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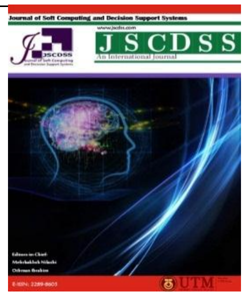

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Background Subtraction Methods in Video Streams: A Review

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Abstract

Background subtraction is one of the most important parts in image and video processing field. There are some unnecessary parts during the image or video processing, and should be removed, because they lead to more execution time or required memory. Several subtraction methods have been presented for the time being, but find the best-suited method is an issue, which this study is going to address. Furthermore, each process needs to the specific subtraction technique, and knowing this issue helps researchers to achieve faster and higher performance in their research. This paper presents a comparative study of several existing background subtraction methods which have been investigated from simple background subtraction to more complex statistical techniques. The goal of this study is to provide a view of the strengths and drawbacks of the widely used methods. The methods are compared based on their memory requirement, the computational time and their robustness of different videos. Finally, a comparison between the existing methods has been employed with some factors like computational time or memory requirements. It is also hoped that this analysis helps researchers to address the difficulty of selecting the most convenient method for background subtraction.

Keywords: Image processing, Computer vision, Background subtraction, Video surveillance

1. Introduction

Background subtraction is a common approach in the image processing and computer vision fields. It means that the foreground of the image is extracted for further processing. Generally a Region of Interest (ROI) of the image can be several objects like humans, cars, texts, and so on in the foreground. After the image preprocessing step which may compose image de-noising, or filtering, object localization is needed that may make use of this method. Background subtraction is a widely used method to detect the moving objects in the videos obtained by static camera. The moving object detection between the source frame and current frame, which called “background model” or “background image” (Piccardi, 2004). Background subtraction is conducted if the image would be a part of a video stream. In shortly, the main goal of the background subtraction process is: obtained the frame sequence by one or more camera, detection of the objects in the foreground, and offer an explanation of the method. It means that detection of the foreground objects are known as the difference between the static background and current frame.

Background subtraction process is usually used in many applications which work on the video, such as video surveillance which is one of the hottest applications today, gesture recognition for interacting between human and machine, and also traffic monitoring, to name a few (Sebastian *et al.*, 2011). On the other word, the applications of background subtraction can be divided into four categories: Optical Motion Capture, Video Surveillance, Human-Computer Interfaces (HCI) for Interacting goals, and Content-based Video Coding.

According to previous research, too many techniques have been employed for background subtraction, which have different weakness and strength points in performance or computational costs. A robust background subtraction method capable to manage duplicate motions from cluttered backgrounds, lighting changes, and changes in the long-term scenes (Tamersoy, 2009).

2. Method

One easy approach for modelling the background is through a single color/grayscale image of moving objects in the scene which acquired without motion or estimated via a temporal median filter (Cucchiara *et al.*, 2005; Heikkilä and Silvén, 2004; Zhou and Aggarwal; 2001).

A. Conventional Methods

The basic category includes several basic approaches like Frame Difference, Static Frame Difference, Weighted Moving Variance, Adaptive Background Learning, Weighted Moving Mean, Adaptive Median, Temporal Mean (McFarlane and Schofield, 1995), and Temporal Median (Calderara *et al.*, 2006; Cucchiara *et al.*, 2005). These methods can be recursive or non-recursive approaches.

