IJREAT International Journal of Research in Engineering & Advanced Technology, Volume 2, Issue 2, Apr-May, 2014
ISSN: 2320 – 8791 (Impact Factor: 1.479)
www.ijreat.org

Detecting Abandon Objects Fastly Through Blob Analysis

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Abstract

Instantaneous Object Detection by BLOB Assessment presents a novel framework for detecting flat and non-flat abandoned objects remains stationary. Abandoned objects are detected by matching a reference and a target video sequence. The reference video is taken by a camera when there is no suspicious object in the scene. The target video is taken by a camera following the same route on the real time and the two videos splitted into frames aligned to find the abandoned object. Above process been achieved through four simple and effective ideas i.e Inter-sequence geometric alignment find all possible suspicious areas, Intra-sequence geometric alignment remove false alarms caused by high objects, Comparison compares two aligned intra-sequence frames to remove false alarms in flat areas, during the comparison backgrounds are cleared using background substraction method, Temporal filtering. In addition to above four effective ideas, integrated BLOB assessment technique to find object efficiently. This strategy has been specifically designed to deal with an unknown and variable number objects.

Keywords: *Inter sequence geomentric alignment, Intra sequence geomentric alignment, Temporal filtering, Comparison, Blob.*

1. Introduction

In recent years, there is a huge proliferation of consumer electronic devices with smart camera platforms, such as smartphones, webcams, tablets, home and portable video game consoles, and others, which require new fast and efficient (i.e., lightweight) computer vision. All these applications include a object detection strategy, which is a key step for high-level analysis tasks, applications such as object detection, tracking, classification, or event analysis. Nowdays surveillance has attracted increasing interest from homeland security, enforcement, and military agencies. The detection of suspicious items is one of the most important applications. These items can be grouped into two main classes, dynamic suspicious behaviors and static dangerous objects. The scope of this project falls into the latter category. Specifically, investigate how to detect flat as well as non-flat static objects in a scene using a static camera.

Despite the importance of object detection strategies, they are still far from being completely solved in complex environments. Thus, there are several problems that must be addressed, such as objects with areas similar to background regions, foreground objects in the training period, gradual and sudden illumination changes, or local changes such as shadows and reflected light. Objects may have arbitrary shape, color or texture, state-of-the art category-specific (e.g., face/car/human) objects detection technology. To deal with this, propose a simple but effective framework based upon matching a reference and a target video sequence. The reference video is taken Units by a static camera when there is no suspicious object in the scene (i.e.) a background image of the entire space, which has to be monitored, is taken initially. The target video is taken by a second camera and observing the same scene where suspicious objects may have been abandoned in the mean time (i.e.) a new image after the arrival of the objects is taken and is subtracted from the background image. When an object is found to be in the same place for a long time, an alarm sounds to alert the guards.

To make things efficient, the videos are initially utilized to roughly align the two sequences by finding the corresponding inter-sequence frame pairs. The symbols and are used throughout this paper to denote the GPS-aligned reference and target video respectively.

On the basis of GPS(Global positioning system) alignment following four ideas are proposed to achieve our objective i.e Inter-sequence geometric alignment based upon homographies to find all possible suspicious areas, Intra-sequence alignment (between consecutive frames of) to remove false alarms on high objects, Local appearance comparison between two aligned intra-sequence frames to remove false alarms in flat areas (more precisely, in the dominant plane of the scene), and Temporal filtering step using homography alignment to confirm the existence of suspicious objects. In addition to it use blob detection algorithm. This algorithm tracks objects that pose threat to the scenario based on the object's attributes. Specific objects are identified based on "interest points" of the image. This algorithm also detects proficiently flat objects.

