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Detection of moving objects: The first stage of an autonomous surveillance system

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ABSTRACT
Object detection is an essential first stage in a surveillance system, primarily because it focuses all the subsequent processes. The standard approach to object detection is background subtraction. At the core of background subtraction is a module that maintains an image that is representative of the scene monitored by a camera. This work compares two background subtraction/maintenance algorithms: adaptive Gaussian mixture model and the Wallflower method. The algorithms are evaluated using video footage of the real world. The Receiver Operating Characteristic (ROC) curves are used to quantify the performance of the algorithms. In our experiments, the adaptive Gaussian mixture model outperforms the Wallflower method.

INTRODUCTION
Video surveillance systems are common in banks, airports, malls and parking lots; and are increasingly being used in cities. This increased usage is largely driven by the decrease in costs required to purchase and install such systems, and the need for improved security. However, these systems generate large volumes of video recordings, and the labour required to monitor them is increasing accordingly. As a result, automated surveillance becomes valuable. In particular, we focus on the low level functions of the systems, which are the detection and tracking of objects, in this case people. The high level functions are the description and understanding of the behaviour of objects. The setting is an indoor environment using a network of four pan-tilt-zoom capable cameras.

Background Subtraction (BS) is an important surveillance system process, mainly because it focuses the attention of subsequent stages on dynamic regions of the image and scene. This minimises the computational cost. The goal of BS is to maintain a frame that is representative of the scene monitored by a camera at all times. An ideal BS algorithm should be able to handle the following challenges:

- Gradual and sudden changes in illumination,
- Background objects that are not static (waving tree, escalator),
- Large homogenously coloured objects (the interior pixels are often undetected),
- Shadows,
- Camouflage (a foreground object has the same colour as the background),
- Ghosts (background objects that suddenly start moving, leave holes in the model of the background),
- Background objects may be moved and must not remain in the foreground forever, and
- Training period absent of foreground objects is not always possible.

WALLFLOWER ALGORITHM
The Wallflower algorithm solves most of the stated challenges. The algorithm comprises the pixel, region and frame level processing stages[1]. At a pixel level, the intensity of each pixel is modelled by a Wiener process using the last P intensity values of that pixel. The region level stage considers the inter-pixel relationships. This solves the foreground aperture problem. The frame level stage addresses the sudden change in large parts of the image, for example when lights are turned on or off. Thus, the algorithm predicts the foreground frame in the next time step. The absolute (pixel-wise) difference of the incoming frame and the predicted model is calculated. A given pixel belongs in the foreground if this quantity for that pixel exceeds a given threshold. The threshold is a constant b times the square root of the expected mean square error.

ADAPTIVE GAUSSIAN MIXTURE MODEL (GMM)
The adaptive GMM algorithm represents each pixel as a linear combination of Gaussian distributions. The user specifies the maximum number of Gaussian distributions that may be used. The algorithm then automatically determines the optimal number of distributions to use at every point in time[2]. This is an extension of the model[3] which uses a fixed number of Gaussian distributions, and only adapts the parameters of the distributions. The results[1] indicate that the Wallflower method out-performs the GMM algorithm[3]. In this work the results of the Wallflower model are compared with the adaptive GMM algorithm[2]. The ROC curves[4] are used to quantify the performance of both methods. A ROC curve is a graphical representation of the relationship between the true positive and the false negative rates as one of the parameters in a model is changed.

RESULTS

Gradually changing lighting conditions
Figures 1 and **2** show results from a video taken in a room with gradually changing lighting conditions. In terms of adaptive GMM, these parameters were used: learning rate = 0.001, Mahalanobis distance threshhold = 16 and the maximum number of Gaussian distributions = 5. For the Wallflower algorithm, P = 50 was used. In both cases the threshold was varied to obtain the ROC curves. The images suggest that the adaptive GMM performs better than the Wallflower algorithm. However, the noise in the Wallflower method can easily be removed during the post-processing stage. Moreover, the area beneath the ROC curve of the Wallflower algorithm is much larger than the one beneath the adaptive GMM ROC curve.

