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Moving object detection using unstable camera for video surveillance systems

Seungwon Lee, Nahyun Kim, Kyungwon Jeong, Kyungju Park, Joonki Paik*

Department of Image, Chung-Ang University, Seoul, South Korea

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ABSTRACT

This paper presents a robust moving object detection method by compensating for motion of an unstable camera. Assuming that global camera motion results in affine transform between two successive frames, local affine motions are separately estimated in multiple pre-specified regions for fast, robust estimation of the global motion. The global camera motion is then estimated by the least squares method using the pre-estimated multiple local affine motions. Given a current frame as the reference, the subsequent frame is registered to the current frame using the estimated global motion. The moving objects are finally detected using difference of Gaussian and non-parametric kernel density estimation from the set of registered three frames. Experimental results show that the proposed method can robustly detect moving objects in unstable imaging environment for intelligent surveillance systems using various types of cameras including pan-tilt-zoom (PTZ) and unmanned aerial vehicle (UAV) cameras.

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1. Introduction

Moving object detection is a fundamental problem in computer vision and video processing, and its applications have widely extended to robot vision, human computer interfaces, and intelligent surveillance systems [1–3].

The detection of a moving object can be considered as a low- or intermediate-level processing step for various object recognition and analysis applications. In general, the background subtraction method using background modeling and the motion-based object detection are used to detect moving object [4,5]. Since the background subtraction method assumes that a camera is fixed, it may fail in detecting objects under critical environments containing as camera jitter, noisy sequences, and illumination changes. The multimodal strategies have been presented for overcoming these limitations. To solve the problems of the repetitive motion like rippling water, flickering monitors, and periodic jitter of a camera, the mixture of Gaussians-based background modeling methods were proposed by estimating the Gaussian distribution in the pixel level [6,7]. However, Gaussian assumption for the pixel intensity distribution does not always hold, and as a result the detection of an object fails if the background is updated when the global camera motion occurs. To overcome limitations of the parametric methods, a non-parametric approach to background modeling was proposed [8]. However, this method is memory- and time-consuming because of the computation of the average of all kernels centered at each training sample for every pixel.

The background modeling-based object detection method is not suitable for video sequences acquired by dynamic cameras such as pan-tilt-zoom (PTZ) and unmanned aerial vehicle (UAV) cameras because the background has to be remodeled at each frame. Therefore, the camera motion compensation and a proper object detection methods are needed for such unstable imaging environment. To overcome the problem of the unstable camera, Lee et al. [9] proposed the local motion-based moving object detection method after the global motion compensation. However, the global motion estimation using elastic registration has the high complexity because the affine motion is estimated in the entire image using multiple iterations. In addition, the error of the inaccurately estimated global motion and the corresponding motion compensation result in performance degradation in estimating local motions.

This paper presents a robust moving object detection algorithm in the unstable camera environment as shown in Fig. 1. The proposed method consists of the global motion estimation step for registering frames and the moving object detection step using the proposed frame difference scheme and non-parametric kernel density estimation. In the global motion estimation step, under assumption that a camera's global motion is modeled as an affine transformation, the affine matrix is estimated between successive

* Corresponding author. Tel.: +82 2 8205300.
E-mail addresses: superlsw@gmail.com (S. Lee), skgus1433@gmail.com (N. Kim), fjqmsa@gmail.com (K. Jeong), kjpark@cau.ac.kr (K. Park), paikj@cau.ac.kr (J. Paik).

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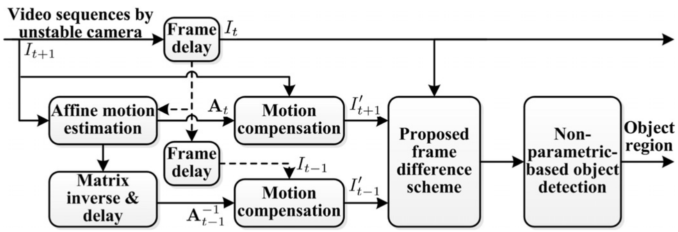

Fig. 1. The proposed moving object segmentation framework.

frames using the estimated global motion. Local affine motions are estimated using the affine model-based optical flow method at the selected four regions for fast global motion estimation [10]. The global camera motion is then estimated by the least squares method using the estimated four local affine motions. The refinement step is finally performed for increasing the accuracy of the global motion estimation.

In the moving object detection step, the subsequent frame is registered to the current frame using the estimated global motion, and the previous frame is also registered to the current frame using the inverse of the estimated global motion of the previous frame. Frame difference between the current and registered adjacent frames may result in the erroneous detection of an object because of the error in estimating affine motions and motion compensated interpolation. To overcome these problems, an average image is generated using the current and two adjacent registered frames. The average frame and two adjacent frames are lowpass filtered by a suitable Gaussian function for robust detection of object by removing spurious patterns.

