DETERMINATION OF COLOR SPACE FOR ACCURATE CHANGE DETECTION

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ABSTRACT

Most change detection methods are based on gray-level images. A gray-level image is regarded as a 1-D projection of three channels of color images. Therefore, more precise change detection results are expected by utilizing color information. We previously developed a change detection scheme using color images. In this paper, we determine which color space should be selected for accurate change detection based on our previous detection scheme. Our method can be applied to various color spaces, including gray-level images. Then we can measure the expected number of error pixels in order to select an appropriate color space which gives the best result among various color spaces. The experiments show that selecting a color space based on measurements results in the fewest error pixels.

Index Terms— Color space, change detection, noise modeling

1. INTRODUCTION

Common applications for change detection include tracking moving objects [1], video surveillance systems [2], traffic monitoring [3] and silhouette detection [4]. For robust and accurate change detection, Liu *et al.*[5] proposed an illumination independent statistical change detection algorithm using circular shift moments (SCSM). Because this noise estimation scheme is very heuristic, however, its detection is usually sensitive when a highly uniform region exists in the images. Li and Leung [6] proposed a method based upon the integration of intensity and textural differences (IITD). They defined a textural difference measure using the cross-correlation and auto-correlation of two frames' gradient vectors.

Most change detection methods, including the works reviewed above, are based on gray-level images. Color images can provide much richer information than gray ones. When we determine an appropriate distance measure to classify corresponding pixels between two consecutive images, we can obtain more accurate detection results. In order to utilize color images, however, the selection of color spaces is a crucial issue. Applying various color spaces can significantly change the detection results. Some works have compared the performance of several color spaces. In [3], they compared different color spaces for foreground and shadow detection. The detection results show different error ratios according to which color space is used. Stokman *et al.* [7] proposed a selection framework for a color model using the principles of diversification for image segmentation and edge detection. By means of statistical formulation and learning schemes, they found the optimal color channels and their weights. A comparison of color image edge detectors in multiple color spaces was also presented in [8]. Edge detectors such as the Sobel operator are evaluated against multiple color spaces.

In the previous work [9], we used the Euclidean color distance of three channels as a difference measure. We showed that each color band's noise does not follow the well-known zero mean Gaussian distribution. To accurately model each channel's noise, we proposed a generalized exponential model (GEM), which estimates the noise distribution on the Euclidean distance which corresponds to unchanged regions. Subtracting the estimated noise distribution from the whole distribution provides the distribution of unchanged regions and chan-ges. The detection then is done by a simple pattern classification step.

In this paper, our aim is to determine an appropriate color space for our previous detection process. At first, we show that our detection process can be applied to various color spaces including gray-level images. We present a criterion for measuring the expected number of error pixels in order to determine which specific color space that has best change detection result corresponding to current image sets. This paper is organized as follows. In Section 2, we briefly review previous change detection schemes [9]. Section 3 presents a criterion in order to determine the appropriate color space. Section 4 gives some experimental results to validate the proposed approach. Finally, we present our conclusions in Section 5.

2. DETERMINATION OF THRESHOLD USING GEM

2.1. Generalized Exponential Model(GEM)

We observe that each channel's noise distribution is between the Laplace distribution and the Gaussian distribution, and is similar to an exponential distribution. We propose a generalized exponential distribution, called the Generalized Exponential Model (GEM), as the noise distribution for each color channel. It is defined as follows:

$$f_{GEM}(x) = \alpha \exp(-|x-u|^t/c) \quad (1)$$

$$\int_{-\infty}^{\infty} f_{GEM}(x) = 1 \quad (2)$$

α is the scale factor that satisfies the probability density function's constraint as shown in Equation 2, t measures the exponential distribution's sharpness, c is the distribution's variance, and u is the distribution's mean. If $t = 2$ and $u = 0$, the GEM becomes the zero-mean Gaussian probability function. This formulation is similar to the Generalized Gaussian model in [10], but those authors applied the GG model to a log-ratio image. Their parameter estimation scheme is also different from ours.