2. Related Works

Almost all current methods for static suspicious object detection are aimed at finding abandoned objects using a static camera in a public place, e.g., commercial center, metro station or airport hall. Porikli et al. propose to use two foreground and two background models for abandoned object detection. First, the long- and short-term backgrounds are constructed separately. Thereafter, two foreground models are obtained based upon the two background models. The abandoned object can be detected by four hypotheses based upon the two foreground and two background models.Spengler and Schiele propose a tracking surveillance system to automatically detect abandoned objects and drawthe operator's attention to such events. It consists of two major parts: A Bayesian multiperson tracker that explains as much of the scene as possible, and a blob-based object detection system that identifies abandoned objects using the interesting points of image.Smith et al. propose to use a two-tiered approach. The first step is to track objects in the scene using a trans-dimensional.MCMC tracking model suited for generic blob tracking tasks. The tracker uses a single camera view, and it does not differentiate between people and luggage. The problem of determining whether a luggage item is left unattended is solved by analyzing the output of the tracking system in a detection process.

Above mentioned techniques exploits the static cameras fixed in some public places. Where the background is stationery. However, for some application scenarios, the space to keep a watch on is too large to use static cameras. Therefore, it is necessary to use a moving camera to scan these places. This paper work put forward a technique where a camera mounted on a moving platform to scan along a specified trajectory for nonflated and flated abandoned objects

3. Proposed Scheme

To overcome the issue experienced above, this paper proposes Instantaneous object detection by blob assessment. In proposed system abandoned objects are detected by matching a reference and a target video sequence. The reference video is taken by a camera when there is no suspicious object in the scene. The target video is taken by a camera following the same route and may contain extra objects and the two videos may aligned to find the abandoned object. GPS is used to roughly align the two videos to reduce computational complexity. It is hard to find the suspicious object on the comparison of the GPS-aligned frames, which potentially have large viewpoint variation. This is because GPS alignment can only guarantee that the corresponding intersequence frame pair is taken approximately at the same geographical location, but cannot guarantee that the camera has the same view angle for R and T. In addition, due to speed variation between and , and the different position of the vehicle, alignment using only GPS information may lead to frame pairs separated by as much as 2 m in 3-D real world. Therefore, a fine geometric alignment is necessary. A feature-based alignment method is a better choice than an appearance-based one when the illumination conditions for and are different. This propose to use 2-D homographies for fine alignment. The reasons are that homographies can align two images by registering their dominant planes, and that any nonflat objects (including suspicious and nonsuspicious ones) on the dominant plane are deformed while flat objects remain almost unchanged after alignment. This scheme show that the deformation caused by homography alignment plays a key role in our detection framework (especially when there is an large illumination variation between and). Therefore two assumptions: the suspicious object is a nonflat 3-D object1 (specifically, more interested in detecting the abandoned objects which has such a height as a suitcase or gift-boxes etc.), and when it is present in the target sequence, it lies on the ground instead of hanging in the sky, being buried underground or covered by other objects.

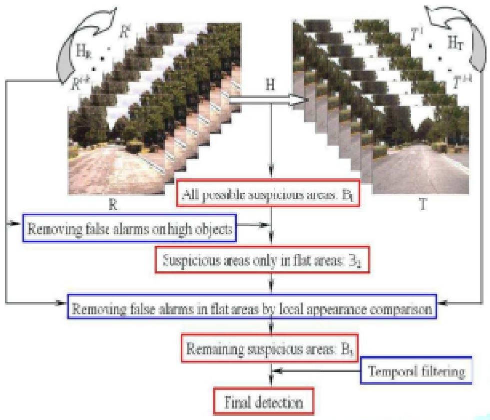

Fig 1: Flow chart Proposed work

With regards to the above assumption use intersequence and intrasequence homography alignment as the basis for object detection, where the homographies are computed based on a modified RANSAC (mRANSAC). Illustrate the flowchart of the proposed framework by the below figure.

On the following figure shows the proposed framework H, Intersequence alignment HR intrasequence alignment between frames Ri, and Ri-k, of R. HT : intrasequence alignment between frames Ti and Ti-k of T. B1, B2, B3 are the remaining suspicious areas in each step.

