A Survey on Moving Object Detection for Wide Area Motion Imagery

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Abstract

Wide Area Motion Imagery (WAMI) enables the surveillance of tens of square kilometers with one airborne sensor. Each image can contain thousands of moving objects. Applications such as driver behavior analysis or traffic monitoring require precise multiple object tracking that is dependent on initial detections. However, low object resolution, dense traffic, and imprecise image alignment lead to split, merged, and missing detections. No systematic evaluation of moving object detection exists so far although many approaches have been presented in the literature. This paper provides a detailed overview of existing methods for moving object detection in WAMI data. Also we propose a novel combination of short-term background subtraction and suppression of image alignment errors by pixel neighborhood consideration. In total, eleven methods are systematically evaluated using more than 160,000 ground truth detections of the WPAFB 2009 dataset. Best performance with respect to precision and recall is achieved by the proposed one.

1. Introduction

Wide Area Motion Imagery (WAMI) sensors enable the surveillance of several tens of square kilometers while using only one airborne sensor platform. Such sensors are comprised of a matrix of multiple cameras. Images of neighboring cameras overlap and are stitched to form an image with larger ground coverage at high resolution. The stitched images are typically collected at 1-2 Hz due to the large data volume (up to 100 megapixels) and can contain thousands of moving objects. An example for WAMI data is given by the publicly available WPABF 2009 dataset [27]. Reliable moving object detection and tracking facilitates automatic behavior recognition, scene understanding, or traffic monitoring at large scale. Solving such tasks efficiently can support various applications in the field of civil safety and security.

Multiple object tracking in WAMI data is based on initial object detections [17] that are obtained by object segmentation approaches based on background subtraction or frame differencing. These detections are used at different stages in the tracking algorithm such as object-to-object association for track initialization or object-to-track association [2]. While missing detections emerge the need for track linking, false positive detections can cause the initialization of false positive tracks. However, both missing and false positive detections are likely to occur since moving object detection in WAMI data is very challenging. Image alignment is applied to compensate for camera motion. Motion parallax and residual errors of the alignment process produce false positive detections. Split and merged detections occur especially in dense traffic scenes where object boundaries become blurred. Weak contrast between object and background, shadows, and occlusions cause missing detections. Finally, due to low object resolution of about \(10 \times 20\) pixels, detection approaches based on appearance features and machine learning are unreliable in WAMI so far [17]. Furthermore, there are two specific additional challenges of the WPABF dataset: sudden changes in camera gain and image stitching seam artifacts. Seam artifacts, i.e. intensity discontinuities in the images, arise due to radiometric changes across different sensors [6]. Sweeping seams can cause bands of large difference in the difference image and produce false positive detections.

In general, the performance of moving object detection in WAMI data is expected to suffer from the aforementioned effects. Although various different detection approaches exist in the literature [19, 20, 30], no systematic evaluation of detection performance has been presented so far. Instead, authors usually focus on developing and evaluating multiple object tracking algorithms that implicitly handle inaccurate detections, e.g. by allowing many to many correspondences (i.e. detection and track sharing) in multiple hypothesis tracking [20]. Common evaluation measures such as precision and recall are reported either with respect to estimated
tracks and not detections [17] or within a limited evaluation setup [22, 8].

In this survey, we systematically evaluate ten existing moving object detection approaches for WAMI data and demonstrate how optimized detection parameters reduce the number of missed and false positive detections considerably. Previous surveys such as Radke et al. [18] summarize change detection methods, whereby the specific characteristics of WAMI and their impact on the detection method are not considered. We, however, explicitly discuss and evaluate WAMI related pre-processing such as suppression of seam artifacts and post-processing such as parallax suppression. Inspired by other authors [2, 6], we choose four image regions of the WPAFB 2009 dataset [27] for our experiments with about 163,000 ground truth (GT) detections in 1,025 frames. Comparability of the evaluated methods is guaranteed by uniform image alignment and pre-processing. Parameters that contribute most to the performance of each method are discussed and their impact on precision and recall is analyzed. Furthermore, the influence of varying traffic density and background scenery on the detection performance is discussed.

