

REVIEW ARTICLE



ISSN: 2321-7758

MOTION DETECTION IN NON-STATIONARY BACKGROUND USING 'ORB' FEATURE MATCHING AND AFFINE TRANSFORMATION FOR VIDEO SURVEILLANCE SYSTEMS

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Article Received: 20/04/2015

Article Revised on:24/04/2015

Article Accepted on:28/04/2015



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International Journal of
Engineering
Research-Online



ABSTRACT

Visual surveillance systems have gained a lot of interest in the last few years due to its importance in military application and security. Surveillance cameras are installed in security sensitive areas such as banks, train stations, highways, and borders. In computer vision, moving object detection and tracking methods are the most important preliminary steps for higher-level video analysis applications.

Moving objects in moving background are an important research area of image-video processing and computer vision. Feature matching is at the base of many computer vision problems, such as object recognition or structure from motion. ORB is used for feature detection and tracking. The objective is to track the moving objects in a moving video. Oriented Fast and Rotated Brief (ORB) which is a combination of two major techniques: Features from Accelerated Segment Test (FAST) and Binary Robust Independent Elementary Features (BRIEF). Mismatched features between two frames are rejected by the proposed method for a good accuracy of compensation. The Residues are removed using Morphological Operation. The Frame Differencing methods are compared with the proposed ORB feature matching algorithm to detect the accuracy and efficiency.

Keywords—Object Detection, Visual Surveillance, motion detection.

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I. INTRODUCTION

The moving object detection in video pictures has attracted a great deal of interest in computer vision. For object recognition, navigation systems and surveillance systems, object detection is an indispensable first step. Object detection has significance in real time environment because it enables several important applications such as Security and surveillance [1] to recognize people, to provide better sense of security using visual information. Moving object detection is the basic

step for further analysis of video [11]. It handles segmentation of moving objects from moving background objects. This not only creates a focus of attention for higher level processing but also decreases computation time considerably. Commonly used techniques for object detection are background subtraction, statistical models, temporal differencing and optical flow[10]. Due to dynamic environmental conditions such as illumination changes, shadows and waving tree branches in the wind object segmentation is a

difficult and significant problem that needs to be handled well for a robust visual surveillance system. The goal is to detect moving objects in moving background robustly with a real-time performance using ORB feature matching. The main objective of moving object detection aims at extracting moving objects that are of interest in video sequences.

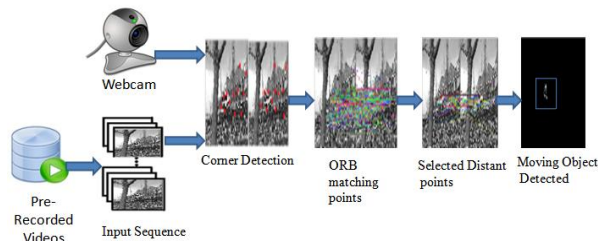


Fig.1. System Architecture

The overall architecture of the system is shown in figure 1. The user stores pre-recorded videos detecting the moving objects in moving background. Object Detection is the identification of an object in a video. The video is divided into many frames based on the size of the video. Feature Detection is used to find some interesting features in the image for example corners, edges, blobs etc. ORB match corresponding points across frames accurately. FAST is a corner detection method, which could be used to extract corner points. Similarity Transform is used to detect the changes in the object shape due to the changes in its structure. So morphology operations are used to remove residues and ghost in the individual frames.

literature survey

This section briefly outlines the related works. The goal of background subtraction is to remove the background in a scene by describing an adequate model of the background [2]. The result is that only interesting objects are left in the scene for tracking and further analysis. This technique generally has a low computational cost. It is done in a pixel by pixel fashion. However, in traditional background subtractions are susceptible to environmental changes, for example, in the cases of gradual or sudden illumination change. These changes alter the background model. The result of background subtraction is always contaminated by a large number of erroneous foreground pixels. However, one drawback is that it is vulnerable to scene dynamics and clutter. It works only for static

background and dynamic background model update is required for dynamic background scenes [3].

Color Histograms are used for object tracking because they are flexible in the type of object that they can be used to track, including vehicles and people. A single feature does not provide enough information about the object being tracked. The problems arise when target object and background have similar color distribution. It may be difficult to distinguish the object from background. Higher level feature descriptors can also be used for object tracking [4].

The method of Frame difference is used to detect moving objects. The method does not have background model. The current frame is simply subtracted from the previous frame and if the difference in pixel values is greater than threshold, the pixel is considered as part of the foreground [12]. The objects must be continuously moving in each frame. If the object does not move for more than frame period it becomes the part of background pixel. Difficult to determine the value of the threshold [5].