1. Median Filtering

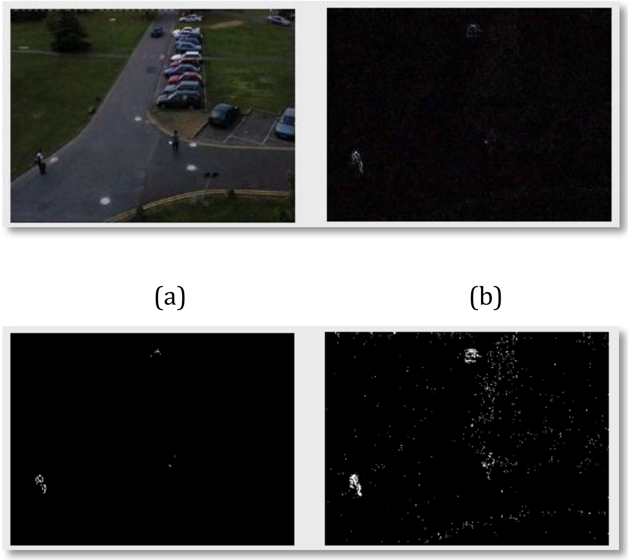
This type of filtering is probably the widespread background subtraction method. Median Filtering is based on the assessment of the background model by calculating the average of each input pixel. Just while after passing more than half of the frame absorbed save, the object is not considered as a background. The benefits of this method are simple construction, very fast process and easy to use. Models and background are not fixed, they change during the time. The drawbacks of these approaches are two important factors. One of them is failing on the track of targets in animated backgrounds and dependent accuracy on the speed of the target and the other is frame rate (Cucchiara *et al.*, 2003; François and Medioni, 1999; Koller *et al.*, 1994; Radke *et al.*, 2005).

2. Frame Difference

This is one of the simplest types of the BS methods. This method considers the previous frame as the background. Consequently in this way, the target is detected by subtracting the current framework of the background (Halevy and Weinshall, 1999; Huwer and Niemann, 2000; Naraghi, 2009).

It is assumed that the background is in the frame at time t and the absolute frame difference is defined at time t + 1. This differentiation value would just display several intensities for the locations of the pixel. It has been changed in two frames and seems that the background has been removed. It should be noted that this technique will only work well when all the background pixels are static and all foreground pixels are moving (Tamersoy, 2009).

A threshold 'Th' is defined this obtained difference image for improving the subtraction. The difference pixel intensities of the image are filtered on the basis of the 'Th' value. The speed of movement objects effects on the accuracy, and faster movements lead to higher thresholds. Then, the computed background is only in the previous frame. It works just in particular conditions of the frame rate and object speed. Shortly, this method is very sensitive to the determined threshold. Fig. 1 shows the process of this method.



(a) (b)

(c) (d)

Fig. 1. Frame difference method, (a) original frame, (b) absolute difference, (c) threshold too high, (d) threshold too low (Piccardi, 2004)

3. Average Filtering

In this method an arithmetic mean is considered for each frame input during the time. The method assumes the object as temporary in time. Background model will affect significantly in a slow or large target (Heikkilä and Silvén, 2004; Zhou and Aggarwal, 2001). Some studies also have been done with the background as the average of the previous n frames (François and Medioni, 1999). These methods are rather fast, but very memory consuming. The memory requirement equals to the n time to size (frame). On the other hand, the background can be considered as the running average. This approach does not need to more memory requirements.

4. MIN-MAX Filtering

Three different values are used in this algorithm to realize which pixel demonstrates the background. The target shows more radiation intensity in the background (Pong and Bowden, 2002)

Another technique with the goal of local adaptation to noise was proposed in (Haritaoglu *et al.*, 2000). Here, every background pixel comes with a maximum M_s, minimum m_s, and a maximum of consecutive frames difference D_s observed over a training sequence. Each background pixel is related to three extremum magnitudes rather than a covariance matrix and a mean vector. The main algorithm just acts on grayscale videos. The results of this algorithm compared to color video sequences are in a loss of data. The background can be updated following object-based and pixel-based methods.

The above mentioned techniques are recursive

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methods that they require less storage in contrast with non-recursive approaches. The most of schemes use forgetting factors or exponential weighting to specify the ratio of contribution of previous observations. They can be used for background subtraction and estimation (Pong and Bowden, 2002). The four following methods are non-recursive techniques.

5. Approximated Median Filtering

A recursive filter to estimate the median of each pixel during the time was presented in (McFarlane and Schofield, 1995). This method has been used by several approaches to subtract the background in the urban traffic monitoring because of its significant speed.

