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Adaptive Background Subtraction Algorithm with Auto Brightness Control for Consumer-type Cameras

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Abstract

This paper presents a new auto brightness control algorithm for adaptive background subtraction. The algorithm is designed to cope with the problem of auto-brightness adjustment feature of consumer-type cameras. The experimental results show the proposed method improves performance of the classification. This will be beneficial to many computer vision applications in term of reducing the cost of implementation and making them more available to the mass consumer market.

Keywords : background modeling, segmentation, brightness control, adaptive system

I. INTRODUCTION

Many vision-based object detection and tracking systems rely on the process of background subtraction which is a technique that detect changes from a learned model of the background scene. By comparing incoming images to a reference background image, the regions of moving pixels in the scene are located.

In many years of background subtraction researches, uni-modal distribution approaches [1,2,3] play a significant role in background modeling scheme and give satisfactory classification rate as shown in [4]. However, these methods do not work well where there are changes in background, i.e., dynamic background. There are four main problems in basic background subtraction algorithm: moving shadow, illumination changes, object relocation, and repetitive background changes. All of those can be defined as "dynamic background." Many of improvements have been established, e.g., [5] which is based on MOG model originally presented in [6]. MOG assertively presents solution for several problems occurred in dynamic background, especially in case of repetitive background motion such as waving trees. Each Gaussian background adaptively refers to real background event. Nevertheless, this and almost other algorithms update each background parameter linearly. There is no learning factor control that is corresponding to the event in the background scene.

Another issue in the current background subtraction techniques is that most algorithms require high-quality professional video cameras of which their parameters can be set and controlled, especially parameters that control the overall brightness of the images. With fixed parameters, the illumination change detected in the scene means only environment has been changed. That simplifies the problem. However, typical consumer-type cameras are

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different. Most of manufacturers develop built-in auto white balance and auto brightness control features to make the cameras easy to use to the consumers. This type of cameras focuses on foreground subjects and adjusts parameters for best foreground quality; ignoring changes in background [7].

Adaptive background subtraction algorithms detect targets by looking for changes in sequence comparing to the background model. Effective systems can adaptively update the brightness of the background model corresponding to brightness changes in the environment. Unfortunately, by using the consumer-type cameras, the detected brightness changes come from two sources. First, environment luminance has been changed. Secondly, the perceived brightness changes are from camera's auto adjustment. This causes a problem for existing background subtraction algorithms; the systems tend to classify erroneously. Moreover, the adaptive algorithms cannot update the background model correctly due to the combined effects of illumination changes. In this paper, we present an adaptive brightness control algorithm designed to compensate brightness changes due to the auto brightness adjustment in consumer-type cameras. The success of this work will be beneficial to many computer vision applications such as security and surveillance systems, video conferencing systems, interactive systems for entertainment, etc. The proposed algorithm will help the application developers to be able to build such systems with more cost-effective solutions. Rather then requiring expensive professional cameras, they can use the reasonableconsumer-type cameras. This could significantly reduce the cost of the systems, and make the systems more affordable to general users in the mass market.

This paper addresses two issues mentioned above: the adaptive background model and auto brightness control in consumer-type cameras. We propose a novel method in updating the background model as well as a technique for coping with camera auto-brightness adjustment.

Ⅱ. ADAPTIVE BACKGROUND SUBTRACTION ALGORITHM

This section presents our proposed adaptive background subtraction algorithm. As mentioned in [8], background model is converted to YCbCr color space and integrated with proposed auto brightness control algorithm, later proposed in Section Ⅲ.

1. Background Model Initialization

First, considering YCbCr color pixels from video sequence. Let $x_{i,j} = \{X_{i,j}[1], X_{i,j}[2], \ldots, X_{i,j}[N]\}$ be a training sequence of single pixel consisting of N frame. A color vector at the pixel of the nth frame is depicted as in eq. (1),

$$\mathbf{X}_{i,j}[n] = (X^{Y}_{i,j}[n], X^{Cb}_{i,j}[n], X^{Cr}_{i,j}[n]) \qquad (1)$$