Kalman filter Object tracking problem can be formulated as a state estimation problem given available observation. Kalman filtering is popularly used for object tracking because it has been shown to be very successful for linear and Gaussian dynamic state estimation problems and is still very reliable in cases like clutter and occlusions. Kalman filter segments moving objects by cluster the image features, which will be wrong if the image features are some mismatch [6].

ORB IMPLEMENTATION DETAILS

A. FAST Keypoint Orientation

ORB [7] can be used to detect local keypoints in an image with good performance and low computational cost. In order to extract keypoint fast and accurate, ORB start by detecting Features from Accelerated Segment Test (FAST) points in the image. The FAST [8] segment test criterion operates by considering a circle of sixteen pixels around the corner candidate p . The detector classifies p as a corner if there exists

a set of 12 contiguous pixels in the circle which are all righter

than the intensity of the candidate pixel $I(p)$ plus a threshold t ,

or all darker than $I(p)-t$. The test examines only the four compass directions for a high speed. If p is a corner then at least three of these must all be brighter than $I(p)+t$ or darker than $I(p)-t$. For rotation invariant, the keypoints orientation is computed by the moments of keypoint's patch:

$$\theta = \text{atan2}\left(\sum_{x,y} yI(x,y), \sum_{x,y} xI(x,y)\right)$$

$I(x, y)$ is pixel's intensity at position x and y of the keypoint's patch.

B. Rotation-Aware Brief

It is needed to describe each keypoint for a good match. The descriptor of ORB is the improvement of Binary Robust Independent Elementary Features (BRIEF). BRIEF is a recent feature descriptor that use simple binary test between pixels in a smoothed image patch [9]. Consider a smoothed image patch, p . A binary test τ is defined by:

$$\tau(p; x, y) := \begin{cases} 1 & : p(x) < p(y) \\ 0 & : p(x) \geq p(y) \end{cases}$$

where $p(x)$ is the intensity of p at a point x , the feature is defined as a vector of n binary test:

$$f_n(p) := \sum_{1 \leq i \leq n} 2^{i-1} \tau(p; x_i, y_i)$$

The test pairs of x and y are selected by PCA for a good discriminative.

OUR IMPROVED MATCHING METHOD FOR DETECTING MOVING OBJECTS

A. Extracting and matching ORB feature

In existing motion compensation methods, the main part of computation time is occupied by features extracting and matching. ORB is an order of magnitude faster than SURF, and over two orders faster than SIFT. So it is reasonable to choose ORB features for a faster computation to improve the motion compensation methods. In addition, ORB descriptor is binary strings. Its similarity is evaluated more efficiently by using the Hamming distance than $2L$ norm which SIFT and SURF are using.

B. Rejecting the mismatched pairs

Although the descriptors in the previous frame can be matched with the next frame robustly by brute-force method, some mismatched descriptors are still existed in traditional matching method. These mismatched descriptor pairs would damage the

estimation results and lead detection failed, as show in SIFT based and SURF based method. So we proposed a method of distance constraint method to reject mismatched descriptor pairs. We know that even if the camera would move fast, the motion distance between two adjacent frames wouldn't be very large. That means if a keypoint located at (x, y) in the previous frame. The matched keypoint would be in the neighbourhood of the same position in the next frame. We assume that this distance is less than d . If the distance between two descriptors positions of the matched pairs is larger than d , this descriptors should be rejected for good matching results.

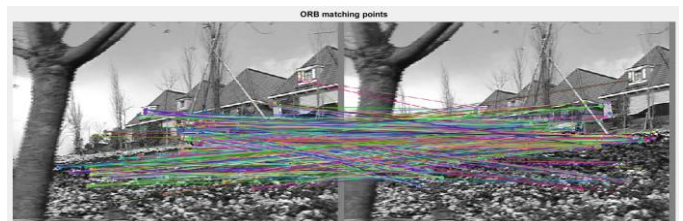


Fig. 2. Matched pairs of ORB feature between two frames.

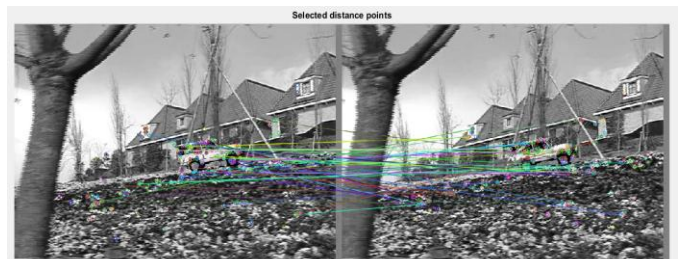


Fig 3. Retained pairs after rejecting mismatched pairs by distance constraint.

