Background subtraction adapted to PTZ cameras by keypoint density estimation

Constant Guillot[1]
constant.guillot@cea.fr
Maxime Taron[1]
maxime.taron@cea.fr
Patrick Sayd[1]
patrick.sayd@cea.fr
Quoc-Cuong Pham[1]
quoc-cuong.pham@cea.fr
Christophe Tilmant[2]
christophe.tilmant@lasmea.univ-bpclermont.fr
Jean-Marc Lavest[2]
J-Marc.Lavest@u-clermont1.fr

[1] CEA LIST
Laboratoire Vision et Ingénierie des Contenus,
BP 94, Gif-sur-Yvette,
F-91191 France
[2] LASMEA UMR 6602,
PRES Clermont Université/CNRS,
63177 Aubière cedex, France

With the increasing use of CCTV cameras many efforts have been made to automate the analysis of video streams in order to improve their efficiency. Wide angle cameras can be used to monitor a wide scene, their interest is however limited by their low resolution when it comes to analysing the scene. Pan Tilt Zoom (PTZ) cameras have two rotation axis and a zoom function which enable focusing on a part of the scene at any suitable resolution. The obvious drawback of the PTZ sensor is its limited field of view.

We propose a background subtraction algorithm adapted to the particular case of a PTZ camera performing a guard tour. The guard tour consists in a set of predefined positions (pan, tilt, zoom), and the background model at each of these position is an image.

Registering images Due to mechanical imprecision on the pan tilt and zoom parameters, the most stable keypoints, the one with the highest Harris scores, are used to register the current image on the background image by robustly estimating a homography. Registering the current image on the background image does not require to compute extra keypoints since we use the same keypoints as those used in the following background subtraction phase.

Matching keypoints SURF descriptors are computed on both background and current image at the positions of Harris keypoints found on both images.

Keypoint density estimation Once we have a set of non matching keypoints, we estimate their density d using a Kernel Density Estimation algorithm (see figure 1).

Let $(p_1, \ldots, p_N)$ be the N non matching keypoints, then

$$\hat{d}_h(x) = \frac{1}{Nh}\sum_{i=1}^{N} K\left(\frac{\|x-p_i\|_{img}}{h}\right), \tag{1}$$

with K being a kernel function, is an estimation of the value of d to the pixel x. The parameters h is a smoothing parameter which specifies the influence of each observation on its neighbourhood.

Background update Let bg_n and img_n be the background image and the current image at step n, and x be a pixel. We apply the following updating rule:

If $\hat{d}_h(x) > s$,

$$bg_n(x) = bg_{n-1}(x). \tag{2}$$

Else,

$$bg_n(x) = bg_{n-1}(x)\frac{N\hat{d}_h(x)}{s} + img_n(x)\left(1 - \frac{N\hat{d}_h(x)}{s}\right). \tag{3}$$

Experimental results This simple yet effective background subtraction algorithm we propose proves to be robust to changes in illumination (see figure 2). A probability density function is computed by examining matching failures between the background model and the query image.

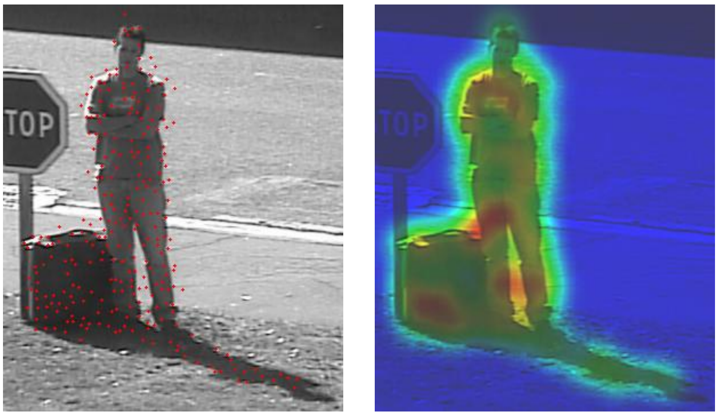

Figure 1: Left: Non matching keypoints between the background image and the current view. Right: The associated density probability function. Blue is for low, green for medium and red for high density values.

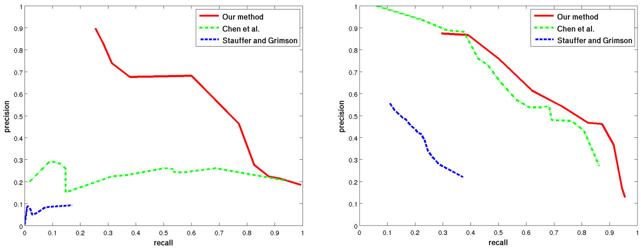

Figure 2: Precision and recall curves for the Light change sequence. Left: curves computed on a subsequence reduced to the period of an important change in illumination. Right: curves computed on a subsequence where there is no sudden change in illumination.

We successfully apply this algorithm to the challenging case of PTZ cameras performing a guard tour and for which illumination issues are critical. Experiments show that the proposed approach is more robust to this phenomenon than other methods. Our algorithm successfully detects blobs with a precision sufficient as a first step toward an object detection application.

[1] Herbert Bay, Andreas Ess, Tinne Tuytelaars, and Luc Van Gool. Surf: Speeded up robust features. In *CVIU*, 2008.

[2] A. Bevilacqua and P. Azzari. High-quality real time motion detection using ptz cameras. In *AVSS*, 2006.

[3] Thierry Bouwmans, Fida El Baf, and Bertrand Vachon. Background Modeling using Mixture of Gaussians for Foreground Detection - A Survey. *Recent Patents on Computer Science*, 2008.

[4] Yu-Ting Chen, Chu-Song Chen, Chun-Rong Huang, and Yi-Ping Hung. Efficient hierarchical method for background subtraction. In *Pattern Recognition*, 2007.

[5] Lionel Robinault, Stéphane Bres, and Serge Miguet. Real time foreground object detection using ptz camera. In *VISAPP*, 2009.