6. Single Gaussian filtering

According to discussion in (Mohamad and Osman, 2013), the average image of a frame sequence is computed in this method. Then, new frame is subtracted with calculating the differentiate value considering a predefined threshold. Wren (1997) presented an approach to allocate a normal distribution with a standard deviation and definitive mean to each pixel by YUV color space.

7. Kalman Filtering

This method is place in the recursive methods category. It is assume that the intensity magnitudes of the pixels. This value pursues a normal distribution. In (Boult *et al.*, 1999) this method has been described in detailed. One considerable difference between this method and the previous methods is applying the state space to object tracking process and the simplest algorithms are based just on the luminance (Boult *et al.*, 1999, Dempster *et al.*, 1977, Halevy and Weinshall, 1999, Montacié *et al.*, 1996, Sebastian *et al.*, 2011).

8. Hidden Markov Models

All previous methods are able to reconcile to quantized changes in lighting conditions. So if remarkable changes occur in the intensity value, serious problems may occur. Markov Model means this definition: modelling the variations in the pixel intensity. According to modes of the environment, Hidden Markov Models designs these variations as discrete states. In (Brutzer *et al.*, 2011, Sen-Ching and Kamath, 2004) one type of HMM has been employed for modeling the pixel intensity in traffic monitoring applications.

B. Statistical Methods

Modelling Background with a single image as in basic methods requires a high accuracy in fixed background without artifacts or noise. This requirement cannot be convinced in real scenario, so some models with background pixel in a probability density function (PDF) learned with a collection of training frames. The background subtraction issue becomes a PDF thresholding problem for a pixel with low probability likely a foreground moving object. The Statistical methods using one Gaussian have two subsequences: Gaussian Average was proposed by Wren (1997) and the Simple Gaussian of Benezeth and his colleagues. It does not cope with multimodal backgrounds (Benezeth *et al.*, 2010).

Many researchers have worked on Statistical methods using multiple Gaussians that is called Gaussian Mixture Model (GMM). Some of these research were done by Stauffer and Grimson (1999), Bouwmans et al. (2008), ivkovic (2004), and Hofmann et al. (2012). In order to account for backgrounds created by animated textures like shaken trees by the wind or waves on the water, some researchers proposed the use of multimodal PDFs techniques (Stauffer and Grimson, 1999) and some improvements of this method have been proposed. For instance, for learning the mixture models, an updating algorithm is presented in (Pong and Bowden, 2002, Zivkovic, 2004).

C. Fuzzy Based Methods

Fuzzy logic is determined by the fuzzy set theory. Fuzzy set theory, fuzzy numbers, fuzzy logic, fuzzy periods, and the calculations of fuzzy make it adaptable to an amendment. On the other hand, the fuzzy logic may deal with terms instead of the human language nature (Tripathi and Mukhopadhyay, 2012).

Fuzzy based techniques include three categories. For the first time, Zhang and Xu the worked on Fuzzy Sugeno Integral with Adaptive-Selective Update (Zhang and Xu, 2006). A Fuzzy Choquet Integral with Adaptive-Selective Update was proposed by (Hofmann *et al.*, 2012). Zhao with his colleagues suggested the Type-2 Fuzzy GMM-UM and GMM-UV with MRF (Zhao *et al.*, 2012).

D. Non-Parametric Methods

One unstructured method was also applied for modelling a multimodal probability density function by Mittal and Paragios (2004). They proposed a Parzen-window estimate at each background pixel. The problem of this method is the memory requirement size time to the kernel values reduced by a LUT method.

More sophisticated techniques are predicted (Goyat *et al.*, 2006) which are based on "Variable Bandwidth Kernels". Goyat et al. worked on VuMeter (Han *et al.*, 2004). Hofmann (Hofmann *et al.*, 2012) proposed a Pixel-Based Adaptive Segmenter (PBAS) as well as Godbehere et al. (Godbehere *et al.*, 2012) studied on GMG.

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E. Mean-Shift Based Estimation

This method was proposed in (Piccardi, 2004). A gradient-ascent method detects the multimodal distribution with its covariance matrix. Fig. 2 shows a mean - shift trajectory in the data space.