By subtracting two adjacent lowpass filtered frames from the current frame, two differences of Gaussian (DoG) images are obtained, one of which has an opposite sign to the other in the moving object region [11]. A moving object can be detected using the property of the DoG and the relationship between temporally adjacent frames. Since the DoG has holes in the center of the object, and is still sensitive to noise, the proposed method uses non-parametric kernel density estimation for filling the holes and removing noisy artifacts. The proposed global affine motion estimation algorithm is computationally efficient because of the fusion of multiple local motions by averaging four locally estimated affine motions. Since the existing background modeling methods are not suitable for dynamic imaging system using PTZ and UAV cameras, the proposed method uses only two adjacent frames without background modeling, which can also reduce the memory space and computational cost.

Experimental results show that the proposed method can robustly detect moving objects in unstable imaging environment for intelligent surveillance systems using various types of cameras including PTZ and UAV cameras.

The paper is organized as follows. Section 2 presents the moving object detection in unstable camera environment. Section 3 summarizes experimental results, and Section 4 concludes the paper.

2. Moving object detection in unstable imaging environment

If camera motion occurs, the conventional motion-based object detection method fails to detect objects because of the global camera motion. To overcome this problem, the proposed method uses the global motion estimation and compensation for robust object detection in unstable imaging environment.

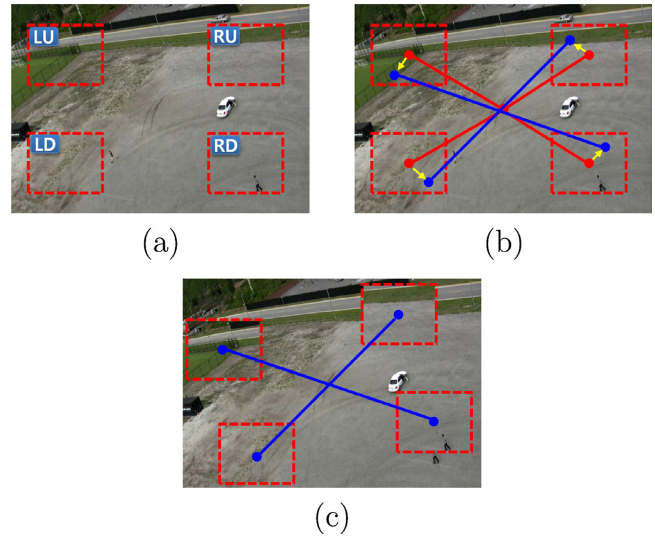

Fig. 2. Concept of the proposed camera motion estimation; (a) local motion estimation at selected four regions (LU: left up, LD: left down, RD: right down, and RU: right up), (b) global motion estimation (red points: center of the each selected region, blue points: moved positions), and (c) refining the global motion estimation. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

2.1. Camera motion estimation

For registering two consecutive frames with irregular camera motions, a motion estimation method used in a digital image stabilization system is adopted. Based on the assumption that the global camera motion is modeled by an affine transformation, the proposed camera motion estimation algorithm estimates the affine matrix between current and subsequent frames.

Fig. 2 illustrates the concept of the proposed camera motion estimation algorithm. After estimating local affine motions in four sub-regions as shown in Fig. 2(a), the global motion is determined using the Gaussian pyramid-based coarse-to-fine approach.

The general affine transform is expressed as follows:

$$\begin{pmatrix} x' \\ y' \\ 1 \end{pmatrix} = \mathbf{H}_A \cdot \begin{pmatrix} x \\ y \\ 1 \end{pmatrix} = \begin{pmatrix} a_1 & a_2 & a_5 \\ a_3 & a_4 & a_6 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} x \\ y \\ 1 \end{pmatrix}, \quad (1)$$

where $\mathbf{H}_A$ represents the affine camera model matrix; a_1, a_2, a_3, and a_4 represent a set of linear affine parameters; and a_5 and a_6 represent the translation parameters. Local affine motions are estimated using the affine model-based optical flow method proposed by Periaswamy [10]. More specifically, if $I(x, y, t)$ is the region in the current image frame, and $I(x, y, t+1)$ is the same region in the subsequent frame, the motion estimation problem assumes that the motion between these two images can be modeled as an affine transform. To estimate the affine matrix, the following quadratic error function is minimized

$$E(\mathbf{a}) = \sum_{x,y \in \Omega} [I(x, y, t) - I(a_1x + a_2y + a_5, a_3x + a_4y + a_6, t+1)]^2, \quad (2)$$

where $\mathbf{a} = (a_1, a_2, a_3, a_4, a_5, a_6)^T$, and Ω represents the support of region.

Since $E(\mathbf{a})$ is a nonlinear function of $\mathbf{a}$, it should be linearized using the first-order Taylor series expansion to explicitly solve the minimization problem for $\mathbf{a}$ as

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