C. Remove ghost and residues

The motion model of a camera can be described by an affine transformation, so the transformation of $(k-1)$ -th frame point $[x \ y]^T$ to the $(k+1)$ -th frame point $[u \ v]^T$ can be written as

$$\begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} m_1 & m_2 \\ m_3 & m_4 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} + \begin{bmatrix} m_5 \\ m_6 \end{bmatrix}$$

$m_1 \rightarrow m_6$ the motion parameters. The equation above can be rewritten as:

$$\begin{bmatrix} x & y & 0 & 0 & 1 & 0 \\ 0 & 0 & x & y & 0 & 1 \\ \dots & & & & & \\ \dots & & & & & \end{bmatrix} \begin{bmatrix} m_1 \\ m_2 \\ m_3 \\ m_4 \\ m_5 \\ m_6 \end{bmatrix} = \begin{bmatrix} u \\ v \\ \cdot \\ \cdot \\ \cdot \\ \cdot \end{bmatrix}$$

Let (x, y) and (u, v) be the descriptor position of matched pairs, the parameters can be solved easily by the least squares method. The previous frame is transformed by the affine transformation of parameters we have estimated, the motion between these two frames can be compensated. Then the Frame difference method is used to detect moving objects. If the objects are moving very fast in the video, then a large part of moving objects area can be detected which will make the detection result more perfectly.

Most of existing method ends at this step, however, residues and ghost would be still appeared in the resulting image through precise compensation, such as SIFT or SURF based method. Part of this problem is because of dynamic background (for instance, swing tree leaves or changing light). We proposed that remove residues and ghost by Logic AND operation between two result frames after Frame difference.

V. MOVING OBJECT SEGMENTATION

Moving objects detection in moving background has been introduced above. Entire algorithm is summarized as follows:

1. ORB features are extracted and matched between two frames.
2. Mismatched descriptor pairs are rejected by the method of distance constraint.
3. Parameters of affine transformation are computed precisely by the rest of matched pairs.
4. The $(k-1)$ -th frame I_{k-1} is transformed to I_{k-1}^1 by the affine transformation.
5. I_{k-1}^1 subtracts I_{k-1} for Frame difference:

$$M_{k+1}(x, y) = \begin{cases} 255 & |I_{k-1}^1 - I_{k+1}| > threshold \\ 0 & else \end{cases}$$

6. Segment moving objects after Logic AND operation between two subtracted images and morphology method.

$$O(x, y) = \begin{cases} 255 & \text{if } M_{k+1}(x, y) = 255 \ \& \ M_{k+2}(x, y) = 255 \\ 0 & else \end{cases}$$

Where $O(x, y)$ is resulting image after detecting moving objects. 255 means moving region, 0 means static region.

SIMULATION AND RESULTS

Experimental results of the proposed method are presented in this section. The video sequences are processed using OpenCV in MATLAB. The Frame Differencing methods are compared with the

proposed ORB feature matching algorithm to detect the accuracy and efficiency. The Figure 4 represents Motion pixels truly detected as motion.

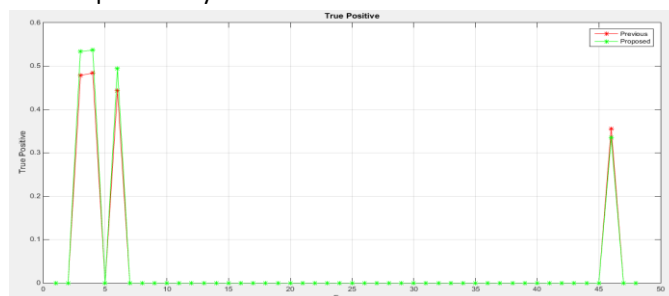


Figure 4: True Positive

The Figure 5 represents Background pixels truly detected as background.

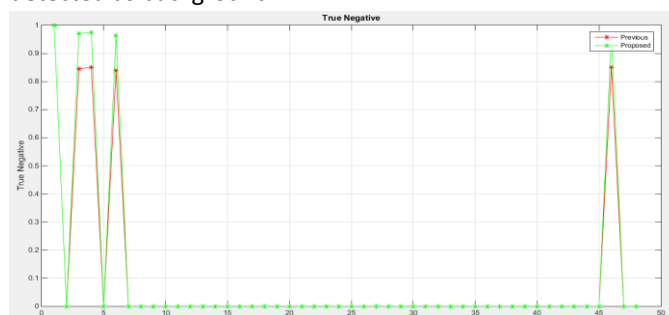


Figure 5: True Negative

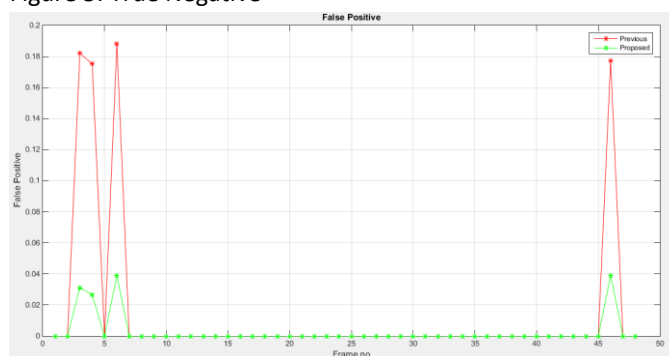


Figure 6: False Positive

The Figure 6 represents Background pixels falsely detected as motion.