,where $X^{Y}_{i,j}[n]$, $X^{Cb}_{i,j}[n], X^{Cr}_{i,j}[n]$ are Y, Cb, Cr components at pixel (i,j) of the n^{th} frame. Assuming Gaussian noise is incurred in the sampling process. The recent history of each pixel, $x_{i,j}$, is modeled by Gaussian distribution centered at the mean pixel value. This process is a stationary background modeling process in which we collect N frames of "empty" scene. So we obtain N color vectors for each pixel. Naturally, we obtain two significant parameters automatically. The first one is "Expected Color Vector,"as in eq. (2),

$$\mathbf{E}_{i,j} = E\{\mathbf{X}_{i,j}[n]\}\ ;\ 1 \le n \le N \qquad (2)$$

where $E\{.\}$ is expectation operation. So, $E_{i,j}(E^Y_{i,j}, E^{Cb}_{i,j}, E^{Cr}_{i,j})$ represents mean of color vectors at pixel (i,j) over N frames. The latter is "Color Covariance Matrix". The covariance matrix, Ci,j, is assumed to be diagonal to reduce computational cost, and can be written as in eq. (3).

$$\mathbf{C}_{i,j} = \mathbf{I}[(\sigma^Y_{i,j})^2 \quad (\sigma^{Cb}_{i,j})^2 \quad (\sigma^{Cr}_{i,j})^2] \tag{3}$$

Next, we compute the distortion of $X_{i,j}[n]$ from its mean, $E_{i,j}$, by considering two orthogonal distortion parameters, "Brightness Distortion" ($\alpha_{i,j}[n]$) and "Color Distortion"($\lambda_{i,j}[n]$).

Brightness distortion implies the brightness intensity of input color vector, $X_{i,j}[n]$, with respect to the expected color vector, $E_{i,j}$, and can be obtained as in eq. (4).

$$\alpha_{i,j}[n] = (\mathbf{X}_{i,j}[n] - \mathbf{E}_{i,j}) \bullet \mathbf{u}_{\mathbf{Y}} \tag{4}$$

Then, simplified and normalized, we get

$$\alpha_{i,j}[n] = \frac{X^Y_{i,j}[n] - E^Y_{i,j}}{\sigma^Y_{i,j}} \tag{5}$$

On the other hand, color distortion isdefined as the orthogonal distance between input color vector and the reference expected color vector, and is given in eqs. (6)-(7). The illustration of background subtraction model is shown in Fig. 1.

$$\lambda_{i,j}[n] = \left\| (\mathbf{X}_{i,j}[n] - \mathbf{E}_{i,j}) - \alpha_{i,j}[n]\mathbf{u}_{\mathbf{Y}} \right\| \tag{6}$$

$$\lambda_{i,j}[n] = \sqrt{\left(\frac{X^{Cb}_{i,j}[n] - E^{Cb}_{i,j}}{\sigma^{Cb}_{i,j}}\right)^2 + \left(\frac{X^{Cr}_{i,j}[n] - E^{Cr}_{i,j}}{\sigma^{Cr}_{i,j}}\right)^2} \tag{7}$$

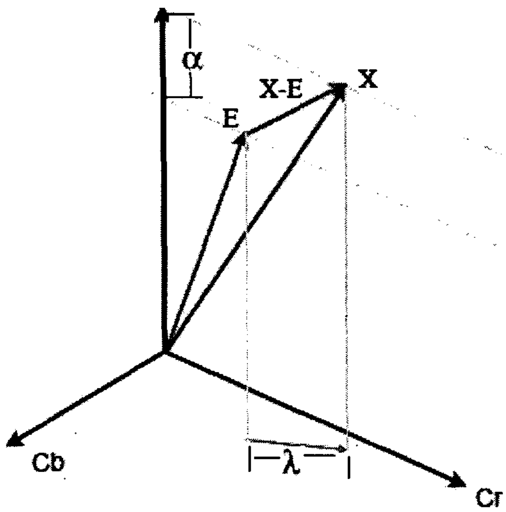

Fig. 1. Background subtraction model

As shown in [3], there are variations of $\alpha_{i,j}[n]$ and $\lambda_{i,j}[n]$; and their values are different for different pixels. Thus, to optimize the detection process, we compute two variation parameters: one represents the variation of brightness distortion ($a_{i,j}$) and another one represents the variation of color distortion ($b_{i,j}$), as defined respectively in eqs. (8) and (9).

$$a_{i,j} = RMS(\alpha_{i,j}[n]) = \sqrt{\frac{\sum_{n=1}^{N}(\alpha_{i,j}[n])^2}{N}} \tag{8}$$

$$b_{i,j} = RMS(\lambda_{i,j}[n]) = \sqrt{\frac{\sum_{n=1}^{N}(\lambda_{i,j}[n])^2}{N}} \tag{9}$$

Then, the initial background model is represented by a "four-tuple" statistical parameters $\Phi_{i,j} = \langle \mathbf{E}_{i,j}, \mathbf{C}_{i,j}, a_{i,j}, b_{i,j} \rangle$ for each pixel (i,j).