The remainder of this paper is organized as follows: Section 2 gives an overview of object detection as well as WAMI surveys in literature. Perspective object detection methods are described in Section 3 and the evaluation results are presented in Section 4. We conclude in Section 5.

2. Related Work

The detection of moving objects is the fundament for various visual surveillance applications. Commonly applied methods for moving object detection are derived from traditional image change detection techniques. A comprehensive overview of image change detection techniques including issues related to pre-processing and principles for performance evaluation is provided by Radke et al. [18]. Several surveys distinguish moving object detection methods for visual surveillance applications using near-ground cameras into background subtraction, temporal differencing and optical flow [10, 29]. Background subtraction techniques calculate the pixel-wise intensity difference between the current image and a background model. Temporal differencing, also called frame differencing, calculates the pixel-wise intensity difference between two or three successive images in image sequences. Optical flow methods detect moving regions in image sequences by means of flow vectors of moving objects over time. A broad number of surveys dealing with background subtraction techniques exists in literature [4, 11, 13]. However, the majority of these methods such as probabilistic approaches [24] are not applicable due to characteristics of WAMI such as the low frame rate and the sensor motion [19].

The applicability of object detection methods depends on the characteristics of the acquired data such as camera angle or altitude. Various object detection methods have already been proposed in WAMI literature. However, the evaluation of these methods is not possible since authors usually focus on object tracking results only and do not provide supplementary object detection results. Furthermore, different dataset and different scenes with particularly self-annotated GT are used for evaluation. A survey of general techniques used to process WAMI data is given by Blasch et al. [3]. The survey provides a summary of published literature in WAMI as well as an overview of state-of-the-art methods from sensor design to data exploitation and future developments, but no explicit overview of applied object detection methods. A rough insight of moving object detection methods based on pixel-level classification is provided by Porter et al. [15], whereas the majority of object detection methods applied on WAMI is not considered.

3. Object Detection Methods

Frame differencing, background subtraction and optical flow are widely used to detect moving objects in aerial videos. Two- or three-frame differencing requires fewer frames than background subtraction methods. Thus, residual errors after image alignment are reduced and the image region used for object detection is maximized as the overlapping area of consecutive frames decreases with the number of frames [20]. Background subtraction allows instead the detection of slow moving objects whose positions partially overlap between consecutive frames. Object detection approaches based on optical flow vectors are not applicable for WAMI [1]. A detailed overview of object detection methods proposed in WAMI literature as well as the performed pre- and post-processing steps are given in the following subsections. An overview of the object detection methods evaluated in the context of this paper is listed in Table 1.

<table>
<thead>
<tr>
<th>Source</th>
<th>Object Detection Method</th>
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<tbody>
<tr>
<td>Saleemi [20]</td>
<td>2-frame + Ghost Handling</td>
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<tr>
<td>Xiao [30]</td>
<td>3-frame</td>
</tr>
<tr>
<td>Keck [6]</td>
<td>3-frame + Box Filter</td>
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<td>Pollard [14]</td>
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<td>Pollard [14]</td>
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<td>Inpaint</td>
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<tr>
<td>Proposed</td>
<td>Median BG + Neighborhood</td>
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Table 1. Evaluated moving object detection methods and corresponding publications.
3.1. Pre-Processing

Prior to moving object detection, the camera motion is compensated by image alignment. Harris corners are detected in consecutive frames. A SIFT-like descriptor is computed at each corner and used to match points in consecutive frames. Outlier matches are rejected using RANSAC. Finally, a frame-to-frame homography is estimated. Deviant image registration methods [6, 8, 21] are not adopted to guarantee similar conditions for the evaluation. In addition, global histogram matching [5] is used to adjust camera gain and illumination variation, followed by local Gaussian mean filtering [21] to reduce seam artifacts.

