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A Review On Foreground And Stationary Foreground Object Detection Techniques

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***Abstract*—Surveillance has now become area of attention in the present era known for safeguarding lives and properties in public places like; Train stations, Airports, Subway stations, and Bus station. Manual (Human) Surveillance seems to be Inefficient and Unreliable. Automatic Surveillance takes center stage in providing first-hand information for human to act which turns out to be faster, efficient and effective in left object detection and theft (Abandoned and Removed object detection).The detection Performance of such system is basically measured in terms of detection rate(DR) and False Alarm Rate(FAR). The approaches presented here focused on detecting abandoned Objects. However, there are some strategies that also allow partially static or temporary static object or removed object. This paper provides a review of the basic approaches of detecting foreground; stationary foreground objects (Abandoned Objects). The aim of this review is to analyze the most recent approaches in the field of surveillance.**

Keywords—Abandoned object, Detection Rate, False Alarm Rate, Surveillance, Stationary Foreground Object,

I. INTRODUCTION

A digital image can be considered as a discrete representation of data possessing both spatial (layout) and intensity (color) information. The word pixel is an abbreviation of 'picture element'. Indexed as an (x; y) or column-row (c; r) location from the origin of the image, it represents the smallest, constituent element in a digital image and contains a numerical value which is the basic unit of information within the image at a given spatial resolution and quantization level. Commonly, pixels contain the colour or intensity response of the image as a small point sample of coloured light from the scene. However, not all images necessarily contain strictly visual information. An image is simply a 2-D signal digitized as a grid of pixels, the values of which may relate to other properties other than colour or light intensity. The information content of pixels can vary considerably depending on the type of image we are processing. A blob is a Collection of Pixels [1].

In a video, there are primarily two sources of information that can be used for detection and tracking of objects: visual features (e.g. color, texture and shape) and motion information. Robust approaches have been suggested by combining the statistical analysis of visual features and temporal analysis of motion information. Atypical strategy may first segment a frame into a number of regions based on visual features like color and texture, subsequently merging of regions with similar motion vectors can be performed subject to certain constraints such as spatial neighborhood of the pixels[2].Most video analytics applications comprise a series of processing steps. These processing steps provide increasingly detailed information about the activities in the scene. Fundamentally, analytics need to detect changes that are occurring over successive frames of video, qualify these changes in each frame, correlate qualified changes over multiple frames, and finally, interpret these correlated changes [1].

Hence, segmentation plays a key role in detecting changes and extracting relevant it for further analysis and qualification. Pixels (picture elements) that have changed are referred to as "Foreground (FG) Pixels"; those that do not change are called "Background (BG) Pixels". In other words, foreground pixels are those remaining after the background has been subtracted. The degree of "change" which is used to identify foreground pixels is a key factor in segmentation and can vary depending on the application. The result of segmentation is one or more foreground blobs, a blob being a collection of connected pixels [2].

Most of the papers reviewed here focused on detecting stationary Foreground object (those that stop and remain static throughout several frames). It has taken centre stage, as it is employed in preventing terrorist incidents in public places (airport, train station, subway station, etc.). On the other hand, retail stores employed the system incorporated with stolen object detection to tackle theft (rare cases).This paper attempts to compare the FG and SFO detection methods and as well outline the advantages and disadvantages of each method. The purpose is to offer an updated and a brief overview of the most relevant method of abandoned object detection in the field of surveillance, the main stages in the detection process, the most typical algorithms applied to each stage, etc. The short description given under each method will help readers to decide and choose which method will serve the intended purpose. There are some strategies that employ detection at pixel level, others use object/blob level, and few adopt the region level detection. The Pixel level detection is considered in this work. Detecting stationary foreground object in a video with quasi- stationary background will be best done using pixel wise background model [4].

II. CHALLENGES OF MOVING OBJECT (MO) AND STATIONARY FOREGROUND OBJECT (SFO) DETECTION

Most SFO detection strategies include algorithms for the detection of FG. Therefore, some of the challenges in the detection of FG are also challenges for the detection of SFOs. In addition, there are some challenges directly associated with the detection of SFOs, which are related to the speed and persistence of the detections and the capability of the algorithms to deal with some specific situations (e.g. SFOs occluded by FG objects) [3].