This background model will be used as an initial model for subtraction. To make the algorithm be able to cope with changes in dynamic scene, adaptive background model update is needed.

2. Adaptive Background Model

After initialization, system starts online processing by using set of static background parameters as seed of adaptation (n=1). To deal with changes in the dynamic scene, we update the background model continuously while performing the subtraction. The 4-tuple dynamic model $\Phi_{i,j}[n] = \langle \mathbf{E}_{i,j}[n], \mathbf{C}_{i,j}[n], a_{i,j}[n], b_{i,j}[n] \rangle$ are constructed and linearly updated as in eqs. (10)-(13),

$$\mathbf{E}_{i,j}[n] = (1-\gamma)\mathbf{E}_{i,j}[n-1] + \gamma \mathbf{X}_{i,j}[n] \quad (10)$$

$$\mathbf{C}_{i,j}[n] = (1-\gamma)\mathbf{C}_{i,j}[n-1] + \gamma(\mathbf{X}_{i,j}[n] - \mathbf{E}_{i,j}[n])^T(\mathbf{X}_{i,j}[n] - \mathbf{E}_{i,j}[n]) \quad (11)$$

$$a_{i,j}[n] = \sqrt{(1-\gamma)(a_{i,j}[n-1])^2 + \gamma(\alpha_{i,j}[n])^2} \quad (12)$$

$$b_{i,j}[n] = \sqrt{(1-\gamma)(b_{i,j}[n-1])^2 + \gamma(\lambda_{i,j}[n])^2} \quad (13)$$

,where parameter γ can be interpreted as a "Learning factor". Thus, $1/\gamma$ effectively defines the time constant that implies speed of the model change or update.

3. Learning Factor Control

Background adaptation always operates when background area is changed, for example in Figure 2. When input color value $X_{i,j}[n]$ has been changed to new value $X_{i,j}[n] + \Delta$, an ideal expectation of color value should change abruptly as $Ideal\ E_{i,j}[n]$. In practical way, we decide to update each parameter by using linear adaptation. The learning factor (γ) mentioned in the previous section indicates speed of background model adaptation.

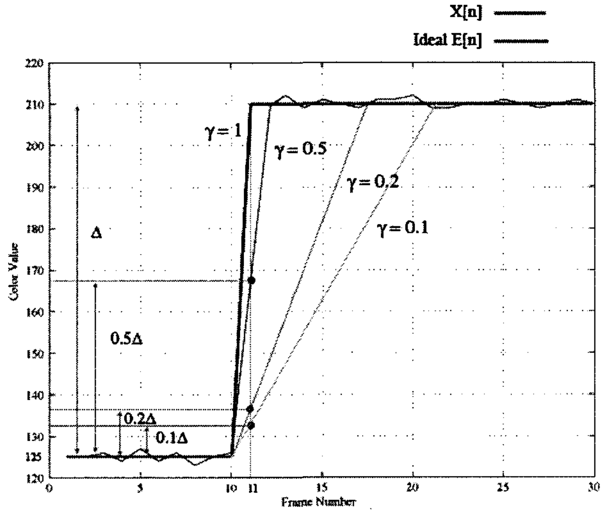

Fig. 2. Various rate of adaptation by varying learning factor

If the value of γ is large, the effect of the relocation of background objects (such as moving chair in the office scene) will be updated quickly. At the same time, the true background model might be rapidly lost in the area that has high frequency of moving foreground objects appearance as well as in the case of moving foreground objects become stationary for a period of time. As a result, we have to reduce speed of adaptation at pixels that represent high activity of foreground objects.