3.1 Sift

Scale-invariant feature transform (or SIFT) is an algorithm in computer vision to detect and describe local features in images. This algorithm does object recognition, robotic mapping and navigation, image stitching, 3D modeling, gesture recognition, video tracking, and match moving. On any image interesting points on the object can be extracted to provide a “feature description” of the object. This description, extracted from a training image, can then be used to identify the object when attempting to locate the object in a test image containing many other objects.

3.2 Intersequence Geometric Alignment

Initially SIFT feature descriptor was used on GPS aligned frame pairs, Apply SIFT algorithm to get a set of SIFT feature descriptors for reference R and target T. Each keypoint of the target frames and the reference frames computed through 128 dimensional sift descriptor. Find the putative matches between these SIFT features of R and T and find the optimal H inter using MRANSAC. Find the best as H temp as H inter. The second image of bottom row, the optimal inliers obtained by MRANSAC. By visually comparing the two images in the last column, MRANSAC gives better alignment than RANSAC. Based upon H inter , the reference frame is warped into to fit the target frame. In the way identify the suspicious flat and non flat objects from the reference videos.

3.3 Intrasequence geomentric alignment

The procedure for intrasequence geometric alignment is similar to that for intersequence alignment. The difference is that both the reference (the frame to be warped) and target frames are from the same video this time. Generally, the choice of depends upon the speed of the moving camera. If the camera moves fast, should be set to a small number, and vice-versa. experimented with the platform moving at an approximate speed of 30 km/h and the displacement of the camera between th and th frames being about 10 m. Since the illumination variation between the intrasequence reference and target frames is usually small, the intrasequence alignment generally aligns the dominant planes very well. It helps to remove the false alarms in the high objects. Below illustrate the way of removing the false alarms on the high objects and the dominant plane

3.3.1 Removal of False Alarms on the high objects

After applying the intrasequence alignment of frames R1 and R2 and thus the aligned the R2 to fit R1. Get the NCC image between R1 and R2. Intially can locate the high-object areas in by setting a suitable threshold value on the NCC image because the high objects in are deformed and the NCC scores at these locations are usually low. The pixels whose NCC values are lower than are treated as possible high-object areas of R1, denoted by the binary image B1. Example of images B1 is shown in figure R2C2. observe that some lower parts of the road area in R1C3 are blurred due to the homography deformation, therefore these areas also have low NCC values, which can explain that some road areas are also highlighted R2C2 in although they are flat. To deal with this problem, tried two principled ways: one is to blur the reference frame by Gaussian filtering and the other is to deblur the transformed target frame by trilinear interpolation. However, the results are not better than a simple adhoc one, i.e., remove from B1 the highlighted clusters whose centroids are lower than 40% of the image height.

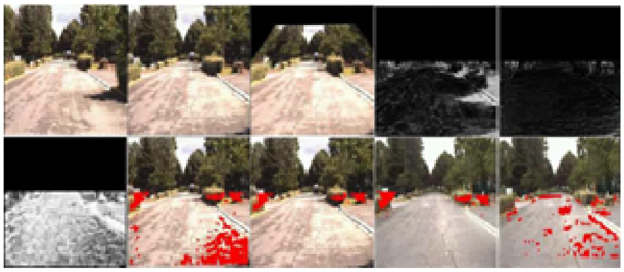

Fig 2: Intersequence gementric alignment

The B1 after such a removal is shown as in below Fig. Correspondingly, the high-object areas in T1 are represented by , which is obtained by transforming based upon , shown as . The remaining suspicious areas after removing are shown in , which can be represented, there is no risk of removing the true suspicious objects lying in the bottom part of the image by getting rid of the highlighted clusters with low-centroids from . Although false alarms in low-end flat regions (road areas) still exist,

3.3.2 Removal of false alarms on Dominant plane

Given that any 3-D objects lying on top of the dominant plane are deformed after the intrasequence alignment, while any flat objects remain almost unchanged, use the difference of grayscale pixel values between and , and that between and for removing false alarms on the dominant plane. In the below diagram explains the Illustration of local appearance comparisons. Ti is shown in the left column and _ is shown in the middle column. A1 and A2 are two exemplar local patches, which are zoomed in at the bottom-left and top-right corners. The last column shows their grayscale intensity difference with the top and bottom one corresponding to A2 and A1 respectively.