A. *Challenges in Moving Object Detection*

These are challenges that are associated with moving objects [3];

- Image noise: It appears either in sequence recorded with poor quality cameras or after applying a compression process on the video.
- Illumination changes: They can be gradual (e.g light variations along the day) or sudden (e.g., turning on the lights in a room) and cause many false detections in large areas of the images.
- Low contrast: The FG detection methods must be able to detect the moving objects in sequences with low contrast. This situation is typical in sequences recorded at night. Camera automatic adjustments: Some automatic adjustments of the modern cameras (e.g. auto focus, gain control, white balance and brightness control) make difficult to achieve successful detections, since these adjustments modify the dynamic of the color level of the pixels.
- Dynamic BG: Many sequences contain BG elements that are not completely static but move periodically or irregularly (e.g., waving flags, trees and shrubs shaken by the wind, escalators, or water waves). Despite being in motion, these moving elements must be considered as part of the BG.
- Camera jitter: The sequences may have been recorded with non-stabilized cameras (e.g., a camera endowed in a mobile phone or fixed cameras affected by the wind). This camera motion typically results in much false detection.
- FG aperture: If a FG object has regions with uniform colors, the changes inside these regions may not be detected.
- Camouflage: A FG object and the BG behind it can have similar appearance, which complicates distinguishing between them. Occasionally, when the camouflage is very intense, the FG object can be detected only if their shape is previously known.
- Shadows (SHs) and highlights (HLs): The shadows and highlights cast by moving objects are commonly detected as part of such the FG, which significantly decreases the quality of the detections. This problem appears in outdoor sequences, where hard shadows typically appear, and also in most indoor scenarios, where the moving objects produce medium and soft shadows and highlights.
- Bootstrapping: In some cases, a training period (images free from FG) to obtain an initial representative BG model is not available.

B. *Challenges in Stationary Foreground Object (SFO) Detection*

There are challenges encountered in detecting SFO. These are [3];

- Occluded SFOs: An abandoned object can be temporarily occluded by a second object. This second object can move in front of the first one, or it can even stop just when it is placed in front of the first object (becoming a new SFO). In these cases, the correct detection of the initial abandoned object can fail both during the occlusion and after it. Moreover, this case is further aggravated if the first object starts moving when it is occluded by the second object. Note that this example can be extended to other cases with multiple objects overlapping simultaneously.
- Long-term SFOs: The FG objects that remain static very long periods of time typically end up not being detected (they are incorporated to the BG).
- Partially-stationary foreground objects (PSFOs): In many video-surveillance scenarios (e.g. airports, malls, offices, etc.) many people become SFOs for a while. However, it is not realistic to assume that these people remain completely static when they stop Walking, since their upper body (torso, arms and head) is not usually completely static. Nevertheless, if the static area of these objects is large enough, they can lead to erroneous detection of abandoned objects.
- Removed objects (ROs): The identification of situations in which a BG object is removed by someone is of great interest in many surveillance applications. However, these situations are easily mistaken with object abandonments.
- Ghost regions (GRs): When a moving object stops moving it will eventually be incorporated into the BG model. If the object now begins to move, the area it previously occupied will be incorrectly detected as a FG blob, commonly referred to as a ghost. This ghost will remain until the BG model adapts to the newly exposed BG. The GRs are typical in scenes with parked vehicles that start moving.

III. FOREGROUND (FG) DETECTION

The first stage in most strategies focused on the detection of SFOs consists of separating the FG from the rest of elements in the scene using a BG subtraction algorithm. As stated in the introduction, BG subtraction is a crucial stage not only in the detection of SFOs but in many computer vision applications such as video surveillance, multimedia or augmented reality. The typical scheme used to detect FG objects by subtracting the background (BG) comprises the following three steps [3]:

i. BG initialization: An initial BG model, which must not contain FG objects, is constructed from data of one or more frames at the beginning of the sequence.

ii. FG detection: By comparing the current frame with the BG model, each pixel is classified as BG or FG.
iii. BG maintenance: The BG model is updated along time to adapt the changes in the BG.