In this research, we control learning factor by determine High-rate factor δ_H and Low-rate Factor δ_L by using hypothesis : "The background at active pixel must be updated slower than one at inactive pixel." State of "active" and "inactive" can be defined by temporal change as in eq. (14).

$$\Delta_{i,j}[n] = \mathbf{X}_{i,j}[n] - \mathbf{X}_{i,j}[n-1] \quad (14)$$

Then, we build change notification mask $M_{i,j}^{CHN}[n]$ as in eq. (15),

$$M_{i,j}^{CHN}[n]=\begin{cases}0: \|\Delta_{i,j}[n]\| < \tau_{CHN}\\ 1: \|\Delta_{i,j}[n]\| \geq \tau_{CHN}\end{cases} \quad (15)$$

,where τ_{CHN} is change notification threshold. Pixel $P(i,j)$ is active when $M_{i,j}^{CHN}[n]=1$. Therefore, learning factor of each pixel must be assigned as eq. (16).

$$\gamma_{i,j}[n]=\begin{cases}\delta_H : M_{i,j}^{CHN}[n]=0\\ \delta_L : M_{i,j}^{CHN}[n]=1\end{cases} \quad (16)$$

4. Online Subtraction and Classification Process

This section describes real-time subtraction process and pixel classification. We start by initializing the online background model by the background model (its seed). For each input nth frame, we compute $\alpha_{i,j}[n]$ and $\lambda_{i,j}[n]$ using Eqs.(5) and (7), and normalize them by on-line background parameters as in eqs. (17) and (18).

$$\hat{\alpha}_{i,j}[n]=\frac{\alpha_{i,j}[n]}{a_{i,j}[n]} \quad (17)$$

$$\hat{\lambda}_{i,j}[n]=\frac{\lambda_{i,j}[n]}{b_{i,j}[n]} \quad (18)$$

Then, pixel mask $M_{i,j}[n]$ can be classified into 4 classes: B: Background, F: Foreground, S: Shadow, H: Highlight by these conditions, as in eq. (19),

$$M_{i,j}[n]=\begin{cases}F: \ \hat{\lambda}_{i,j}[n]>\tau_{\lambda} \ or \ \hat{\alpha}_{i,j}[n]<\tau_{\alpha lo}, else\\ B: \hat{\alpha}_{i,j}[n]<\tau_{\alpha 1} \ and \ \hat{\alpha}_{i,j}[n]>\tau_{\alpha 2}, else\\ S: \ \alpha_{i,j}[n]<0, \ else\\ H: otherwise\end{cases} \quad (19)$$

, where

τ_{λ} is background chrominance threshold,
$\tau_{\alpha 1}$ is upper background luminance threshold, and
$\tau_{\alpha 2}$ is lower background luminance threshold

These thresholds are calculated based on a given detection error-rate (r)provided by the user. $\tau_{\alpha lo}$ is user-defined threshold to limit degree of shadow in case of too dark objects.

Ⅲ. AUTOMATIC BRIGHTNESS CONTROL

In laboratory experiment, adaptive background subtraction algorithm gives satisfactory result. However, in user-based environment, situation is different. There usually is auto brightness adjustment in consumer-type cameras that is designed for improving foreground lightness. This auto adjustment causes background brightness changesdespite environment brightness is stationary. So, we need auto brightness control algorithm for brightness suspension in background region.

The proposed brightness control algorithm is a pre-processing stage of adaptive background subtraction. It receives an input frame from camera and outputs an adjusted input color vector $X_{i,j}[n]$ to background subtraction algorithm.

We define $\mathbf{I}_{i,j}[n]=(I_{i,j}^{Y}[n], I_{i,j}^{Cb}[n], I_{i,j}^{Cr}[n])$ as the original YCbCr pixel values of the current input frame n at pixel location (i,j). $\mathbf{X}_{i,j}[n]=(X_{i,j}^{Y}[n], X_{i,j}^{Cb}[n], X_{i,j}^{Cr}[n])$ is adjusted YCbCr pixel values of Ii,j[n]. The objective of this algorithm is to alleviate the brightness changes in background region caused by camera's auto brightness adjustment, and slightly update the background model in case of global illumination change occurs. The main idea of the proposed algorithm is based on change detection that is obtained by temporal differencing between the current image and the previous adjusted image. The difference color vector is defined as in eq. (20).

$$\mathbf{D}_{i,j}[n] = \mathbf{I}_{i,j}[n] - \mathbf{X}_{i,j}[n-1] \tag{20}$$

We adopt the method of calculating "brightness distortion" and "color distortion" mentioned in Horprasert et al. [3]. We define "brightness change," $\beta_{i,j}[n]$, as brightness component of the difference color vector Di,j[n] as in eqs. (21)-(22).

