g_\mathbf{i}$ of a pixel $\mathbf{i}$ using

$$g_\mathbf{i}^c = g_\mathbf{i} + a_c \times G_s, \tag{11}$$

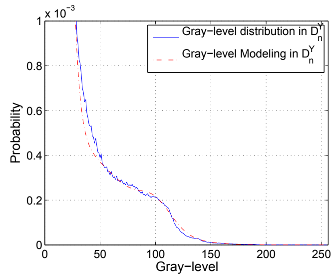


Fig. 3. Gray-level distribution modeling for D_n^Y.

where a_c is a compensation coefficient that is determined by p_s, G_s is the gray-level that a significant pixel may have in D_n^Y, $g_{\mathbf{i}}^c$ is the compensated gray-level of **i**, and $g_{\mathbf{i}}$ is the original gray-level of **i** in D_n^Y. In this paper, we use a quadratic function to compute a_c as

$$a_c = \left(\frac{p_s - p_h}{1 - p_h}\right)^2. \qquad (12)$$

We can see in (12), the more significant a pixel in color channels is, the higher the p_s is, thus the higher the a_c is.

The value of G_s is estimated by the statistical model of the gray-level distribution of D_n^Y under change hypothesis $\mathcal{H}_1$. Ten real-world videos with different contents and different noise levels are used to statistically model the gray-level distribution of D_n^Y under $\mathcal{H}_1$. Fig.3 shows the modeling result. As can be seen, the significant changes in D_n^Y can be modeled as a Gaussian RV with pdf $N(100, 15^2)$. We then obtain $58 \leq G_s \leq 142$ with the false alarm 0.0025. In this paper, we set $G_s = 93$.

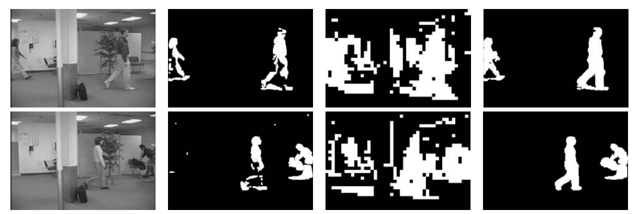
Using the proposed gray-level compensation, *weak* differences (or changes) in D_n^Y that are caused by objects having similar gray-levels as the background are converted (compensated) to *strong* changes while *weak* changes caused by artifacts (e.g., shadows) are not. Thus the proposed algorithm compensates weak changes only inside object regions. These regions are estimated by the region scatter estimation [9] which is perfromed on difference frames $\{D_n^Y\}$.

3. EXPERIMENTAL RESULTS

The evaluation is performed by applying the gray-level based CD method in [1] with and without the proposed gray-level compensation algorithm to five real-world videos containing different contents. We apply the proposed method for CD to segment moving objects (change masks) from stationary background. To this end, we binarize $D_n^{Y_c}$ using [9] to obtain binary frames $\{B_n\}$. Alexandropoulos *et al.*'s color-based CD method [7], which is proposed for real-time surveillance applications, is also used in our simulations as a reference method. We used a background frame as R_n (see Fig.1).

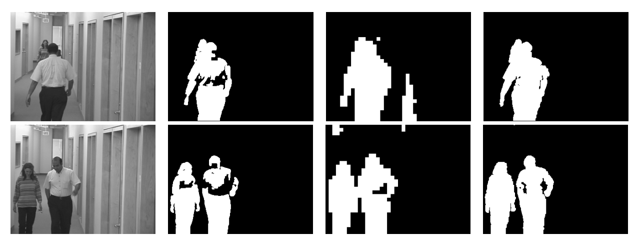
Sample results are shown for indoor "Ekrlb" (678 frames of size 360×244), "2Meet" (691 frames of size 320×240), and "Putobj" (655 frames of size 320×240), and outdoor "Road" (300 frames of size 352×288), and "Vnj" (293 frames of size 360×244). The test videos used in simulations are different from the training videos used for modeling the gray-level distribution of D_n^Y under $\mathcal{H}_1$ in Sec.2.3.