To be robust against illumination changes or permanent BG changes (e.g. a door that is opened or an object moved by someone), objects that stop moving must be integrated in the BG model. However, by doing this the SFOs are also absorbed by the BG. Consequently, the third step in this scheme is crucial for SFO detection strategies, since they must be able of selectively updating the BG model.

The FG detection methods used to detect SFOs vary widely. The authors in [8] use non-statistical models that, in the simplest cases, are never updated. On the other hand, other strategies use popular statistical BG modeling approaches [9, 10, 11] that are able to deal with very complex scenarios (e.g. dynamic BG and illumination changes). Moreover, some authors modify these typical approaches to improve the results in some situations (e.g. long-term SFOs or object removal). Strategies that are based on using three BG models were also proposed [12, 13]. However, it is possible to find some of them using single BG mode l[7,14]. The FG detection methods have been classified into 6categories, which are described in the following subsections. Table 1 shows a summary of the foreground detection algorithms (main) in the reviewed strategies. This summary allows a quick comparison between the analyzed method identifying the advantages and disadvantages of the methods that are described in the following sub-sections.

To be robust against the typical noise of the camera sensor, gradual illumination changes and camera automatic adjustments, some strategies try to statistically model the variations of each pixel with a Gaussian distribution, which is updated at each instant to try to adapt changes. The FG pixels will be those whose Mahalanobis distance to the Gaussians is greater than a predefined threshold [3].

For general purpose stationary object detection, sub-sampling based approaches performed by modeling each pixel with a Gaussian distribution thereby obtaining a good results adding a low computational cost in the overall system [14]. The method in [26] is similar to semantic analysis module, where a background model based on mixture between average and running Gaussian average methods. The main advantage is that it can compensate a video signal with a time varying noise level.

A. Median Models (MM)

Some algorithms employ median filtering to model the BG. Background modeling is done using approximate median model(AMM).For Foreground processing, Dual Background subtraction method followed ANDING operation of frames to find out static object. The system is quite immune to complex condition but has to be more immune to shadows and lighting condition [15].The strategy in [16] is similar to [15] but instead of the ANDING operation, the tracking algorithm is used to supplement the dual background subtraction. Dual-time background subtraction is used as an input to the AMM with tracking stage completing the detection [17]. The techniques [16, 17] are dynamic, easily adaptive and instinctive in nature.

B. Frame Differencing/Background Subtraction

This method identifies the presence of moving object by considering the difference between two consecutive frames, by subtracting second image from the first image using image subtraction operator in consecutive frame to get the desired output. It is an efficient method for detecting gray level changes between images by using frame differencing algorithm .The algorithm may be subdivided into three parts. Initial step is the selection of perfect reference or background. Second step is the arithmetic subtraction operation and the third step is the selection of a suitable threshold. Reference image can be selected as a frame which is temporally adjacent image from a dynamic sequence. This method lacks in obtaining the complete contour of the object [18]. This could arise due to suitable threshold selection that will be applied throughout the video frame, as each frame has its unique feature. A three (3) frame differencing is used to lessen this shortcoming [18].

In order to overcome the defects of frame differencing, a hybrid algorithm three (3) frames differencing and background subtraction successfully segment moving regions in video. Dynamic background (updating the reference image) can be achieved through three(3) frame differencing(fi,fi-5,fi+5).Thereafter, moving object is obtained via Background Subtraction[19].The complete feature data of target is obtained using this method, but a little complexity is observed due to the fusion.