$$\beta_{i,j}[n] = \mathbf{D}_{i,j}[n] \bullet \mathbf{u}_Y \tag{21}$$

$$\hat{\lambda}_{i,j}[n] = \frac{\lambda_{i,j}[n]}{b_{i,j}[n]} \tag{21}$$

$$\beta_{i,j}[n] = \frac{I^Y_{i,j}[n] - X^Y_{i,j}[n-1]}{\sigma^Y_{i,j}} \tag{22}$$

"Color change," $\varphi_{i,j}[n]$, is defines as in eqs. (23)-(24),

$$\varphi_{i,j}[n] = \left\| \mathbf{D}_{i,j}[n] - \beta_{i,j}[n]\mathbf{u}_Y \right\| \tag{23}$$

$$\varphi_{i,j}[n] = \sqrt{\frac{(I^{Cb}_{i,j}[n] - X^{Cb}_{i,j}[n-1])^2}{(\sigma^{Cb}_{i,j}[n])^2} + \frac{(I^{Cr}_{i,j}[n] - X^{Cr}_{i,j}[n-1])^2}{(\sigma^{Cr}_{i,j}[n])^2}} \tag{24}$$

Then, a "change"is detected if its magnitude exceeds acceptable threshold. In our previously proposed adaptive background subtraction algorithm [8], we define τ_φ as color change threshold. A condition, $\varphi_{i,j}[n] > \tau_\varphi$, implies new objects may present in the scene and/or the background may change. We define $\tau_{\beta 1}$ as an upper brightness change threshold and $\tau_{\beta 2}$ as a lower brightness change threshold. Brightness change is detected if $\beta_{i,j}[n] > \tau_{\beta 1}$ and $\beta_{i,j}[n] < \tau_{\beta 2}$. After calculating the brightness and color changes, the original input color vector will remain the same, $\mathbf{X}_{i,j}[n] = \mathbf{I}_{i,j}[n]$, if only the color changes are detected. However, if only brightness changes is detected ($\varphi_{i,j}[n] \le \tau_\varphi$), the original input color vector will be updated as in eqs. (25)-(27),

$$X^Y_{i,j}[n] = (1-\rho) X^Y_{i,j}[n-1] + \rho I^Y_{i,j}[n] \tag{25}$$

$$X^{Cb}_{i,j}[n] = I^{Cb}_{i,j}[n] \tag{26}$$

$$X^{Cr}_{i,j}[n] = I^{Cr}_{i,j}[n] \tag{27}$$

,where ρ is brightness weighting factor, i.e., compensation weighting. If brightness changes due to the camera's auto brightness adjustment, the brightness component of the background model should be kept close to the one in the previous frame ($\rho \to 0$). If brightness changes are due to the illumination changes in scene, brightness component of the background

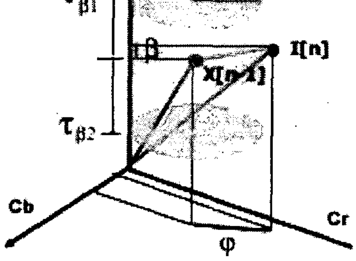

Fig. 3. Change detection and classification model

model should be set close to the one in the current input frame ($\rho \rightarrow 1$). Change detection model shown in Figure 3

Ⅳ. EXPERIMENTAL RESULTS

To experiment, we compared the detection result from the system with an adaptive background subtraction proposed in Section II with and without brightness control proposed in Section III. The experimental videos are a sequence of a person in indoor office, as shown in Fig. 6, and sequence of video conferencing, as shown in Fig. 8. Both sequences are captured by Sony EVI-D100P, which adjusts brightness automatically to enhance the subject region. In this experiment, we do not perform post-processing operation such as dilation and erosionsuch that we could have fair measurement of the efficiency of the proposed algorithm.