Figure 1: Results from video sequence with a gradually changing illumination

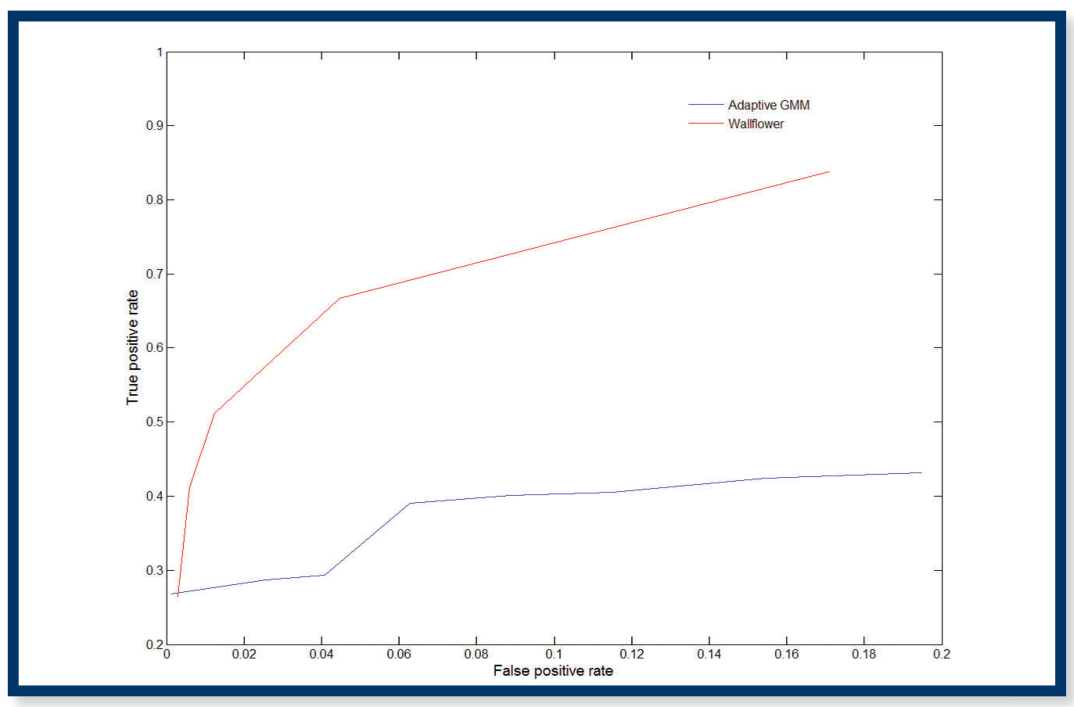

Figure 2: The ROC curve

Camouflage
The performance of adaptive GMM algorithm does not change with the change in the threshold parameter. As a result, only the ROC curve for the Wallflower algorithm is shown in **Figure 4**. The images in **Figure 3** suggest that adaptive GMM outperforms Wallflower. The same parameter values that were used in the first test are used here.

Figure 3: Images show how the methods handle camouflage

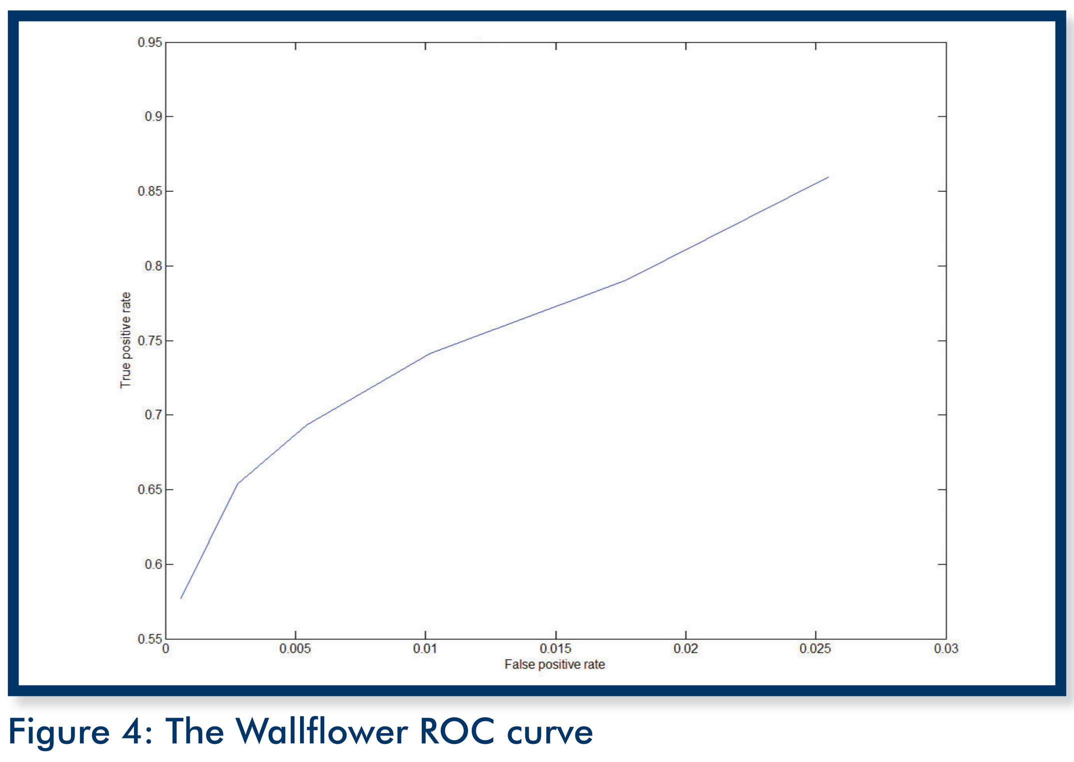

Figure 4: The Wallflower ROC curve

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DISCUSSION AND CONCLUSION
The background image obtained using the Wallflower algorithm is always noisier compared to that using adaptive GMM. However, most of the noise can be removed during post-processing. The binary images suggest that adaptive GMM outperforms Wallflower, but the ROC curves suggest otherwise. The ROC curves indicate that adaptive GMM is not very sensitive to the changes in the parameters. Wallflower is computationally expensive because for each pixel, a history of P intensity values must be maintained and their weight recalculated at every time step. The weight of the ROC curves is undermined because the ultimate goal is to enclose detected objects (rather than pixels) in boxes; classify and then track them. The conclusion is that adaptive GMM outperforms Wallflower.

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