We estimate the histograms of three channels in a certain color space in order to approximate the noise distribution. The histograms have the distribution of noise and changes at the same time. But because the changes are uniformly distributed, the histogram is dominated by the noise distribution shown in Figure 3. Therefore, the GEM's parameters are obtained by applying the Levenberg-Marquardt algorithm to the histograms. The LM algorithm's initial values are fixed for all experiments at $t = 1.5$, $u = 0$, $c = 2$ and $\alpha = 10,000$.

2.2. Estimating the noise distribution on the Euclidean distance

From the modeling of each channel noise we can estimate the distribution of the Euclidean distance for the unchanged regions. Assume that random variables X, Y and Z are independent and follow the GEM distribution. Then, the 3-D Euclidean distance is

$$W = \sqrt{X^2 + Y^2 + Z^2} \quad (3)$$

, and its probability density of the 3-D Euclidean distance is

$$f_w(w) = \alpha_4 \int_0^{2\pi} \int_0^{\pi} w^2 \sin\theta \cdot e^{\left(\frac{-(|w\sin\theta\cos\phi - u_1|)^{t_1}}{c_1} - (\frac{(|w\sin\theta\sin\phi - u_2|)^{t_2}}{c_2} - (\frac{(|w\cos\theta - u_3|)^{t_3}}{c_3}\right)} d\theta d\phi \quad (4)$$

. A detailed derivation of this is referenced in [9]. Using this probability density, we can estimate the noise distribution on the Euclidean distance of channels in a color space. Because the GEM parameters t, u and c for each channel are estimated in Section 2.1, the only unknown parameter is the scale factor, α_4. We can obtain this parameter by using the Levenberg-Marquardt algorithm. The initial value is set at $10,000$, the same as in the GEM estimation.

We can regard the noise distribution obtained above as the distribution of unchanged regions. Next, we can obtain the distribution of changes by subtracting the histogram of

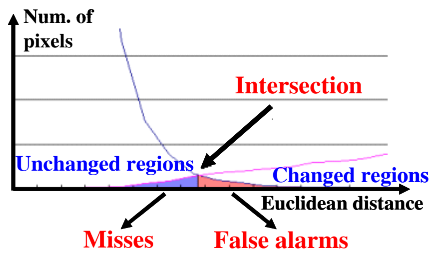

Fig. 1. The histogram of Euclidean distance between two consecutive images

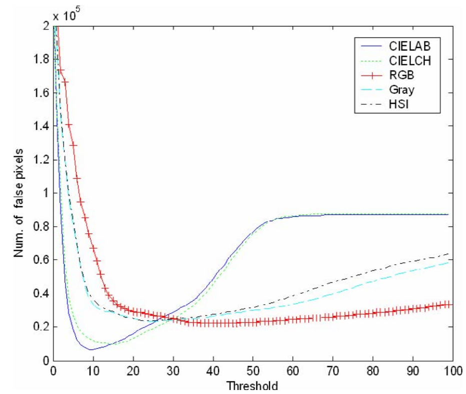

Fig. 2. The number of false pixels when detection changes by thresholding the Euclidean distance in various color spaces

unchanged regions from the original histogram. Then we can determine the intersection, the optimal threshold where the histogram of unchanged regions meets the histogram of changes as shown in Figure 1.

3. DETERMINATION OF APPROPRIATE COLOR SPACE

The GEM model covers most color spaces such as RGB, CIELAB, CIELCH and so on. But each color space's ability to detect changes differs according to the camera used, the captured scene and the illumination status. Figure 2 shows the number of false pixels corresponding to changes in the threshold of various color spaces with the target image set shown in Figure 5(a),(b). In this case, CIELAB and CIELCH show better results than other color spaces. The difference in the number of false pixels at the optimal threshold between the CIELAB and RGB color spaces is almost 20,000 pixels.

