

Background Subtraction Fusing Colour, Intensity and Edge Cues

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Abstract This paper presents a new background subtraction algorithm for known mobile objects segmentation from a static background scene. Firstly, a casuistry of colour-motion segmentation problems is presented. Our approach first combines both colour and intensity cues in order to solve some of the colour motion segmentation problems presented in the casuistry, such as saturation or the lack of the colour when the background model is built. Nonetheless, some colours problems presented in the casuistry are not solved yet such as dark and light camouflage. Then, in order to solve this problems a new cue —edge cue— is proposed. Finally, our approach which fuses colour, intensity and edge cues is presented, thereby obtaining accurate motion segmentation in both indoor and outdoor scenes.

Keywords: Motion Segmentation; Background Subtraction; Colour Segmentation Problems; Colour, Intensity and Edge Segmentation.

1 Introduction

The evaluation of human motion in image sequences involves different tasks, such as acquisition, detection (motion segmentation and target classification), tracking, action recognition, behaviour reasoning and natural language modelling. However, the basis for high-level interpretation of observed patterns of human motion still relies on *when* and *where* motion is being detected in the image. Thus, segmentation constitutes the most critical step towards more complex tasks such as Human Sequence Evaluation (HSE) [3]. Therefore, motion segmentation is the basic step for further analysis of video.

Motion segmentation is the extraction of moving objects from stationary background. Different techniques have been used for motion segmentation such as background subtraction, temporal differenc-

ing and optical flow [4]. The information obtained from this step is the base for a wide range of applications such as smart surveillance systems, control applications, advanced user interfaces, motion based diagnosis, identification applications among others. Nevertheless, motion segmentation is still a open and significant problem due to dynamic environmental conditions such as illumination changes, shadows, waving tree branches in the wind, etc.

In this paper an evolved approach based on [2] for handling non-physical changes such as illumination changes is presented. Huerta et al. [2] cope with those changes based on a casuistry of colour-motion segmentation problems combining colour and intensity cues. Nevertheless, some problems presented in the casuistry still remain: colour and intensity segmentation cannot differentiate dark and light camouflage from the local and global illumination changes. In order to solve these problems a new cue – edges – is proposed and colour, intensity and edge cues are combined.

2 Problems on Colour Models

Colour information obtained from the recording camera is based on three components which depend on the wavelength λ : the object reflectance R , the illuminant spectral potency distribution E and the sensor wavelength sensitivity S :

$$S_r = \int_{\lambda} R(\lambda)E(\lambda)S(\lambda)d\lambda. \quad (1)$$

where S_r is the sensor response.

Unfortunately, the *sensitivity of the sensor* may depend on the luminous intensity which can cause changes in the observed chrominance. In addition, if the *illuminant changes*, the perceived chrominance changes too, so the colour model can be wrongly built.

Case Analysis (Colour Model Casuistry)					
Cues	Chromatic	Equal			Different
	Brightness	Lower	Equal	Higher	-
Description	Base case	Global shadow Local shadow	Background	Global Highlight Local Highlight	Foreground
	Anomalies	Dark Camouflage Dark Foreground	Camouflage	Light Camouflage Light Foreground	Sensitivity of Sensor Change of illuminant Gleaming surface Saturation Minimum Intensity

Figure 1: This table analyzes the differences between an input image and the background model.

Fig. 1 shows a Colour Model Casuistry based on a background model which separates the chrominance from the brightness component. The Base Case is the correct operation of the theoretical colour model, and the anomalies are problems that may appear. The theoretical base case solves some of the segmentation problems, as sudden or progressive global and local illumination changes, such as shadows and highlights. However, some problems remain.

First, foreground pixels with the same chrominance component as the background model are not segmented. If the foreground pixel has the same brightness as the background model appears the *Camouflage* problem. A *Dark Camouflage* is considered when the pixel has less brightness and it cannot be distinguished from a shadow. Next, *Light Camouflage* happens when the pixel is brighter than the model, therefore the pixel cannot be distinguished from a highlight.