C. Optical flow

It is based on calculation of optical flow (OF) field of image or video frame. Clustering is performed on the basis of the obtained optical flow distribution information obtained from the image (video frame).This method allows in obtaining the complete knowledge about the movement of the object and is useful to determine moving target from the background .When an observer moves in a straight line through a stationary scene, the optic flow field forms a radial pattern. The center of this pattern, where the image motion is zero is known as focus of expansion. A moving object in the scene may introduce image velocities that are not in match with this pattern, and this inconsistency can be used to detect the presence of a moving object. Discontinuities in optical flow can help in segmenting images into regions that corresponds to different object. The various applications of optical flow are object motion detection, action recognition, facial expression recognition, vehicle navigation etc. The disadvantages are large quantity of calculations are required to obtain optical flow information, and cannot be used in real-time without specialized hardware.

The OF method is mainly used for non-stationary cameras (moving cameras) [20].

In [8] a Gaussian filter is used in smoothing the individual frame, then optical flow field determined with an existing optical flow algorithm, after post processing the output, use self- adaptive window approach to identify the moving object areas. Optical Flow is hardly used due to noise problem, complexity, and has high computational cost.

D. Neural Networks (NN)/Neural Fuzzy

The background (BG) model of this technique is represented by means of the weights of a neural network suitably trained on several clean frames. The network learns how to classify each pixel as BG or FG. These methods have shown to be able of dealing with most typical challenges in FG detection. However, as they depend on a training period, they fail when abrupt changes occur in the scene (e.g. abrupt light changes) and in bootstrapping sequences [3]. A hybrid approach (neural-fuzzy method) is presented in [20].The segmentation map for self-organizing map(SOM) detection is computed using fuzzy inference system(FIS). Different threshold was chosen for each frame in a video (to handle variation in their illumination and saturation).The FIS will mimic human adjustment of segmentation threshold by this method. This Threshold is utilized by the SOM in the neural stage for detection purpose. This hybrid approach gives a better result as compared to the frame difference method, but it is more complex.

E. Gaussian Mixture Model (GMM)

For background (BG) of scene that are dynamic in nature (e.g. tree branches, bushes, water surface or flags), a generalization based on a mixture of Gaussians can be used to model such variations (changes cannot be modeled using One Gaussian distribution per pixel).

Stauffer and Grimson proposed a Gaussian Mixture Model (GMM)[9] to deal with scenarios with dynamic BG. This method allows the BG model to be a mixture of several Gaussians (typically between 3 and 5).Each pixel is labeled as foreground or Background based on its probability [4]. Every current pixel is separately modeled by a mixture of Gaussians which are updated online by incoming image data. In order to detect whether a pixel belong to FG or BG, Gaussian distribution of mixture model for that pixel are evaluated [2].

Most of the strategies for detecting SFOs use a GMM to subtract the BG, since these models typically allow dealing with a large amount of challenges in MO detection: image noise, illumination changes, low contrast, camera automatic adjustments, dynamic background, FG aperture and camouflage [3]. Some of the reviewed work use the GMM with little or no modification. The Authors in [21] employed the original GMM method for BG subtraction, so also those of [11,22,23] adopted same. Background segmentation is performed using the original GMM, but using a complete covariance matrix for every pixel[24]. Four Gaussians are used to represent the color at every pixel. In the interest of real time operation, after an initialization period, not all frames need to be processed. Processing only every tenth (10th) frame is still a high enough rate considering the temporal scale at which the events of interest occur. The difference in the update equations, initialization method and the introduction of shadow detection algorithm make the work presented in [10] distinct from the original GMM (the former having fast learning rate and shadow free). An Advanced GMM algorithm is used for segmentation with Bayesian Inference for event analysis to make the system more efficient[12].An intermittent update scheme[IUS] based GMM is used for FG detection in the technique presented in [13].The essence of co-opting the IUS (not all frames are updated here) is to retain the abandoned objects in the FG. Two separate BG (short-term and long-term) that is implemented as pixel wise multivariate Gaussian models by the authors in [6]. Background parameters are updated online using a Bayesian update mechanism imposed at different learning rates.