The color space determination's goodness is measured by the expected number of false pixels (ENFP) as shown below.

$$ENFP = \sum_{dis<thr} His_{change}(dis) + \sum_{dis>thr} His_{noise}(dis) \quad (5)$$

In Equation 5, $His()$ means a histogram on the Euclidean distance between consecutive frames, dis is a Euclidean distance

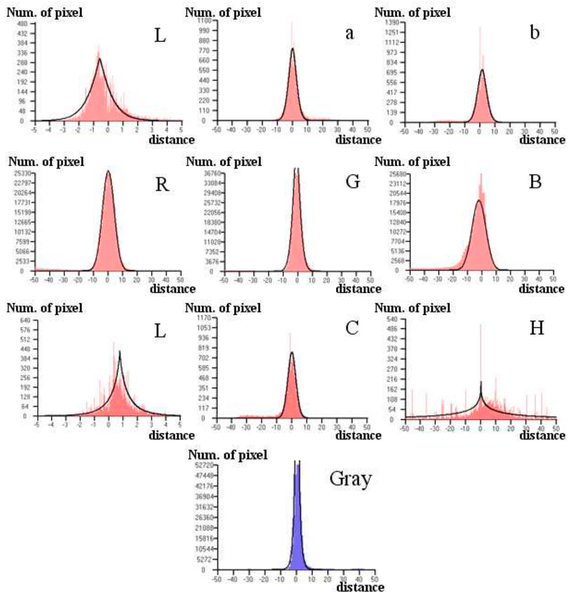

Fig. 3. The estimation result of the noise distribution of each channel in various color spaces

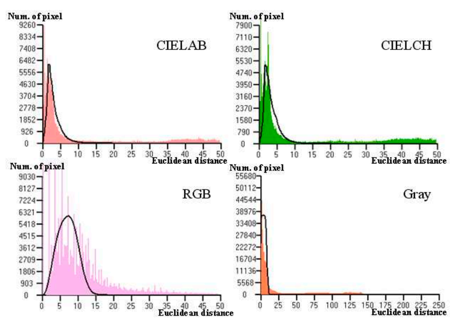

Fig. 4. The estimation result of the noise distribution on 3-D Euclidean distance in various color space

and thr is a determined threshold. ENFP means the summation of the regions of misses and false alarms in Figure 1. This criterion is possible because we have the estimated distribution of noise and changes. If the estimated distribution approximates well the actual distribution, ENFP is a good measure for color space determination.

4. EXPERIMENTAL RESULTS

This section applies the proposed algorithm to detect changes in consecutive image frames that are captured in indoor and outdoor environments. The image resolution for our experiments is 640x480 pixels with 24 bit RGB color bands.

Figure 3 shows estimation results in several color spaces, including a gray-level space, fitted to the channels' histograms. All channels are well estimated by GEM because GEM covers variations in steepness, variance and mean shift. Although

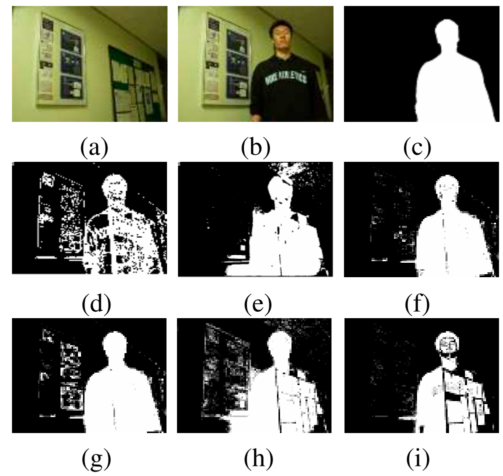

Fig. 5. The result applied to indoor scene: (a) background (b) foreground (c) ground truth (d) SCSM (e) IITD (f)-(i) the proposed method in CIELAB, CIELCH, RGB, Gray, respectively

the histogram of H in the CIELCH color space has some noisy peaks because of its hue characteristics, GEM still estimates its distribution well. Figure 4 shows the result of estimating the noise distribution on the Euclidean distance in several color spaces. These estimation results are well fitted to the various histograms, but the result of RGB might be shown that the estimation is not accurate. The curve of RGB in Figure 2 is almost flat in some range, which means that the boundary between changes and noise distribution can be ambiguous. Therefore, although the modeling of each channel shown in Figure 3 is accurate, the modeling of Euclidean distance cannot show an accurate boundary. But, as shown in the detection results in Figure 5, the threshold for RGB is nearly optimal because it has the almost the same amount of missing pixels and extra pixels.