Secondly, *Dark Foreground* denotes pixels which do not have enough intensity to reliably compute the chrominance. Therefore it cannot be compared with the chrominance background model. On the other hand, *Light Foreground* happens when the present pixel is saturated and it cannot be compared with the chrominance background model either.

Further, the perceived background chrominance may change due to the *sensitivity of the sensor*, or *local* or *global illumination changes*. For instance, background pixels corresponding to shadows can be considered as foregrounds. *Gleaming Surfaces*, such

as mirrors, cause that the reflect of the object is considered as foreground. On the other hand, due to saturation or minimum intensity problems the colour model cannot correctly be build. Therefore, a background pixel can be considered foreground erroneously. *Saturation problem* happens when the intensity value of a pixel for at least one channel is saturated or almost saturated. Therefore, the colour model would be build wrongly. The *minimum intensity problem* occurs when there is not enough chrominance to build a colour model. This is mainly due to pixels do not have the minimum intensity value to built the chrominance line.

3 Handling Colour-based Segmentation Problems

The approach presented in [2] can cope with different colour problems as dark foreground and light foreground. Furthermore, it solves saturation and minimum intensity problems using intensity cue. Nevertheless, some colour segmentation problems still remains, since the intensity and colour model cannot differentiate dark and light camouflage from local and global illumination changes.

This approach is enhanced from [2] by incorporating edges statistics, depending on the casuistry. First, the parameters of the background model are learnt; next the colour, intensity and edge models are explained; and finally the segmentation procedure is

presented.

3.1 Background Modelling

Firstly, the background parameters and the Background Colour and Intensity Model (BCM-BIM) are obtained based on the algorithms presented in [2, 1]. The BCM computes the chromatic and brightness distortion components of each pixel and the intensity model. The BIM is built based on the arithmetic media and the standard deviation over the training period.

The Background Edge Model (BEM) is built as follows: first gradients are obtained by applying the Sobel edge operator to each colour channel in horizontal (x) and vertical (y) directions. This yields both a horizontal and a vertical gradient image for each frame during the training period. Thus, each background pixel gradient is modelled using the gradient mean $(\mu_{xr}, \mu_{yr}), (\mu_{xg}, \mu_{yg}), (\mu_{xb}, \mu_{yb})$, and gradient standard deviation $(\sigma_{xr}, \sigma_{yr}), (\sigma_{xg}, \sigma_{yg}), (\sigma_{xb}, \sigma_{yb})$ computed from all the training frames for each channel. Then, the mean $\mu_m = (\mu_{mr}, \mu_{mg}, \mu_{mb})$ and the standard deviation $\sigma_m = (\sigma_{mr}, \sigma_{mg}, \sigma_{mb})$ of the gradient magnitude are computed in order to build the background edge model.

3.2 Image Segmentation

The combination of colour and intensity models permits to cope with different problems. The pixel is classified as FI (Foreground Intensity) or BI (Background Intensity) using BIM if the BCM is not feasible. If the BCM is built but the current pixel has saturation or minimum intensity problems, then the pixel is classified using the BCM brightness as DF (Dark Foreground), LF (Light Foreground) or BB (Background Border). Finally, the remained pixels from image are classified as F (Foreground), B (Background), S (Shadow) or H (Highlight) using the chrominance and the brightness from BCM. See [2] for more details.

To obtain the foreground edge subtraction several steps are followed. Firstly, the Sobel operator is used over the new image in horizontal (x) and vertical (y) directions to estimate the gradients for every pixel $(r_x, r_y), (g_x, g_y), (b_x, b_y)$. Then, the magnitude of the current gradient image is calculated $V_m = (V_{mr}, V_{mg}, V_{mb})$. In order to detect the Fore-

ground pixels, the difference between the mean magnitudes of current image and background model is compared with the background model standard deviation magnitude. Therefore, a pixel is considered as foreground if:

$$V_m - \mu_m > k_e * \max(\sigma_m, \bar{\sigma}_m) \quad (2)$$

where K_e is a constant value used as a threshold, and the average standard deviation $\bar{\sigma}_m = (\bar{\sigma}_{mr}, \bar{\sigma}_{mg}, \bar{\sigma}_{mb})$ is computed over the entire image area to avoid noise.