3.2. Frame Differencing

Object detection methods based on frame differencing are widely used in WAMI. Saleemi and Shah [20] proposed to calculate the pixel-wise difference between two consecutive frames by

$$D(x, y) = |I_t(x, y) - I_{t-1}(x, y)|,$$

where $D(x, y)$ is the intensity value difference at pixel $(x, y)$ and $I_t$ and $I_{t-1}$ denote the intensity values of frame $t$ and the aligned frame $t-1$. Two-frame differencing minimizes the number of consecutive frames required for object detection. Consequently, residual errors after image alignment are reduced compared to three-frame differencing. However, each moving object produces two motion blobs in the difference image: a true object at its position in the current and an additional one at its position in the previous frame. This so called ghosting effect [20] is handled by rejecting blobs with smaller mean gradient magnitude and intensity standard deviation in the current frame compared to the previous frame.

In order to avoid ghosting effects, Xiao et al. [30] proposed three-frame differencing. The difference image for three consecutive frames is given by the minimum of the difference image between frame $t$ and $t-1$ and the difference image between frame $t$ and $t+1$:

$$D(x, y) = \min(|I_t(x, y) - I_{t-1}(x, y)|,$$

$$|I_t(x, y) - I_{t+1}(x, y)|)$$

The additional frame produces additional noise due to imprecise image registration and parallax effects. Suppression of such errors can be achieved by using the minimum differences of each pixel in small neighborhoods [14, 21]. The minimum difference between a pixel in the current frame $I_t$ and all pixels $(x_i, y_j)$ in the neighborhood $N$ is calculated by

$$D(x, y) = \min_{i,j}(|I_t(x, y) - I_{ref}(x_i, y_j)|),$$

where $I_{ref}$ denotes either the intensity values of frame $t+1$ or $t-1$.

False positive detections due to imprecise image registration can be reduced by applying a box filter to the difference image [6]. The box filter locally averages the images and the filtered value is subtracted from the initial difference image.

3.3. Background Subtraction

Background subtraction methods detect moving objects by calculating the difference image $D(x, y)$ between an image $I_t$ and its corresponding background model $I_{BG}$:

$$D(x, y) = \min(|I_t(x, y) - I_{BG}(x, y)|)$$

Several background modeling approaches have been explored for WAMI. Perera et al. [12] used 30 consecutive images to model each pixel as a mixture of Gaussians [24]. However, the high number of frames [9, 19] as well as the sensitivity to illumination changes [20], parallax and registration drift [14] make Gaussian mixture models (GMM) inapplicable for object detection in WAMI.

Pollard and Antonie [14] replaced the traditional GMM with an Interval Gaussian Mixture Model (IGMM). Instead of modeling each pixel by a mixture of Gaussians, each pixel $(x, y)$ is described as an interval limited by a minimum value $\mu_{min}$ and maximum value $\mu_{max}$. Pixels that deviate more than a single global standard deviation value $\sigma$ from this interval are considered as moving pixels. The interval is updated according to learning rate $\alpha$:

$$\mu_{min}^{t+1}(x, y) = (1 - \alpha)\mu_{min}^{t}(x, y) + \alpha I_t^{t+1}(x, y)$$

$$\mu_{max}^{t+1}(x, y) = (1 - \alpha)\mu_{max}^{t}(x, y) + \alpha I_t^{t+1}(x, y)$$

$I_{min}$ and $I_{max}$ are the minimum and maximum intensity values in a small neighborhood around $(x, y)$. Thus, false positive detections due to imprecise image registration are reduced.

A background model based on running mean and standard deviation calculated with a recursive filter is proposed by Kent et al. [7]. Pixels considered as moving are detected by comparing the difference between the intensity value $I_t$ and the local mean $\mu$ to a local threshold. The local threshold is given by the standard deviation $\sigma$ multiplied with a scaling factor $s$:

$$|I_t(x, y) - \mu_{t-1}(x, y)| > s \cdot \sigma_{t-1}(x, y)$$

Calculating the pixel-wise intensity median of consecutive frames is the commonly applied background modeling approach to detect objects in WAMI. The number of frames used for background modeling range from 8 [8] to 16 [16]. Median background models require about four times less the number of frames than mean background models for comparable results [19]. Noise in the difference image caused by parallax effects can be reduced by incorporating background gradient information. Reilly et al. [19] proposed to subtract the background gradient magnitudes from
the difference image. Liang et al. [8] modified this approach by replacing the subtraction of the gradient magnitudes with an additional threshold operation. If the background gradient magnitude exceeds a given threshold \( \delta \), the value of the corresponding pixel in the difference image is set to 0:

\[
D_t(x, y) = \begin{cases} 
0, & \text{if } \nabla B(x, y) > \delta \\
D_t(x, y), & \text{else}
\end{cases}
\]  