The background model used in the experiment is shown in Figs. 6(a) and 8(a), respectively. Current input frame with the effect of camera auto brightness adjustment is shown in Figs. 6(b) and 8(b), respectively. Classification mask from adaptive background subtraction is shown in

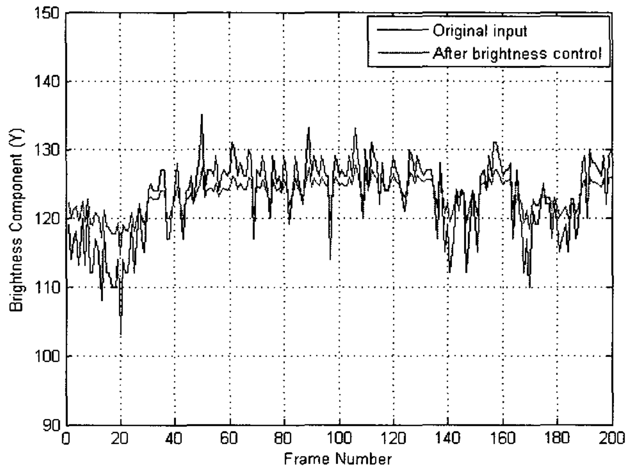

Fig. 7. Variation of brightness component of an interesting pixel that is affected by auto brightness adjustment of camera. The input sequence is same as in the Figure 6. The blue line is the brightness variation of the original video sequence, while the red is the brightness variation after applying the proposed brightness control algorithm.

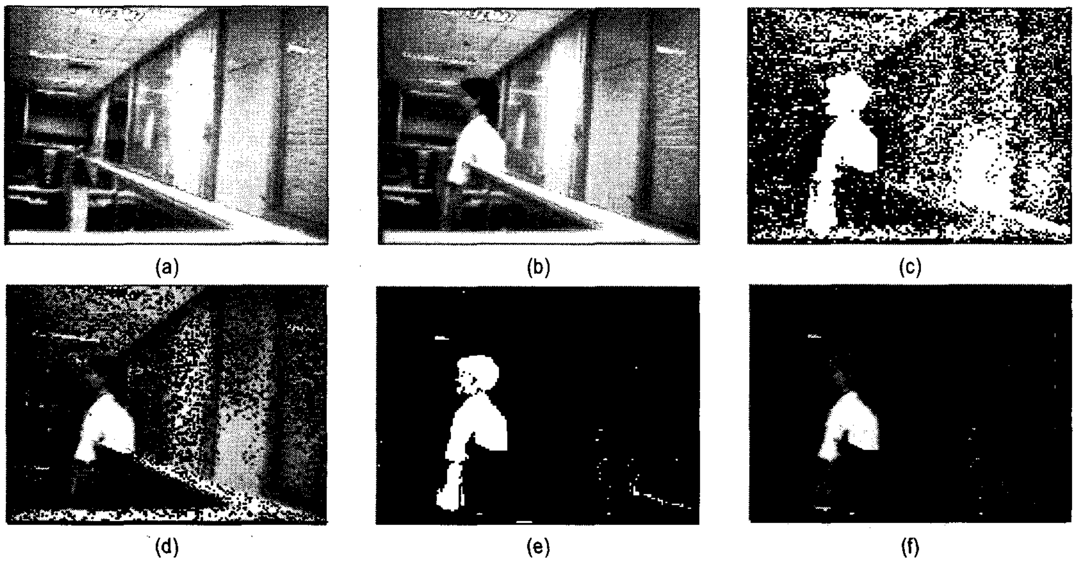

Fig. 6. Experimental result shows a sequence of a person in an indoor office. (a) Background model. (b) An input frame. (c)-(d) Classification mask and segmentation result from a typical background subtraction algorithm. (e)-(f) Classification mask and segmentation result from the background subtraction with proposed brightness control algorithm

