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3—27 Detecting Perceptual Color Changes from Sequential Images for Scene Surveillance

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Abstract

This paper proposes a methodology for detecting the appearance of matte-surfaced objects on a scene using color information and spatial thresholding. First, a difference image is obtained via a pixel-wise comparison of the color content of a 'clean' reference image and a sample image. Then, spatial thresholding of the difference image is performed to extract any objects of interest, followed by morphological post-processing to remove pixel noise. We study the applicability of two alternate color spaces (HSV, CIE Lab) for computing the difference image, and similarly, two alternate spatial thresholding methods based on Euler numbers and stochastic Poisson model are evaluated. We demonstrate the performance of the proposed approach in scene surveillance, where the objective is to monitor a shipping dock for the appearance of needless objects such as cardboard boxes. In order to analyze the robustness of the approach, the experiment includes three different types of scenes categorized as 'easy', 'moderate', and 'difficult', based on scene properties such as the heterogeneity of the background and the existence of illumination changes and shadows. The experimental results show that relatively good recognition accuracy is achieved on 'easy' and 'moderate' scenes, whereas 'difficult' scenes remain a challenge for future work.

1 Introduction

A scene surveillance system should give a clear indication of the changed objects in a given scene. In many cases intensity information is not sufficient to detect inanimate scene changes, which is demonstrated in Figure 1. Particularly, traditional change detection methods have difficulties in recognizing static matte surfaced objects from a background of similar intensity. Previously proposed techniques for detecting changes between two consequent images have been based on pixelwise or local neighborhood image differencing, for the purpose of intruder detection [7][8][9] and vehicle tracking [6]. Many of the developed object detection systems incorporate motion information to precisely locate the actual objects of interest from noise [1][2][3]. Makarov's approach for scene surveillance adapts to slow changes in background by dynamically updating the background information [4]. To overcome the problems of changing illumination conditions, methods such as Shading Model [11] and Circular Shift Moments [10] have been presented. These techniques work rather well when intensity differences are sufficiently large to detect actual changes in a scene. Also, Young *et al.* [5] compared some illumination compensation and frame differencing techniques. Rosin [12] presented multiple change detection methods based on thresholding difference images. Paschos and Valavanis [13] used color and texture information in automated surveillance system based on scene segmentation, demonstrating the advantages of xyY and HIS color spaces over RGB color space in finding chromaticity changes for the purpose of wetland monitoring.

Figure 1. *Matte surfaced objects often cannot be detected using plain intensity information.*

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2 Methodology

The proposed approach comprises of following steps: reference image acquisition, sample image acquisition, calculation of the difference image, spatial thresholding of the difference image into a binary image, morphological post-processing of the binary image to remove pixel noise, and scene change detection from the post-processed binary image.

The acquisition of the reference image and the sample images is described shortly in experiments. Given a reference image R and a sample image T, the difference image D is computed in two alternate color spaces, CIE Lab and HSV. The pixel-wise chromaticity difference in the CIE Lab color space is defined as:

$$D_{Lab} = \sqrt{(\Delta a)^2 + (\Delta b)^2} \quad \begin{aligned} &where \\ &\Delta a = a_R - a_T \\ &\Delta b = b_R - b_T \\ &a, b = color\ channels \end{aligned}$$

The pixel-wise chromaticity difference in HSV color space is defined as:

$$D_{HSV} = \sqrt{(\Delta S_X)^2 + (\Delta S_Y)^2} \quad \begin{aligned} &where \\ &\Delta S_X = S_R \cos(H_R) - S_T \cos(H_T) \\ &\Delta S_Y = S_R \sin(H_R) - S_T \sin(H_T) \\ &H = hue \\ &S = saturation \end{aligned}$$

Similarly, two alternate approaches for the spatial thresholding of the difference image are studied, based on Euler numbers and stochastic Poisson model. Rosin [12] compared four approaches to threshold intensity images by modeling either signal or noise properties of the image using either spatial properties or intensity distributions. Rosin concluded that spatial thresholding gave better results in comparison to intensity distribution based methods. In this study we extend two spatial thresholding methods to separate relevant color changes instead of intensity differences.

The first approach is thresholding by modeling the signal using Euler numbers [12][14]. It is based on calculating Euler numbers as a function of the chromaticity difference, and observing the point where the Euler number becomes stable and undisturbed by background noise. The determination of the threshold value is illustrated in Fig. 2.

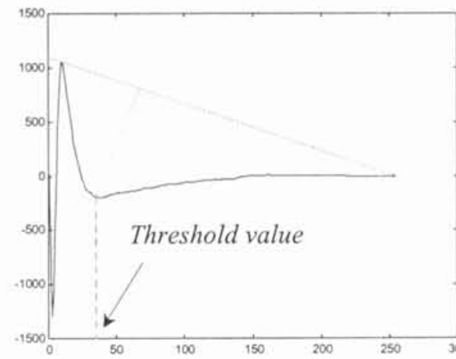

Figure 2. *The Euler number plotted as a function of difference and the determination of the threshold value.*

The second approach is thresholding by modeling the spatial distribution of the noise using stochastic Poisson model. We assume the noise to be random, which is verified by comparing spatial data to the Poisson noise model. As the threshold we use the value that maximizes the test for randomness, relative variance:

$$V_r = \frac{s^2}{\bar{x}}$$

where s^2 and $\bar{x}$ correspond respectively to the variance and mean of the thresholded pixels' distribution in 32x32 sized local windows.