Subsequently, the pixels classified as foreground are divided into two different types: the first one comprises the foreground edges belonging to the current image —*positive edges*— which were not in the background model, and the second one comprises the edges in the to the background model which are occluded by foreground objects —*negative edges*—.

3.3 Fusing Colour, Intensity and Edge Models (BCM-BIM-BEM)

The edge segmentation is not good enough to segment the foreground objects isolatedly. It can sometimes handle dark and light camouflage problems and it is less sensitive to global illumination changes than intensity cue. Nevertheless, problems like noise, false negative edges due to local illumination problems, foreground aperture and camouflage prevents from an accurate segmentation of foreground objects. Furthermore, due to the fact that it is sometimes difficult to segment the foreground object borders, it is not possible to fill the objects, and solve the foreground aperture problem.

Since it is not possible to handle dark and light camouflage problems only by using edges due to the foreground aperture difficulty, the brightness of colour model is used to solve this problem and help to fill the foreground object.

A sketch of the system which fuses colour, intensity and edge cues can be seen in Fig. 2.

Nonetheless, a dark and light intensity mask¹ (DI/LI) gives a lot of information, since it contains not only the dark and light camouflage but also the global and local illumination changes. Therefore, to

¹This mask come from the Brightness thresholds $T_{\alpha lo}$ and $T_{\alpha Hi}$ used in [2]

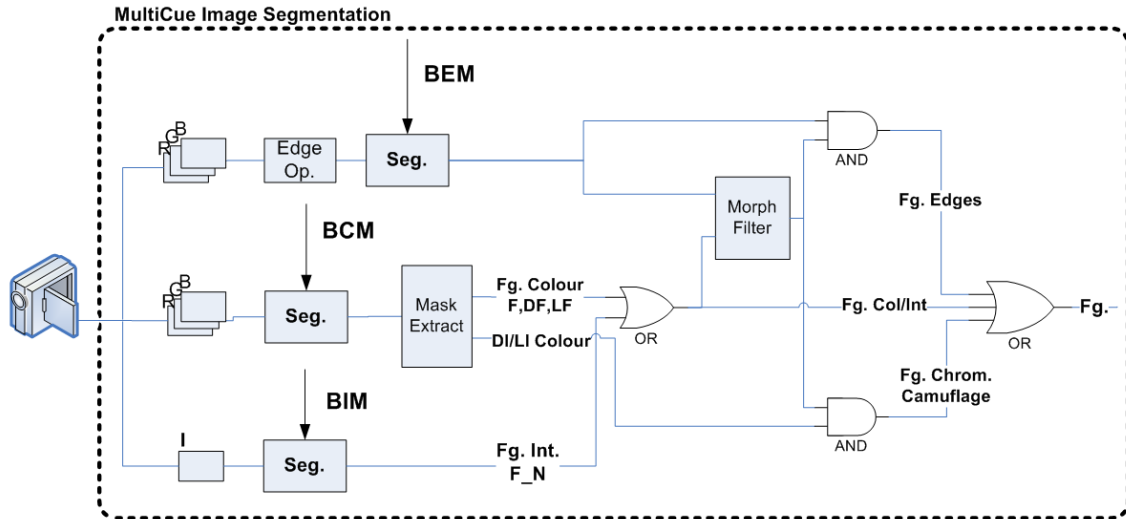


Figure 2: Overview of the system fusing colour, intensity and edge cues.

avoid the false positives due to global and local illumination changes, an edge mask is created by applying several morphological filters to the edge segmentation results. Thus, the edge mask is applied to the dark and light intensity mask, thereby allowing only the foreground objects detected by the edge mask to be filled with the dark and light intensity mask. In this way solving the dark and light camouflage problem. Morphological filtering over the edge segmentation results is needed to know whether the interior of the foreground objects are segmented or not, due to foreground aperture problem.