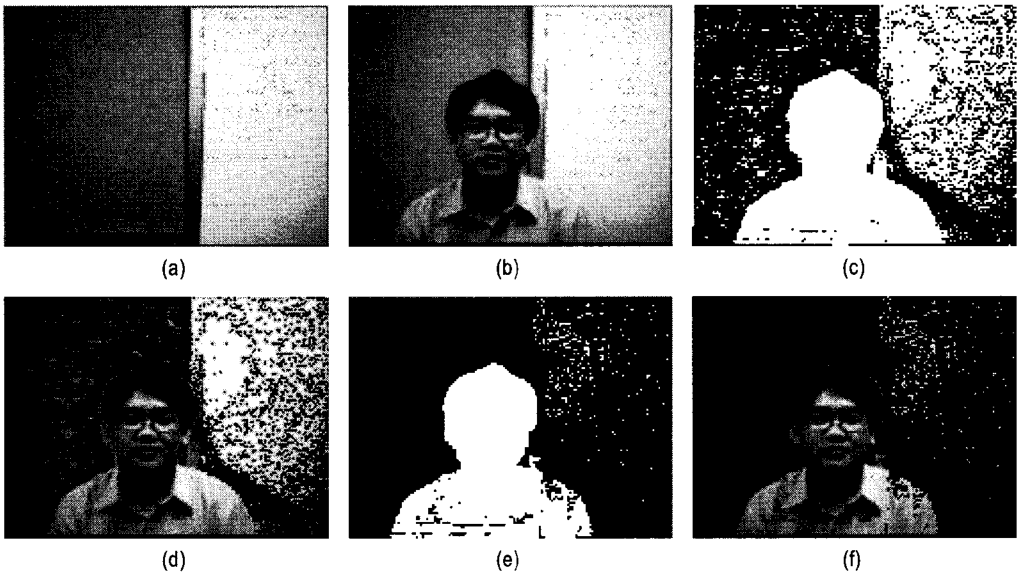

Fig. 8. Experimental result shows a sequence of a person sitting in front of a PC with a web-cam and using video conferencing program. (a) Background model. (b) An input frame. (c)-(d) Classification mask and segmentation result from a typical background subtraction algorithm. (e)-(f) Classification mask and segmentation result from background subtraction with proposed brightness control algorithm

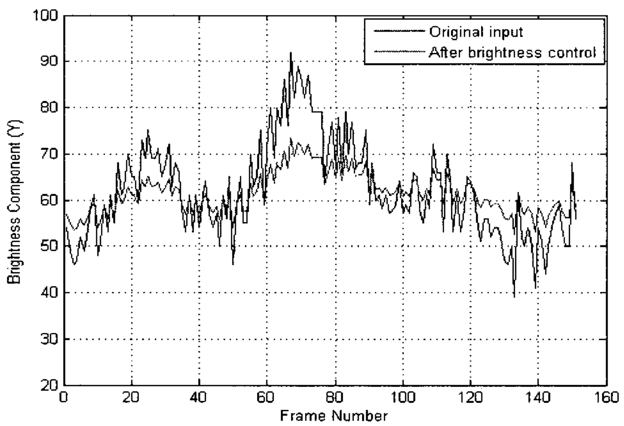

Fig. 9. Variation of brightness component of an interesting pixel that is affected by auto brightness adjustment of camera. The input sequence is same as in the Figure 8. The blue line is the brightness variation of the original video sequence, while the red is the brightness variation after applying the proposed brightness control algorithm.

Figs. 6(c) and 8(c), respectively. Segmentation result from adaptive background subtraction is shown in Figs. 6(d) and 8(d), respectively. Classification mask after brightness control is shown in Figs. 6(e) and 8(e), respectively. The result after brightness control is shown in Figs. 6(f) and 8(f), respectively.

The results in Figs. 6 and 8 show that the proposed algorithm improves the performance of background subtraction classification process in terms of reducing the number of false positive pixel. To further support this claim, we illustrate the improvement of our proposed algorithm in term of brightness control. We have observed the brightness level of the pixels belonged to the background region for all the frames in the sequence. In general, we observed that the brightness level of background pixels after our proposed brightness control is more uniform that that of without our proposed algorithm. In Figs 7 and 9, we show the results of an example pixel. Fig. 7 shows brightness component of sequence in Fig. 6 at pixel (33,9) over 200 frames. Fig. 9 shows brightness component of sequence in Fig. 8 at pixel (38,24) over 160 frames. It is obvious that brightness component is smooth than original input. Brightness control can reduce abruptly changes of brightness level from original input resulted from auto brightness adjustment in consumer-type cameras.

V. CONCLUSION

Consumer-type cameras usually have a feature of automatic brightness adjustment. However, this function focuses only on the quality of foreground region and changes background luminance, thus reduces the performance of background subtraction. We then propose an adaptive brightness control for keeping background brightness more stable. The experiment results show the proposed algorithm can reduce false positive which improves the performance of background subtraction classification process.

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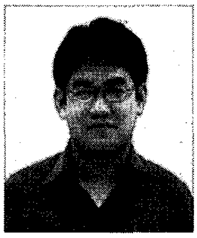

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