The binary image obtained via thresholding is then subjected to morphological post-processing: holes in objects are removed by the closing operator and individual noise pixels are removed by the opening operator.

Any objects in the post-processed binary image correspond to scene changes between the reference image and the sample image. Different global and object-specific features can be computed: the total/relative area of changes, the average color and the shape of an object etc.

3 Experiment in scene surveillance

We demonstrate the performance of the proposed approach in scene surveillance, where the objective is to monitor a shipping dock of a premise for the appearance of needless objects such as cardboard boxes, paper and foam. This type of litter on a shipping dock can lead to a hazard such as fire, due to an act of sabotage or accident.

In order to analyze the robustness of the approach, scenes from three different shipping docks categorized as 'easy', 'moderate', and 'difficult' were included. The categorization was based on scene properties such as the heterogeneity of the background and the existence of illumination changes and shadows. The 'easy' dock had a homogeneous, uniformly colored background with no substantial shades, while the 'moderate' dock had heterogeneous multi-colored background. The 'difficult' dock had heterogeneous and complicated multi-colored background and shades caused by complicated surface structure. The image data included 98 images in total: 31, 28, and 39 images for the 'easy, 'moderate', and 'difficult' scenes, respectively. For each scene the imagery included a reference image from a 'clean' dock and sample images with a varying quantity of objects of different color and shape on the dock. The imaging took place outdoors, hence the images were subject to illumination changes due clouds. The images were taken using Olympus Camedia C-1400L camera with an image resolution of 640x512 pixels.

A prototype of the scene surveillance application was developed in Matlab-environment. The user can control various parameters such as the selection of the color space and the thresholding method. Given a reference and a sample image, the system determines the 'filthiness' of the scene, which corresponds to the percentage of the area of observed changes to the total area of the scene. If 'filthiness' exceeds a user-defined threshold, an alarm is generated to the user to clean up the dock for safety reasons.

The image data was examined with four different combinations of a color space and a thresholding method: (ab, Euler), (Lab, Euler), (Lab, Poisson) and (HSV, Poisson). Luminance information (L) was also included in two combinations to analyze the relative performance of luminance and chrominance information. A sample image was deemed to be correctly identified, if the difference between the detected object area and the correct object area defined manually was at most 35%. In the case of the 'easy' scene, the (Lab, Euler) combination achieved the best result by identifying correctly 26 of the 30 sample images. The (HSV, Poisson) combo provided the most successful analysis of 'moderate' scene by recognizing 26 of the 27 samples. The 'difficult' scene turned out to be a real challenge, as only 18 of the 38 samples were correctly identified by the (HSV, Poisson) combination, while the other three combinations failed miserably. The explanation is that the complicated scene structure confuses the spatial thresholding due to large local differences in scene properties. An example of successful object detection in the 'moderate' dock is given in Fig. 3.

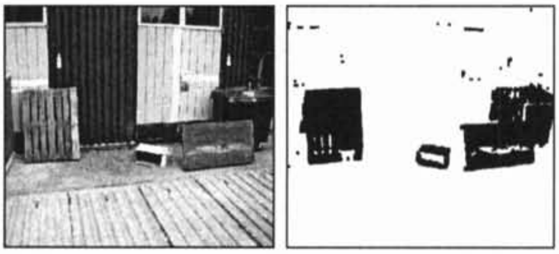

Figure 3. *Original (left) and final post-processed binary image (right), when the HSV color space and threshold based on stochastic Poisson model are used.*

The system successfully detected objects that had equal luminance to the background, which underlines the usefulness of color information. However, problems occurred in detecting changes that had equal chrominance with the background, e.g. white objects over a gray background. This can be circumvented by using both chrominance and luminance information (Lab). Unfortunately, it makes the system vulnerable to environmental changes such as shadows and illumination.

Few interesting remarks can be made of the relative performance of the color spaces and thresholding methods. HSV color space has larger noise variation in its hue channel than the CIE Lab's channels a and b. Consequently, CIE Lab handles color changes better at lower levels of object luminance. Additionally, CIE Lab produces more uniform surfaces, which facilitates more efficient object area extraction.

Thresholding based on Euler number seemed to slightly overestimate the threshold value, while the Poisson model based method seemed to underestimate it. For this reason the Poisson model based threshold, together with the HSV color space, succeeded considerably better for the 'difficult' scenes.

4 Conclusions and Future Work

A prototype for color change based scene surveillance system was developed in this study. The system successfully detected color changes in 'easy' and 'moderate' scenes, for which the best performance was achieved in CIE Lab color space using thresholding based on stable Euler number. However, system failed to detect changes in 'difficult' scenes because of a rather complicated background scene structure. Performance for difficult scenes could be improved by including region of interest (ROI) selection, which would reduce the observed scene's background complexity. The alarm criterion based on the area of the detected changes had difficulties with scenes with strong perspective structure. This can be bypassed by positioning the camera perpendicular to the observed scene and by avoiding large local variances in scene depths. Also, objects of color similar to the background caused problems, which can be addressed by using luminance information in addition to color. However, this makes the system vulnerable to illumination changes and shades. Future work includes a more thorough evaluation of the system's robustness against changes in daytimes and lighting conditions.

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