(8)

Instead of incorporating background gradient information, noise in the difference image caused by parallax effects can be reduced by calculating the minimum differences of each pixel in small neighborhoods as described in Eq. 3 for frame differencing. The combination of median background modeling and neighborhood consideration is expected to be a powerful approach that has not been reported yet.

Aeschliman et al. [1] generated a static background model based on a modified inpainting algorithm proposed by Telea [26]. Pixels corresponding to objects obtained by an initial difference image between the current and previous frames as well as object pixels of the previous frame are replaced based on directional and smoothness constraints until the background model is complete.

3.4. Others

Vesom [28] presented object detection in WAMI by performing signal decomposition based on phase congruency and time-frequency analysis. He introduced a metric to distinguish between independent motion, parallax or no motion in ground stabilized video. Precondition for this approach is a precession of the sensor so that pixels representing structural motion caused by parallax effects undergo regular periodic intensity variations whereas independent motion causes irregular intensity variations. However, acceptable precision rates require multiple precession cycles and consequently limit the applicability of this method.

Sun et al. [25] proposed to detect objects by means of so-called detection response maps (DRM) that represent the likelihood of object presence based on object-like shape, scale, and texture. After spatial registration, response maps are generated by applying object classifiers to the incoming image. Then, objects are detected by differencing between response maps, followed by thresholding. The proposed approach is more robust to false positives. However, the used classifier results in high computational costs and makes the application of this approach difficult for large images.

3.5. Post-Processing

Except for the background model approaches proposed by Kent et al. [7] and Pollard and Antone [14], quantile thresholding [23] is used to distinguish pixels coming from difference images or background subtraction into object and non-object pixels. The quantile value \( q \) defines the percentage of the brightest pixels of a given difference image that are accepted as moving pixels. Thus, instead of a fixed threshold value for all frames, an adaptive threshold value \( T_q \) is chosen based on the pixel gray-value distribution of the difference image. The adaptive threshold value results in less sensitivity to illumination changes, whereby the number of objects per frame is expected to be almost constant. In case of the methods proposed by Kent et al. [7] and Pollard and Antone [14], pixels are separated into object and non-objects by means of weighted standard deviation. After thresholding, morphological operations are used to remove single pixel detections and to fill in holes or gaps in object contours. Finally, object blobs are obtained by connected component labeling. Object blobs below a specified minimum blob size are rejected.

Further reduction of false positive detections can be achieved by considering context knowledge about road networks [19, 22, 30] or applying object classification [8, 9, 22]. Road information can be used to discard false positives which do not directly appear on the road whereas object classification schemes discriminate between real vehicles and non-vehicles so that false positives identified as non-vehicles can be removed. Both object classification schemes and the embedding of road information based on context knowledge about road positions such as Geographic Information System (GIS) or feedback of tracking results are not considered as the main focus of this paper lies on object detection without context knowledge.

4. Experimental Results

Eleven object detection methods are considered for the evaluation. The object detection methods proposed by Perera et al. [12], Vesom [28] and Sun et al. [25] are not evaluated due to their limited eligibility for WAMI. A full list of the evaluated object detection methods is given in Table 1. The performance of the selected methods is evaluated on four image regions of the WPAFB 2009 dataset [27]. The WPAFB 2009 dataset comprises 1,025 frames with annotated GT for moving, stopping, and even some parked objects. However, since the evaluated methods can detect moving objects only, we remove stopping and parked objects from the GT for our experiments. Thus, the number of GT objects is reduced from originally 460,612 to 163,158. This is necessary in order to determine the correct number of missing detections (recall).