TABLE I: SUMMARY AND GENERALIZATION OF PROS AND CONS OF EACH FG DETECTION TECHNIQUES

Techniques	Authors	Pros	Cons
BSFD	[19]	-Can handle temporary stopping - complete feature data of target is obtained	-A little bit complex -Suitable for Moving camera
GMM	[6,9,10,11, 12,13,21,22,23]	-Occlusion free -Can handle temporary stopping -Can handle scene with dynamic BG -Reliability in scenes with camouflage, noise, shadows, illumination changes	-Sensitive to model -Prior Knowledge required -Does not explicitly handle spatial tendencies -Convergence is slow
Fuzzy-neural	[20]	-Unsupervised with automatic parameter update -Perfect segmentation of dynamic object	-Complexity
Optical Flow	[8]	-Can detect motion from moving camera and moving Background -It helps in segmenting images into regions that corresponds to different object	-Sensitive to noise -Sensitive to light changes -Not suitable for real time without specialized hardware - Large quantity of calculations are required to obtain optical flow information

Single Gaussian	[7,14]	-Robust against typical noise of camera sensor, gradual illumination changes. - it can compensate a video signal with a time varying noise level.	-Cannot model non-static BG region
Median Models	[15,16,17]	-Robustness to noise -Computational efficiency	-Do not model variance of pixels -Not able to deal with illumination changes, and camera automatic adjustment

IV. STATIONARY FOREGROUND OBJECT (SFO) DETECTION

Once the foreground has been detected using any of the detection method, it is necessary to discriminate between moving objects (MOs) and stationary foreground objects (SFOs). Some authors have opted by algorithms that directly analyze the results provided by the BG subtraction stage. On the other hand, some strategies include image analysis stages specifically oriented to the detection of SFOs. There are also some approaches that deal with other typical challenges, such as the detection of long-term SFOs, PSFOs. The authors [22, 27,28] include an additional stage to detect ROs. Table II gives the summary of these methods.

A. Tracking of Foreground

Most of the reviewed work used the tracking algorithm to determine stationary foreground objects. The algorithm allows detecting short term and long term SFOs and additionally deal with occluded SFOs. Detecting of PSFO becomes impossible since they work at object level. The strategy in [7] stated that the object should remain static for 50 consecutive frames for it to be declared abandoned. The methods in [7,12,13,16,17,21] used blob statistics such as object size/area, centroid position, to determine if an object is static or not. Kalman based filter are used for the same purpose [9,11]. A shadow detection based using computational color spaced is introduced to replace the Grimson et al's Kalman filter for increased speed [10].To round it off, it should be noted that some of these tracking-based strategies include additional stages to detect ROs. Some of them are based in the analysis of edges [27], whereas other works analyze multiple types of information (e.g., shape, contours and color) in [7].

B. Dual Foreground Comparison (DFC)

The strategy proposed by Porikli et al in [6], try to identify the SFOs by comparing two binary FG masks at pixel level. These masks are obtained from two BG models constructed with different learning rates. The models are constructed using multiple Gaussians. However, other modeling choices can also be found in the literature: non statistical models (basic) Single Gaussian Models (SGMs), Median Models(MMs),and Cluster Models (CMs) [3].

At every frame, they estimate the long and short term foregrounds by comparing the current frame I by the background models BL and BS. Two binary foreground masks were obtained FL and FS, where F(x, y) = 1 indicates that the pixel (x, y) is changed. The long term foreground mask FL shows the color variations in the scene that were not there before including moving objects, temporarily static objects, as well as moving cast shadows and illumination changes that the background models fail to adapt. The short-term foreground mask FS contains the moving objects, noise, and so forth. Depending on the foreground mask values, they postulate the following hypotheses below;

i. FL(x, y) = 1 and FS(x, y) = 1, where (x, y) is a pixel that may correspond to a moving object since I(x, y) does not fit any backgrounds.
ii. FL(x, y) = 1 and FS(x, y) = 0, where (x, y) is a pixel that may correspond to a temporarily static object.
iii. FL(x, y) = 0 and FS(x, y) = 1, where (x, y) is a scene background pixel that was occluded before.
iv. FL(x, y) = 0 and FS(x, y) = 0, where (x, y) is a scene background pixel since its value I(x, y) fits both backgrounds BL and BS.

