Background subtraction using generalised Gaussian family model

H. Kim, R. Sakamoto, I. Kitahara, T. Toriyama and K. Kogure

Proposed is a robust method to detect foreground regions from colour video sequences using a generalised Gaussian family model and multiple thresholds. Experiments show that the proposed algorithm works better than conventional approaches in various environments.

Introduction: Background subtraction is one of the most common approaches for detecting foreground objects from video sequences. The Gaussian mixture model is the most representative background model [1] and has been widely incorporated with other methods [2, 3]. However, these approaches require high computational complexity and have a trade-off in learning rates. Elgammal *et al.* proposed a nonparametric approach using kernel density estimators (KDE) to quickly adapt to background changes [4], but this approach consumes a lot of memory when updating recent background statistics. Recently, Kim *et al.* proved that pixel variance in a static scene over time in indoor scenes taken with the latest camera is closer to a Laplace distribution than a Gaussian [5], but the Laplace model has limitation for use in various environments.

In this Letter we propose to model the background using a generalised Gaussian family (GGF) model of distributions to cope with problems from various changes in background and shadows.

Background modelling: Pixel variation in a static scene over time is modelled with the GGF distribution, defined as:

$$p(x:\rho) = \frac{\rho\gamma}{2\Gamma(1/\rho)}\exp(-\gamma^{\rho}|x-\mu|^{\rho}) \text{ with } \gamma = \frac{1}{\sigma}\left(\frac{\Gamma(3/\rho)}{\Gamma(1/\rho)}\right)^{1/2} \quad (1)$$

where $\Gamma(\bullet)$ is a gamma function and σ^2 is a variance of the distribution. In (1), $\rho = 2$ represents a Gaussian distribution while $\rho = 1$ represents a Laplace distribution. In the proposed method, we restrict the GGF model to Laplace and Gaussian for simplicity. The models for each pixel in the background are decided by calculating excess kurtosis g_2 of the first m frames. Excess kurtosis measures whether the data are peaked or flat relative to a normal distribution and calculated using (2), where n is the number of samples and μ is the mean. The excess kurtosis of Gaussian and Laplace distributions is 0 and 3, respectively. The optimised parameters of the background models can be estimated by maximising the likelihood of the observed data [6]:

$$g_2 = \frac{n\sum_{i=1}^{n}(x_i-\mu)^4}{\left(\sum_{i=1}^{n}(x_i=\mu)^2\right)^2} - 3 \quad (2)$$

However, independent RGB channels are very sensitive to noise and changes in lighting conditions. Therefore the background is modelled in two distinct parts: a luminance component calculated by a weighted mean of RGB channels and a hue component in hue-saturation-intensity (HSI) colour domain. The models are updated by the selective running average in the background subtraction process [1, 4].

Background subtraction: First, the initial region classification is performed by subtracting the intensity components of the current frame from the background model. We classify the initial object region into three categories using two thresholds based on background subtraction BD, as in (3). L_I and L_B indicate the luminance components of pixel p in the current frame and the background model, respectively, and b is a scale parameter of the background model:

$$BD(p) = |L_I(p) - L_B(p)|$$
$$\begin{cases} BD(p) < K_1 b(p) & \Rightarrow \text{background} \\ K_1 b(p) \le BD(p) \le K_2 b(p) & \Rightarrow \text{suspicious} \\ K_2 b(p) \le BD(p) & \Rightarrow \text{foreground} \end{cases} \quad (3)$$

We then refine the suspicious regions from the initial classification by using a hue component because the shadow or lighting changes the colour property of the background much less than the luminance. We apply (3) to the hue component in a similar manner with a single parameter, K_3, and classify the suspicious regions into the background and foreground regions. The absolute of difference in (3) should be an angle distance because of the angular nature of the hue component.

Thresholds $K_1 - K_3$ are determined by training data with the following condition, where β was empirically set to 3 because false negative errors are generally more uncomfortable to the eye and less acceptable to many vision systems than false positive errors:

$$(K_1, K_2, K_3) = \underset{K_1,K_2,K_3}{\arg\min}\begin{pmatrix} \beta \times \text{false negative error} \\ + \text{false positive error} \end{pmatrix} \quad (4)$$

Results: We applied the proposed algorithm to various video streams including indoor/outdoor scenes taken with an IEEE-1394 camera/a normal camcorder. The IEEE-1394 camera provides 1024 × 768 RGB video streams and the normal camcorder provides 720 × 480 interlaced DV streams.