The four image regions shown in Fig. 1 are selected with regard to the image regions evaluated by Keck et al. [6] and Basharat et al. [2]. Each image region consists of 2,278 × 2,278 pixels and represents different challenges such as traffic density and varying scenery. Precision and recall are used to evaluate the performance of the selected object detection methods. In order to be consistent with the
literature, the centroid of each blob is considered as a detection. Thus, each detection is represented by a point. Detections with annotated GT within a radius of 20 pixels are defined as true positives otherwise as false positives. The distance is set to 20 pixels, which is approximately 5 m [2], since the blob centroid is often shifted from the annotated GT position due to merged objects and appendant shadows.

The performance of each method is affected by several parameters. In this paper, all relevant parameters are separately optimized for each object detection method with regard to precision and recall. As described in Section 3.5 quantile thresholding or thresholding based on standard deviations are applied to distinguish pixels into objects and non-objects. We expect that the chosen quantile value and the thresholds based on standard deviation, respectively, have the highest impact on the object detection performance. Thus, they are varied in order to generate precision-recall curves.

All methods are influenced by the minimum blob size as well. The minimum blob size is used to reject blobs below the expected minimum size of an object. Precision-recall curves for various minimum blob sizes are shown in Fig. 2(a). In this example, 3-frame differencing is used to detect moving objects in Scene 1. The number of missed detections increases with increasing minimum blob sizes as small objects or partially detected objects are discarded. In contrast, the precision of detected objects is getting better since the number of false positives due to noise decreases. Optimal minimum blob sizes vary from 60 to 80 pixels depending on the method used.

Further parameters are only relevant for particular methods. Optimization of parameters that contribute most to the performance of these particular methods is illustrated by means of Scene 1 in Fig. 2(b)-(e). The performance of median background subtraction methods depends on the number of frames used for median background computation. Precision-recall curves for various numbers of frames are depicted in Fig. 2(b). The precision of detected objects decreases with the number of frames as more and more false positives are generated by imprecise image alignment and parallax effects. The number of true positive detections is almost the same for 6 to 10 frames but declines considerably with even less frames. The reason for the increasing number of missed detection is an inadequate estimation of the background especially in areas with dense traffic and intersections. The best performance for all median background subtraction methods is achieved by using 6 frames.

Considering small neighborhoods is used to suppress errors due to imprecise image alignment and parallax effects. Fig. 2(c) visualizes the impact of the neighborhood size on the detection performance of 3-frame differencing. The precision increases with the neighborhood size as more false positive detections caused by image alignment are parallax effects are suppressed. Practical neighborhood sizes are in the range of \(3 \times 3\) to \(5 \times 5\) pixels. In case of median background subtraction as depicted in Fig. 2(d), slightly larger neighborhood sizes achieve the best performance as more errors due to imprecise image alignment are accumulated.

The mean background approach [7] and the IGMM approach [14] update pixel-wise running mean and interval boundaries respectively according to a learning rate \(\alpha\). The learning rate is a value between 0 and 1. Higher values compensate scene changes such as illumination variations quickly whereas lower values prevent the model from rapidly assimilating objects as background. Precision-recall curves for the IGMM approach and various learning rates are exemplary given in Fig. 2(e). Optimal learning rates are in the range from 0.5 to 0.7. Higher learning rates exhibit more missed detections since objects are assumed to belong to the background. Lower learning rates are prone to scene changes and result in more false positives and thus worse precision. Best performance for the mean background approach is achieved for learning rates between 0.8 and 0.9.

The influence of the gradient magnitude threshold \(\delta\)
on the performance of median background subtraction + gradient magnitude thresholding (GMT) [8] is depicted in Fig. 2(f). As given in Eq. 8, gradient magnitudes above this threshold are expected to be caused by parallax and registration errors and set to 0. The precision of this approach increases with lower threshold values as more errors are suppressed. The recall of threshold values between 40 and 80 is almost constant but decreases considerably with lower threshold values as more and more objects are suppressed.

In case of gradient magnitude suppression (GMS) [19], the weighted gradient magnitude is subtracted from the difference image instead of thresholding. Higher weighting factors result in less errors due to imprecise image alignment and parallax but result in more missed objects as well. Best performance is achieved for weighting factors about 0.5.