This edge mask could be applied to the Background Colour Model (BCM) to avoid some of the segmentation problems, such as the false positives due to noise, the changes in chrominance due to local illumination changes, and partially solve the ghost problem (only when the background is homogeneous). Nevertheless, it is sometimes difficult to detect all the foreground objects because whose borders are not accurately segmented due to edge segmentation problems, such as noise, false negative edges and camouflage. Therefore, it is not possible to apply a morphology filling to the objects in order to solve the foreground aperture problem. Consequently, some part of the objects is lost in the edge mask. For that reason, the edge mask cannot be applied over the BCM segmentation, since the foreground object will not be segmented if it or a part of it is not detected inside the edge mask, even if the

BCM can segment it. Hence, a lot of true positives will be lost.

Since the mask cannot be applied to the BCM and BIM, their segmentation results can be used to solve part of the problems of BEM, thereby helping to achieve foreground object detection more accurately than before, when the morphological filtering was only applied over the edge segmentation results. Therefore, the BEM results are combined with the BCM and BIM results to achieve a better edge mask which will be applied later over the dark and light intensity mask to segment the dark and light camouflage problem.

The Edge mask is built using a low threshold to segment positive edges, in order to accurately obtain the borders of the foreground objects, and a high threshold is applied to segment negative edges, in order to reduce noise and to avoid the problem with the false negative edges (edges which do not belong to any occluded edge by a foreground object) caused by local illumination changes, thus achieving a better foreground object detection.

The BEM give us a high number of true positives which were not obtained using the BCM and BIM. Furthermore, negative edges can solve part of the camouflage problem, since these edges are foreground edges which are occluded by foreground objects. Nevertheless, as it has been above mentioned, BEM segmentation results also contain a lot of false positives due to noise, and false negative edges. In