The problems of this method are too slow pat and also needs to *n* * size (frame) memory requirements. But there are some solutions to overcome these problems. One of them is computational optimizations, and the other using it to detect the background probability density function modes at initialization time, using computationally lighter which is propagation mode.

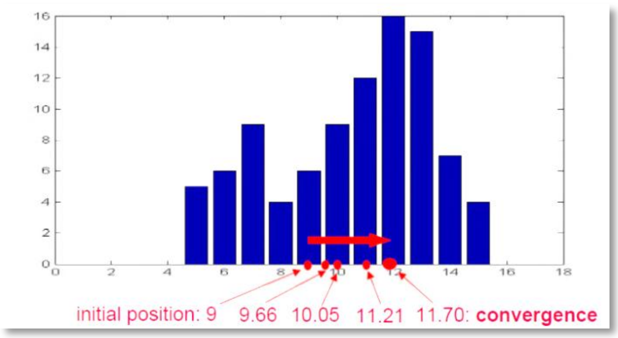

Fig. 2. Mean-shift based estimation (Piccardi, 2004)

F. Combined Estimation and Propagation

Han and his colleagues studied on Sequential Kernel Density Approximation, that used some mean-shift modes at 56 initialization times. In order to merge the existing modes, the heuristic procedures are applied. It is faster than the KDE, and has low memory requirement as presented in Fig. 3 (Han *et al.*, 2004).

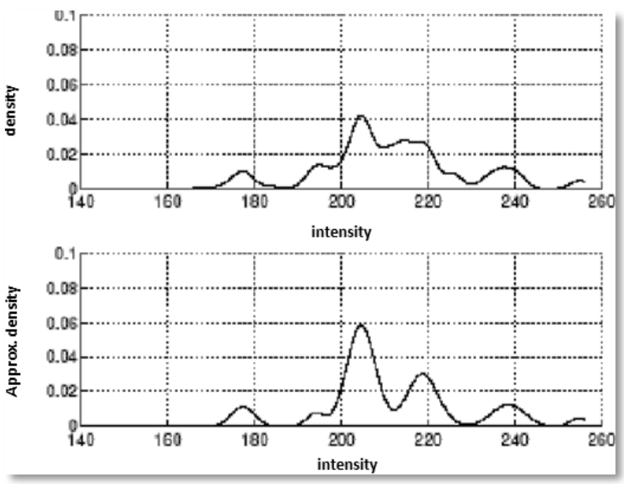

Fig. 3. Above: Exact KDE, below: Sequential KD Approximation (Han *et al.*, 2004)

G. Methods Based on Eigen Features

Eigen background / SL-PCA was proposed by Oliver (2000). The major key factor of Eigen background is about its ability in the background model learning from unconstrained video sequence. While past methods use pixel level statistics, this technique uses neighboring statistics. This method also has more global definition of background that leads to more robust unstable backgrounds. As a result, the Principal Component Analysis (PCA) by Eigen vector decomposition reduces the space dimension. Furthermore, Principal Component Analysis can be applied to a sequence of n frames to calculate the Eigen backgrounds, and finally it is faster than a Mixture of Gaussian approach.

3. Challenges of Background Subtraction for Video Surveillance

BS methods have to deal with various challenges due to the nature of video supervision. Besides the standard challenges, many of the background subtraction challenges have studied in literature before (Sebastian *et al.*, 2011). A comprehensive review is covered in (Calderara *et al.*, 2006). The following challenges are realized as follows:

Gradual or sudden illumination changes: It is necessary to adapt the BS methods to changes of the environment. For instance, in outdoor environments on a day, the light intensity usually varies. On the other hand, the sudden changes are not covered by the background technique. They occur suddenly, for example, with a sudden switch of the light. It may leads to false positive detections.

Dynamic background: Some parts in the video may contain moving objects, but should be regarded as background. Such movement can be irregular or periodical like waving trees.

Bootstrapping: If initialization data regardless objects in the foreground is not available, the background is initialized by the bootstrapping method (Brutzer *et al.*, 2011).