Fig. 3(a) shows the precision-recall curves of all object detection methods with optimized parameters for Scene 1. The optimal performance (most right and upper point) of 2-frame differencing is considerably better than of 3-frame differencing. In order to improve the performance of standard 3-frame differencing, box filtering and neighborhood consideration are applied as described in Section 3.2. 3-frame + box filter shows slightly higher precision and recall than simple 3-frame differencing. However, the impact of the box filter to reduce seam artifacts is marginal since seam artifacts are already suppressed by the applied pre-processing. In contrast, considering a small neighborhood outperforms significantly standard 3-frame as well as 2-frame differencing as errors caused by imprecise image alignment and parallax effects are suppressed.

Standard median background subtraction exhibits by far the poorest performance of all evaluated methods. The reason for the poor performance is the higher number of frames used since more errors due to imprecise image alignment and parallax effects are accumulated. GMS, GMT and neighborhood consideration (N) are used to cope with these errors. All three approaches result in significantly improved performance, whereas N slightly outperforms GMS and GMT that are almost similar. The impact of neighborhood consideration on standard median background subtraction is visualized exemplarily for the image region shown in Fig. 4(a). The image region contains a road with road markings, a building and a parking lot. Road markings, parked vehicles and the contours of the building that are clearly visible in the difference image for standard 3-frame differencing (see Fig. 4(b)) are considerably reduced by neighborhood consideration (see Fig. 4(c)) and consequently less false positives are detected. Median BG + GS, median BG
The optimal performance of the further background subtraction methods is roughly the same as of 2-frame differencing, whereas IGMM outperforms running mean and inpaint. However, the performance of all three methods is worse compared to approaches that compensate explicitly for parallax and registration errors.

The precision-recall curves of all methods for Scene 2, 3, and 4 are depicted in Fig. 3(b)-(d). Almost all methods show an improved performance for Scene 2 and Scene 3 compared to Scene 1, but considerably worse for Scene 4.

Both Scene 2 and 3 are expected to be less challenging due to lower traffic density and rarely stopped and slow moving vehicles whereas stopped vehicles are not considered as true positives in this context. Scene 4 comprises instead a residential area densely covered with buildings and trees. Median BG + GMS, median BG + GMT, median BG + N and 3-frame + N show the best performance for all scenes, whereas median BG + N exhibits the best performance overall. Thus, N indicates better suppression of errors than GMS and GMT. 3-frame + N slightly outperforms the other methods for Scene 4 since the residential area densely covered
with buildings and trees is more error-prone to image alignment and parallax effects that are accumulated by the number of used frames. Instead, the weaker recall for Scene 1 indicates that median background models are more effective to detect slow moving objects in dense traffic. Standard median BG exhibits the poorest performance especially for Scene 4 as errors caused by image alignment or parallax are not suppressed. Accordingly, standard median BG is not appropriate for areas densely covered with buildings or trees. The precision of IGMM for Scene 3 that is expected to be less challenging is considerably worse. The adaptive interval model and the fixed standard deviation used to segment pixels in object and non-object is not able to compensate for severe illumination changes and consequently results in a large number of false positive detections. The same difficulty is observed for the running mean approach which shows even poorer performance for Scene 3. Absolute numbers and additional experiments are provided in the supplementary material.

5. Conclusions and Outlook

In this paper, we have presented a detailed overview of methods for moving object detection in WAMI data. Ten relevant methods were taken from the literature and evaluated on four different challenging image regions of the WPAFB 2009 dataset. Important parameters of each method were identified and optimized with regard to precision and recall. Furthermore, we evaluated different approaches for the suppression of errors caused by imprecise image alignment and parallax effects. This is crucial to improve the detection performance. The best performance overall is achieved by median background subtraction + pixel neighborhood consideration. Our systematic evaluation helps to understand the properties of different moving object detection approaches which is important for subsequent multiple object tracking that is fully dependent of initial detections up to now. Future work should focus on a survey on existing multiple object tracking algorithms in order to study the impact of optimized moving object detection.

References