Fig.4 and Fig.5 show the superiority of the proposed method. The CD in [1] fails to detect changes for many frames of "Ekrlb" and "2Meet" due to the similarities between objects and background in gray-level. The CD in [7] is sensitive to local changes (e.g., shadows). The [1] CD with the proposed method get clear and stable change masks. In Fig.6, the [1] CD loses the box in the lady's hand, and mistakenly divides an object into parts. The [7] CD suffers due to shadows. The [1] CD with the proposed algorithm accurately detects all objects and generates complete change masks.



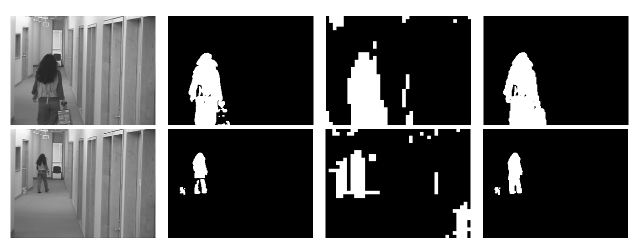
(a) (b) (c) (d)

Fig. 4. "Ekrlb": (a) original F_{82} and F_{302}, (b) - (d) masks of [1], [7], and the [1] CD with prop. algorithm.



(a) (b) (c) (d)

Fig. 5. "2Meet": (a) F_{231} and F_{473}, (b) - (d) masks of [1], [7], and [1] CD with the prop. algorithm.

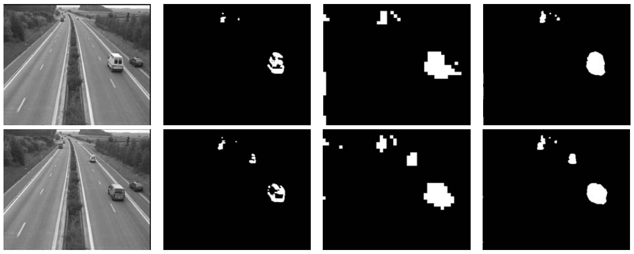


(a) (b) (c) (d)

Fig. 6. "Putobj": (a)F_{140} and F_{474}, (b) - (d) masks of [1], [7], and [1] CD with the prop. algorithm.

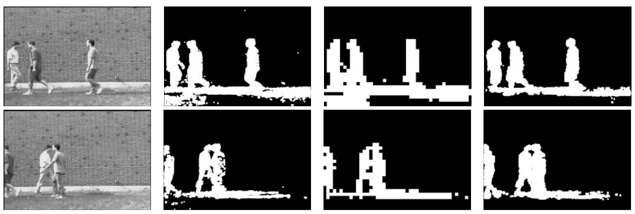
As shown in Fig.7 and Fig.8, the [1] CD includes considerable gaps and holes into change masks due to the similarities between objects and background in gray-level. The

[7] CD is sensitive to local changes, e.g., shadows and partial background movement. The proposed algorithm significantly improve the performance of the [1] CD.



(a) (b) (c) (d)

Fig. 7. "Road": (a) F_{115} and F_{145}, (b) - (d) masks of [1], [7], and [1] CD with the prop. algorithm.



(a) (b) (b) (c)

Fig. 8. "Vnj": (a) F_{184} and F_{208}, (b) - (d) masks of [1], [7], and [1] CD with the prop. algorithm.

Without performing complex CD in all color channels of a video, the proposed method improves the quality of gray-level CD while it slightly increase the computation time. Under Linux OS using C++, the average computation time of the [1] CD with and without the proposed algorithm for CIF videos is 0.0483s and 0.0456s per frame (including thresholding), respectively. The method in [7] requires 0.0518s per frame.

4. CONCLUSION

A color-based gray-level compensation algorithm is proposed for fast change detection in this paper using the YUV color model. Under no-change hypothesis, the gray-level distribution of Y channel and the maximum-intensity distribution in U and V channels are statistically modeled. Based on the estimation of object-regions, pixel-based significance tests are performed in Y, U and V channels using the statistical models. The gray-levels of non-significant pixels belonging to object-regions are compensated based on their significance probability if they are significant in color channels. Experimental results show that the proposed algorithm can significantly improve the quality of difference frames without significantly increasing the computation time.

This study shows that color information significantly improves the change detection in cases where objects have similar gray-levels as the background. It also shows that complex operations are not necessarily need to be performed in all color channels when using color information in video processing.

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