Video noise: Video signal is commonly superimposed by noise. Background subtraction methods for video surveillance has some degraded signals which affected by compression artifacts or sensor noise (Brutzer *et al.*, 2011).

Camouflage: Deliberately or not, some objects in a video can differ from the background appearance. It leads to make an incorrect classification. This is an important case in surveillance applications especially.

Shadows: Shadows are made by foreground objects that they often complicate processing procedure background subtraction. Consequently, it is superior to dismiss most of these unimportant parts. Fig. 4 shows the typical process of background subtraction.

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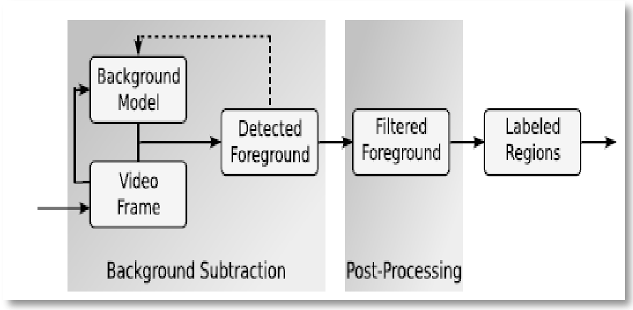

Fig. 4. Typical process of background subtraction with post processing in surveillance applications (Brutzer *et al.*, 2011)

4. Discussion

Recently, Tian et al. (2013) proposed a selective Eigen background modeling and subtraction method that can keep robust in crowded scenes as shown in Fig. 5. Three "selectivity" mechanisms are integrated with their methods, including selective training, selective model initialization and pixel-level selective reconstruction. Using these mechanisms, their method can significantly increase the purity of the trained Eigen backgrounds and obtain an improved quality of the reconstructed background image, consequently leading to a better subtraction performance in crowded scenes. Extensive experiments on the TRECVID-SED and Road video datasets show that this method outperforms several Eigen and non-Eigen background methods remarkably. They used of three Eigen background algorithms: C-EigenBg, BS-EigenBg, PS-EigenBgNVF and compared the results with other non-Eigen background algorithms like GMM, Bayes, Codebook, PBAS, and Vibe.

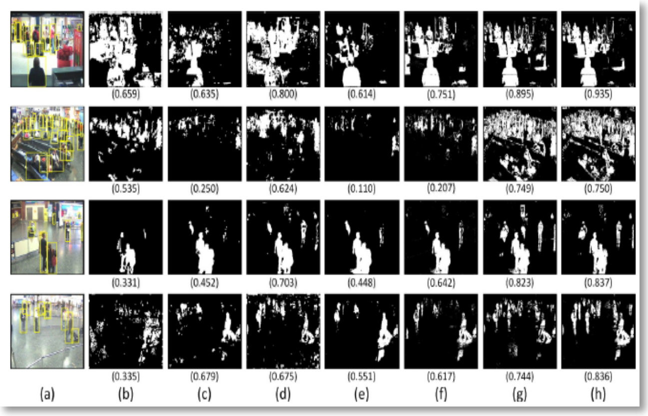

Fig. 5. Visualizing several subtraction results of non-Eigen background methods, (a) The original frames, (b) GMM, (c) Bayes, (d) Codebook, (e) PBAS, (f) ViBe, (g) PS-EigenBgNVF, and (h) PS-EigenBg (Tian *et al.*, 2013).

Rai et al. (2013) also present a segmentation method based on the neural network where the moving can be extracted in the video. The proposed framework is multilayer to match the frame complexity in a video stream and address the segmentation problems. The neural network gathers inputs that exploit spatial-temporal correlation between pixels. Each of units produce imperfect results, but the neural network combines their results, for getting better overall segmentation, although it is trained with noisy outcomes from a simpler technique.

This algorithm converges from an initial step. All pixels are considered as a part of the background to a step where just the appropriate pixels are categorized as background. Results are displayed to demonstrate the effect of the approach compared to a more memory intensive MoG method. As it can be seen in Fig. 6, the video of that method (Luque *et al.*, 2008) fails in segmentation process of the foreground objects. Both false negative and false positive pixels are seen in these results. MoG makes better results than the Luque technique, but the proposed method obtains the best overall results. They have applied experimentally best manual thresholding and morphological operations for three mentioned methods. The Fig. 6 illustrates the results of the three methods on four frames in a video.