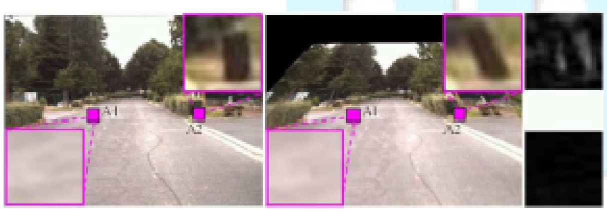

Fig 3: Intrasequence geomentric alignment

3.4 Comparison

To get the better understanding and exactly to find out the suspicious objects on the target frame, the target frame been compared with the reference frame through the local appearance comparison method. Apply the local appearance comparison to find out the difference of the intrasequence alignment Btintra. The left suspicious areas after the local appearance comparison are computed by

$$B3=B2\cap(Btintra-(Btintra\cap Brintra))$$

3.5 Temporal Filtering

Use of temporal filtering on B3 to get our final detection. Let n be the number of buffer frames used for temporal filtering. Assume that Ti is the current frame, and the remaining suspicious object areas in Ti after intersequence and intrasequence alignment is denoted by Bi3 . Stacking B3i-3, B3i-2, B3i-1 and Bi3 into temporal buffer Tbuffer, also stack the homography transformations between any two neighboring frames of the buffer into Hbuffer . Based upon these transformations B3i-3, B3i-2, B3i-1 are respectively transformed to the state which temporally corresponds to the th frame, and are intersected with respectively Bi3. The final detection map is the intersection of these intermediate intersection. Set a threshold for the size of the smallest nonzero cluster in the final detection map

3.6 Blob

A blob (binary large object) is an area of touching pixels with the same logical state. All pixels in an image that belong to a blob are in a foreground state. All other pixels are in a background state. In a binary image, pixels in the background have values equal to zero while every nonzero pixel is part of a binary object. You can use blob analysis to detect blobs in an image and make selected measurements of those blobs. Blob analysis consists of a series of processing operations and analysis functions that produce information about any 2D shape in an image. Use blob analysis when you are interested in finding blobs whose spatial characteristics satisfy certain criteria. In many applications where computation is time-consuming, you can use blob analysis to eliminate blobs that are of no interest based on their spatial characteristics, and keep only the relevant blobs for further analysis. You can use blob analysis to find statistical information-such as the size of blobs or the number, location, and presence of blob regions. With this information, you can perform many machine vision inspection tasks, such as detecting flaws on silicon wafers, detecting soldering defects on electronic boards, or Web inspection applications such as finding structural defects on wood planks or detecting cracks on plastics sheets. You can also locate objects in motion control applications when there is significant variance in part shape or orientation.

4. Conclusion

In this term paper put forward detecting nonflat abandoned objects by a moving camera. Intend algorithm finds these objects in the target video by matching it with a reference video that does not contain them. Employed four main ideas: the intersequence , intrasequence geometric alignment, the local appearance comparison, and the temporal filtering based upon homography transformation. Our framework is robust to large illumination variation, and can deal with false alarms caused by shadows, rain, and saturated regions on road. It has been validated on fifteen test videos. Additionally, proposed a BLOB assessment tracking strategy that enhanced the detection of abandoned objects more accurate. Thus, able to increase the number of correct detections, decrease the amount of misdetections, and achieve and additional reduction of the computational and memory requirements.

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