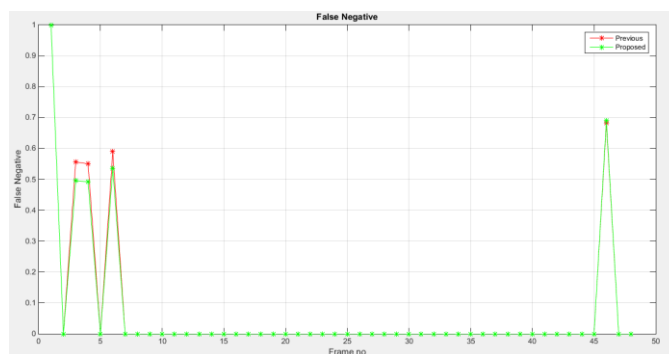


Figure 7: False Negative

The Figure 7 represents Motion pixels falsely detected as background.

CONCLUSION

In this paper, a real-time video of moving object detection in moving background got by moving camera based on ORB feature matching is presented. The motion can be compensated accurately and quickly after rejecting mismatched descriptor pairs. The camera motion can be compensated accurately by rejecting mismatched descriptor pairs, because of the using of ORB features, the motion can be compensated accurately and quickly after rejecting mismatched descriptor pairs. Compared with other motion detection algorithms, the proposed method is much better to detect the moving objects.

REFERENCES

- [1]. Songyun Xie, Wanpeng Zhang, Wang Ying, and Khalid Zakim "Fast Detecting Moving Objects in Moving Background using ORB Feature Matching" International Conference on Intelligent Control and Information Processing (ICICIP) 2013.
- [2]. Ka Ki Ng and Edward J. Delp, Object Tracking Initialization using Automatic moving Object Detection, Proceedings of the SPIE Conference on Visual 7 Information Processing and Communication, vol.7543, San Jose, CA, January 2010.
- [3]. Samera. J. H. Jean and F. L. Lian, "Robust Visual Servo Control of Mobile Robot for Object Tracking Using Shape Parameter," Control Systems Technology, IEEE Transactions on, vol. 20, pp. 1461-1472, 2012.
- [4]. B M. Teutsch and W. Kruger, "Detection, Segmentation, and Tracking of Moving Objects in UAV Videos," in Advanced Video and Signal-Based Surveillance (AVSS), 2012 IEEE Ninth International Conference on, 2012, pp. 313-318.
- [5]. H. Ying, X. qiu, J.Song and X.Ren, Particle filtering object trackingbased on texture and color, Proceedings of the IEEE International Symposium on Intelligence Information Processing and Trusted Computing, Huanggang ,China, October 2010,pp. 62 6630.
- [6]. I. Haritaoglu, D.Harwood, and L.S. Davis, W4: Real-time surveillance of people and their activities,IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 22, no.8. Washington, DC,USA:IEEE Computer Society, August 2000,PP. 809830.
- [7]. E. Rublee, V. Rabaud, K. Konolige, and G. Bradski, "ORB: an efficient alternative to SIFT or SURF," in Computer Vision (ICCV), 2011 E International Conference on, 2011, pp. 2564-2571.
- [8]. E. Rosten, R. Porter, and T. Drummond, "Faster and better: A machine learning approach to corner detection," Pattern Analysis and Machine Intelligence, IEEE Transactions on, vol. 32, pp. 105-119,2010.
- [9]. M. Calonder, V. Lepetit, C. Strecha, and P. Fua, "Brief: Binary robust independent elementary features," Computer Vision–ECCV 2010, pp. 778-792, 2010
- [10]. Mr. Mahesh C. Pawaskar, Mr. N. S.Narkhede and Mr. Saurabh S. Athalye," Detection Of Moving Object Based On Background Subtraction", 2014
- [11]. Rafael C. Gonzalez, Richard E. Woods "Digital Image Processing" Pearson Education South Asia Ltd pp 630-639
- [12]. M. Kalpana Chowdary, S.Suparshya Babu, S.Susrutha Babu, Dr.Habibulla Khan "FPGA Implementation of Moving Object Detection in Frames by Using Background Subtraction Algorithm" International conference on Communication and Signal Processing, April 3-5, 2013, India ©2013 IEEE pp 1032-1036.