Figures 5 and 6 show the result applied to indoor and outdoor scenes. Indoors, the results of CIELAB and CIELCH show the best performance even if they are compared to other change detection methods. Outdoors, the results of CIELAB and RGB show the best performance. Table 1 shows the value of ENFP. According to the quantitative evaluation shown in Tables 2 and 3, the detection results for each color space have the same order of accuracy as expected by ENFP. this shows that we can determine appropriate color space based on ENFP. We notice that the order of ENFP can be changed according to the input image set. When we apply our algorithm based on CIELAB and CIELCH color spaces to an indoor scene, the results are much better than the existing change detection methods [5, 6], although we classify each pixel using only the threshold obtained by GEM modeling. The same results can be obtained in the outdoor scene by using CIELAB and RGB color spaces. Therefore, by calculating ENFP, we can determine the appropriate color space automatically ac-

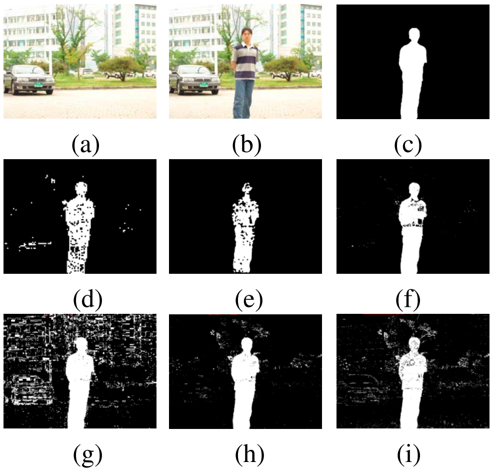

Fig. 6. The result applied to outdoor scene: (a) background (b) foreground (c) ground truth (d) SCSM (e) IITD (f)-(i) the proposed method in CIELAB, CIELCH, RGB, Gray, respectively

Table 1. The value of ENFP

Scenes	CIELAB	CIELCH	RGB	Gray
Indoor	1164	1309	1802	1746
Outdoor	726	5440	2326	3794

cording to environmental changes such as scene, camera and illumination changes.

5. CONCLUSIONS

In this paper, we determine appropriate color spaces for accurate change detection. Most change detection methods are based on gray-level images because of the problem of handling three channels. We show that the GEM can be applied to various color spaces. By using the GEM, we can determine the optimal threshold to classify the changes. In order to determine the best color space, we define ENFP. The estimations of distribution of noise and changes are so accurate that ENFP gives a good measure of color space selection. Color spaces selected by ENFP as the best detectors show much improved results compared with other existing methods.

Table 2. Quantitative evaluation of an indoor scene

method	False negative (missing pixels)	False positive (extra pixels)	Error pixels
SCSM[7]	55837 (64.1%)	3691 (1.7%)	62528
IITD[8]	6594 (7.5%)	14723 (6.7%)	21317
CIELAB	**2611 (0.8%)**	**4183 (1.3%)**	**6794**
CIELCH	**1340 (0.4%)**	**11226 (3.7%)**	**12566**
RGB	9460 (3.1%)	24400 (7.9%)	33860
Gray	20915 (6.8%)	2701 (0.9%)	23616

Table 3. Quantitative evaluation of an outdoor scene

method	False negative (missing pixels)	False positive (extra pixels)	Error pixels
SCSM[7]	4509 (1.5%)	4102 (1.3%)	8611
IITD[8]	6322 (2.1%)	100 (0.0%)	6422
CIELAB	**1770 (0.6%)**	**755 (0.2%)**	**2525**
CIELCH	186 (0.0%)	36832 (12.0%)	37018
RGB	**324 (0.1%)**	**4482(1.5%)**	**4806**
Gray	1214 (0.4%)	10334 (3.4%)	11548

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