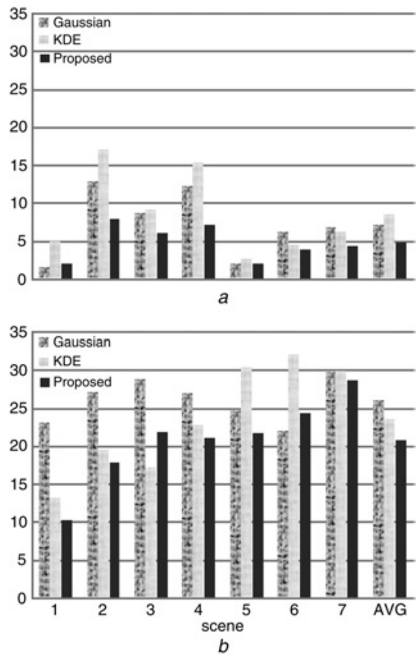

Fig. 1 *Segmentation errors to ground-truth (%)*

a False negative error
b False positive error

We evaluated the performance of the proposed foreground extraction algorithm. We randomly selected 12 frames from seven different scenes (i.e. 84 images in total) and created ground-truth segmentation masks by manual segmentation. We then compared the segmentation error of the proposed algorithm with a Gaussian-based algorithm [1] and a KDE-based algorithm [4]. We compared the results by calculating the percentage of erroneous pixels, as shown in (5):

$$\text{error} = \frac{\text{number of erronous pixels}}{\text{number of real foreground pixels}} \times 100\,(\%) \quad (5)$$

Fig. 1 shows objective evaluations of the proposed algorithm. False negative error means the foreground is falsely classified as the background; false positive error is the background being falsely classified as the foreground. The average error rates of the proposed algorithm are lower than those of the conventional methods in most scenes. Fig. 2 shows the foreground detection results of various scenes: the left image shows the captured image, and the right image shows the extracted foreground in each pair. The final foreground is extracted using a silhouette extraction technique that wraps the object with four drapes to smooth the foreground boundaries and eliminate holes inside the regions [5]. Video clips displaying the results can be downloaded from the following addresses.

Indoor scene: http://www.3dkim.com/research/seg/Segmentation2.wmv
Outdoor scene: http://www.3dkim.com/research/seg/Seg-Outdoor.wmv

Downloaded 01 Feb 2008 to 133.186.34.100. Redistribution subject to IET licence or copyright; see http://ietdl.org/copyright.jsp

Fig. 2 *Results of foreground detection*

Conclusion: We proposed a background subtraction algorithm against variations in the background. The results show that the proposed GGF background model and multiple thresholds approach work very well in various situations.

Acknowledgment: This research was supported by the National Institute of Information and Communications Technology.

© The Institution of Engineering and Technology 2008
30 October 2007
Electronics Letters online no: 20083126
doi: 10.1049/el:20083126

H. Kim, R. Sakamoto, I. Kitahara, T. Toriyama and K. Kogure (*Knowledge Science Laboratory, ATR, Kyoto 619-0288, Japan*)

E-mail: hskim@atr.jp

References

1 Stauffer, C., and Grimson, W.E.L.: 'Adaptive background mixture models for real-time tracking'. Proc. CVPR, Fort Collins, Colorado, USA, 1999, pp. 246–252
2 Lee, D.S., Hull, J.J., and Erol, B.: 'A Bayesian framework for Gaussian mixture background modeling'. Proc. ICIP, Barcelona, Spain, 2003, Vol. 3, pp. 973–976
3 Porikli, F., and Tuzel, O.: 'Human body tracking by adaptive background models and mean-shift analysis'. Proc. PETS-ICVS, Austraia, 2003
4 Elgammal, A., Harwood, D., and Davis, L.S.: 'Non-parametric model for background subtraction'. Proc. ECCV, Dubin, Ireland, 2000, Vol. 2, pp. 751–767
5 Kim, H., Sakamoto, R., Kitahara, I., Toriyama, T., and Kogure, K.: 'Robust silhouette extraction technique using background subtraction with multiple thresholds', *Opt. Eng.*, 2007, **46**, (9), p. 097004
6 Lee, J.Y., and Nandi, A.K.: 'Maximum likelihood parameter estimation of the asymmetric generalized Gaussian family of distribution'. Proc. SPW-HOS, Caesarea, Israel, 1999

Downloaded 01 Feb 2008 to 133.186.34.100. Redistribution subject to IET licence or copyright; see http://ietdl.org/copyright.jsp