The short term background is updated at a higher learning rate than the long-term background. Thus, the short-term background adapts to the underlying distribution faster and the changes in the scene are blended more rapidly. In contrast, the long-term background is more resistant against the changes [6].The method has low computational load, occlusion free. But, It cannot discriminate different types of objects (classifier needed), and has high false alarm rate.

C. Gaussian Stability

The reviewed work [22] determines that a pixel is part of a SFO by analyzing the stability of the Gaussians in a GMM associated to such pixel. When a moving object (MO) appears in a pixel, a new Gaussian is created in its GMM, which represents the new value of the pixel. If the object stops moving, that new Gaussian will begin to gain importance in the mixture model. So, if one is able to identify this situation, it will be possible to determine when the MOs become SFOs [3].In [22] region growing is used to classify object detected as either Abandoned or removed.

Gaussian stability (GS)-based detection methods are computationally efficient and easy to implement. Additionally, they depend on few parameters, which increase their usability.

Most of the GS methods perform the detections at pixel level. Therefore, they are suitable for the detection of PSFOs. However, since they use only one BG model, they do not allow dealing with occluded

SFOs. Additionally, if a SFO remains static for too long, the Gaussian used to model the SFO will become more important than the Gaussian modeling the BG. Consequently, the long-term SFOs are not detected [3].

TABLE II: SUMMARY AND GENERALIZATION OF PROS AND CONS OF EACH SFO DETECTION TECHNIQUES.

Techniques	Authors	Pros	Cons
Tracking of Foreground	[7,9,10,11,12,16, 17,21,25,27,28]	-Allows detection of both short-term and long term SFOs -Deal with Occlusion	-Fail to deal with PSFOs
Dual Foreground Comparism	[22]	-Good for crowded sequence -Can handle occluded scene	-Long-term SFO challenge -Low usability as models must be adopted to each analyze sequence -Fail to classify different objects. -It has high false alarm rate
Gaussian stability	[25]	-High Computational efficiency and easy to implement -Increase usability due as it depends on few parameters suitable for the detection of PSFOs	-Fail for occluded scenes -Misdetection of long-term SFOs
Classifiers	[6]	-Cope with long-term SFOs -Best for crowded sequences -Cope with Occluded SFOs	-Requires training period -

D. Classifiers

Methods for object classification for video analytics vary widely and depend on the application. Classification techniques are also dependent on the number of distinct classes to be detected. Binary classifiers are used to separate object blobs into one of two classes, e.g. a person or a nonperson. Multi-class classifiers separate object blobs into one of many classes, e.g. a person, vehicle or animal. Note that a classifier can only provide a prediction for an object belonging to a class or, alternatively, provide the likelihood of an object being in a certain class. In addition, a classifier may also provide the likelihood of an object not belonging to a given class. Image features are used to discriminate one class from another. A simple classifier that separates persons from vehicles can be constructed by examining the aspect ratio of the segmented blob.

People tend to be taller than wider, while cars are wider than taller. Other features that can be useful are histograms and outlines [1].

A rule based classifier is utilized in the work by Sawant et al [25] which subdivide moving object into five (5) classes: Temporary Static(TS),Moving Person(MP),Still Person(SP),Unattended Object(UO),and Unknown(U).It uses features such as velocity of a blob, and exponent running average as a basis for the classification.

V. CONCLUSION

This article gives a brief review of the recent trends in abandoned object detection. Foreground and stationary foreground detection methods and the challenges cope by each of these methods were highlighted to serve as a basis for selecting the appropriate method or a combination for a particular problem. Thus, there is no universally chosen technique for detection of abandoned object, but the purpose and challenges to cope by the method is the overriding consideration in making selection. For instance, the GMM method despite its slow convergence is the most popular, reliable and multi-purpose FG detection technique to date since it handles camouflage and slight variation in BG (swaying tree, illumination changes, etc.), whereas the frame difference is simple and appropriate for moving camera situation. For the SFO detection, the tracking based approach dominates the field of video surveillance due to its simplicity and accuracy, edging the dual FG technique among others.

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