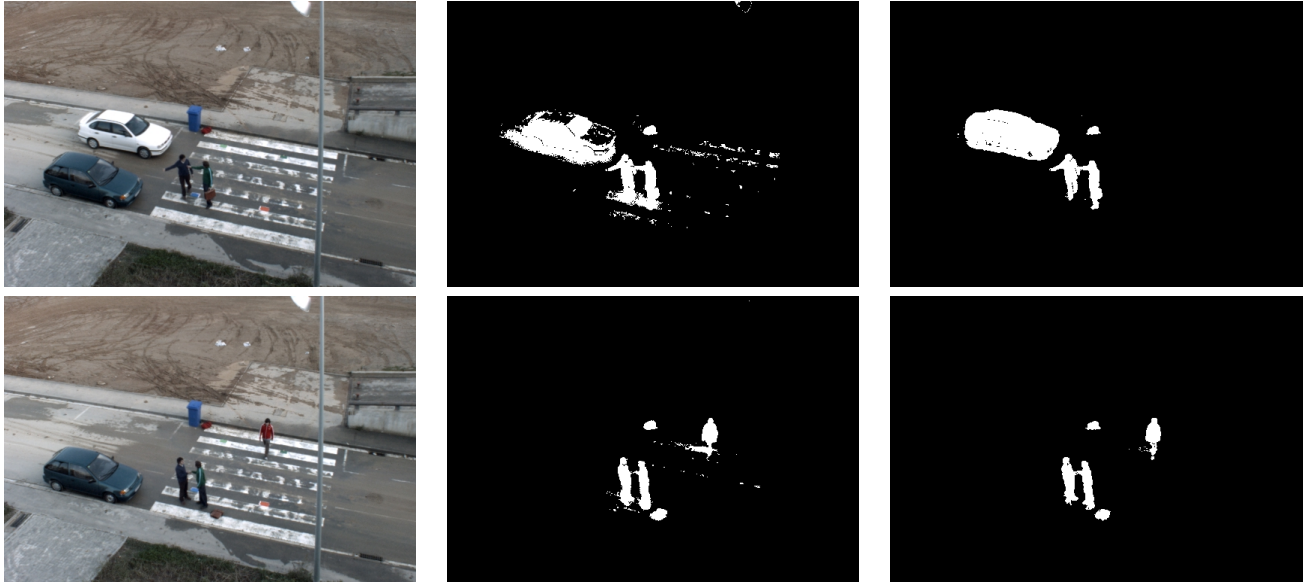


Figure 3: Foreground segmentation results from HERMES database: First column is the original image; Second column results from [1]. First row shows that part of car is not segmented due to light camouflage problem. Moreover, car and agents shadows are segmented due to dark foreground problem. Second row shows that trousers of agent three are segmented, thereby handling dark camouflage problem. However, shadows are also segmented due to dark foreground and saturation problem; Third column results from our final approach. First row shows that the car is segmented and light camouflage problem is solved. Second row shows that the trousers are also segmented, thereby coping with the dark camouflage problem. Furthermore, shadows are not segmented, thus handling the dark foreground and saturation problem. See text for more details.

order to avoid these problems, the edges incorporated to the segmentation process have a high threshold. Since the BCM and the BIM results are good enough, the BEM results added to the segmentation process will be restricted in order to improve the segmentation results avoiding losing performance. Therefore, the edge segmentation only includes true positives avoiding incorporating false positives.

4 Experimental Results

Our approach has been tested with multiple and different indoor and outdoor sequences under uncontrolled environments, where multiples segmentation problems appear.

The first column of Fig. 3 show two significant processed frames from *Hermes_Outdoor_Cam1* sequence (HERMES database, 1612 frames @15 fps, 1392 x 1040 PX). In this Fig. , agents and vehicles are segmented using different approaches: the approach by Horprasert et al. [1] (second column), and our final approach, which fuses colour, intensity

and edge cues (third column). These compare the different motion segmentation problems found in the sequence.

First row from Fig. 3 shows a frame with global illumination and light camouflage problem (the white car is camouflaged with the grey road). The results from [1] (second column) shows that part of the car is not segmented due to light camouflage problem. Furthermore, this approach only differentiates between dark camouflage from global and local illumination problems based on an intensity threshold. Therefore, shadows from the white car and agents are segmented as dark foreground erroneously. The third column shows that these problems are solved using our approach.

Second row from Fig. 3 shows a frame with an illumination change and dark foreground problem (the trousers of the agent are camouflaged with the crosswalk when he is crossing it). In this case, the both approaches are able to cope with this problem. Nevertheless, the approach proposed in [1] segments the shadow of the agent due to the above explained problem with the dark foreground, moreover the satura-



Figure 4: Foreground region segmentation applying our approach to different datasets, such as PETS and CAVIAR, among others.

tion problem due to the crosswalk colour. In our approach it is solved as it can be seen in the third column.

By using the combination of cues features, each of them can be used in a more restrictive way without compromising the detection rate. Nevertheless, false positive rate is cut down. The Fig. 4 shows that our approach works in different datasets, such as PETS and CAVIAR, among others.

5 Conclusion

The approach proposed can cope with different colour problems as dark and light camouflage. Furthermore, it can differentiate dark and light camouflage from global and local illumination problems, thereby reducing the number of false negatives, false positives and increasing the detected foreground regions.

Experiments on complex indoor and outdoor scenarios have yielded robust and accurate results, thereby demonstrating the system ability to deal with unconstrained and dynamic scenes.

In the future work updating process should be embedded to the approach in order to solve incorporation objects and ghost problems. Furthermore, the use of a pixel-updating process can reduce the false positive pixels obtained using the dark and light intensity mask due to intense illumination problems. In addition, the detected motionless objects should be part of a multilayer background model.

Furthermore, a colour invariant normalisations or colour constancy techniques can be used to improve the colour model, thereby handling illuminant change problem. These techniques can also improve the edge model in order to avoid false edges due to

intense illumination changes. Further, an edge linking or a B-spline techniques can be used to avoid the lost of part of foreground borders due to camouflage, thereby improving the edge mask. Lastly, the discrimination between the agents and the local environments can be enhanced by making use of new cues such as temporal difference technique.

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