Abstract—A novel and high-quality system for moving object detection in sequences recorded with moving cameras is proposed. This system is based on the collaboration between an automatic homography estimation module for image alignment, and a robust moving object detection using an efficient spatio-temporal nonparametric background modeling.

I. INTRODUCTION

The recent proliferation of electronic devices with a camera has greatly increased the demand for computer vision applications [1]. Many of these applications need to include high-quality moving object detection methods as a first step for higher level analysis tasks (e.g. tracking, mixed or augmented reality). Among the many methods proposed in the last decades to detect moving objects [2], two main general statistical modeling background approaches must be outlined: mixture-of-Gaussians (MoG), based on parametric methods [3], and nonparametric modeling, using kernel density estimation [4]. The growing computational power of current processors is causing an increasing preference for the latter, since it shows better adaptation capabilities and more natural handling of spatial uncertainties caused by camera instability and dynamic backgrounds [5].

Most parametric and nonparametric algorithms have been designed for static cameras [6]. However, there is a significant need for efficient strategies for moving object detection in sequences recorded with moving camera platforms (e.g. cellular phones, vehicles, or robots), able to handle apparent displacements due to sensor movement and not to the presence of moving agents.

We propose a novel and efficient system for moving object detection in sequences recorded with non-static cameras. This system automatically estimates the homography compensating the apparent scene background motion induced by the moving camera, and creates a spatio-temporal kernel-based background model from reference pixel observations from previous images, adapted spatially using the inferred transforms. Robust homography estimation is necessary to spatially align each current sample with its corresponding reference data, while spatio-temporal modeling is required to avoid the inevitable inaccuracies in data alignment. In addition, final detection results are fed back into the estimation of subsequent homographies, reducing thus the influence of foreground features and improving the accuracy of the resulting alignment.
the set of spatially-adapted pixels $\mathbf{x}\in\gamma = \{x^n, h^n_B(s^n)\}$, is then incorporated to the set of reference samples used in $\gamma\mathcal{E}$ to create the nonparametric model in the virtual canvas.

The probabilistic foreground/background classification of the pixels of such virtual canvas is also the basis for the classification of each original input pixel $x^n$, obtained by transforming the probabilistic classification performed on the canvas and applying the inverse of the transformation $h^n_B$ to obtain the final interpolated probability mask for $I^n$ (from canvas to image domain, see Fig. 1).

III. RESULTS

The proposed strategy has been tested in two sequences, $S1$ and $S2$, recorded with non static cameras and containing critical situations for moving object detection strategies. $S1$ is an indoor sequence captured by a camera panning from right to left. $S2$ is an outdoor sequence captured by a shaking camera and presenting continuous background jolts in all directions.

Figure 2.a depicts one original image from each test sequence. The detections obtained with the strategy in [7], which is an improved version of the spatio-temporal nonparametric method for non-static cameras in [6], are depicted in Fig. 2.b. The detections obtained with the proposed mosaicing-modeling feedback appear in Fig. 2.c. These results show that the proposed strategy avoids most false detections due to camera motion and that it obtains compact detected regions.

Finally, Fig. 3 shows the overall recall, precision and $F$ percentages [6] (evaluating jointly both recall and precision as $F = \frac{2 \times \text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}}$) obtained with the proposed strategy and with the modeling in [7] for different spatial kernel widths ($\sigma$). As expected, in the modeling proposed in [7], the amount of false detections decreases (higher precision) as the used spatial bandwidth increases. However, the amount of correct detections also decreases (lower recall), which results in low $F$ values. As our strategy updates the spatial position of the background reference data, we provide both high recall and precision percentages using a small spatial bandwidth. So, we clearly obtain the best $F$ values.

IV. CONCLUSION

A novel moving object detection algorithm for sequences recorded with non-static camera has been proposed, suitable for the computer vision applications demanded by portable device users. To this end, the motion of the scene background is compensated through automatic homography estimation. The aligned data are used as reference to model the background with a spatio-temporal nonparametric modeling, avoiding misdetections due to the inevitable inaccuracies in data alignment. The detection results are fed back to the homography module to reduce the influence of the foreground in the motion compensation. The obtained results have shown that the proposed strategy significantly improves the quality of previous approaches in the considered moving settings.

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