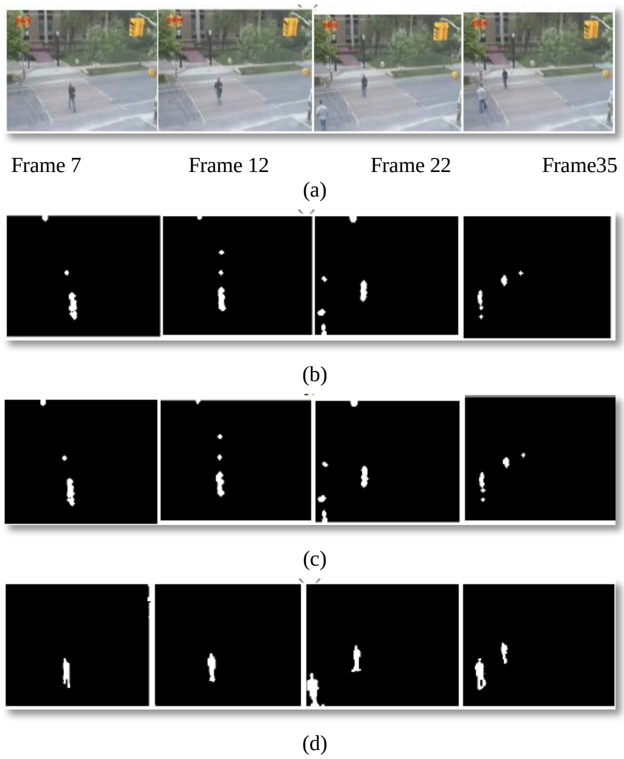

Fig. 6. (a) Original frames, (b) Results of R. M. Luque method, (c) Results of Mog method, (d) Results of proposed method (Luque *et al.*, 2008)

Benezeth and his co-workers tested the BS algorithms on series of videos demonstrating different scenarios and different challenges (Benezeth *et al.*, 2010).

According to the illustrated curves in Fig. 7, the MinMax method is less effective than the others, because it works on grayscale data. The other techniques produce the same results for isolated pixels. On the other side, the complexity of some certain approach such as KDE or GMM does not include any advantage as to precision. The simple methods like Basic method are as efficient as sophisticated ones related to videos in good conditions.

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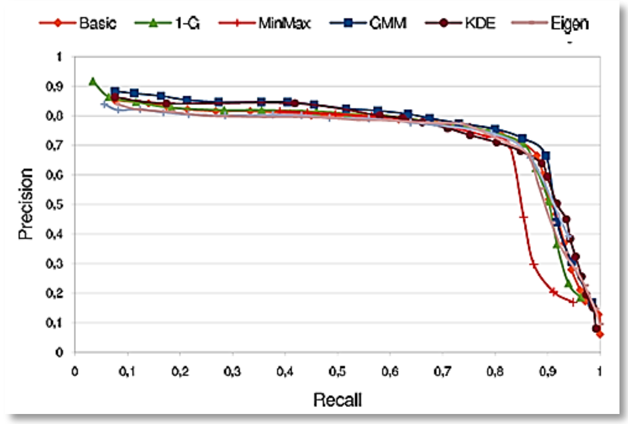

Fig. 7. Precision/Recall curves for noise-free videos with static backgrounds (Benezeth *et al.*, 2010)

The MinMax and simple Basic approaches are forcefully penalized as their global and non-adaptive threshold does not suit animated backgrounds. On the other side, results obtained with the 1-G method are good despite its unimodal nature. This can be described by this fact that the 1-G threshold is weighted as local by a covariance matrix. The GMM, KDE, and CBRGB methods caused to the most accurate results. In Fig. 8, seven masks are presented so the researchers can visualize the differentiations between the BS techniques.

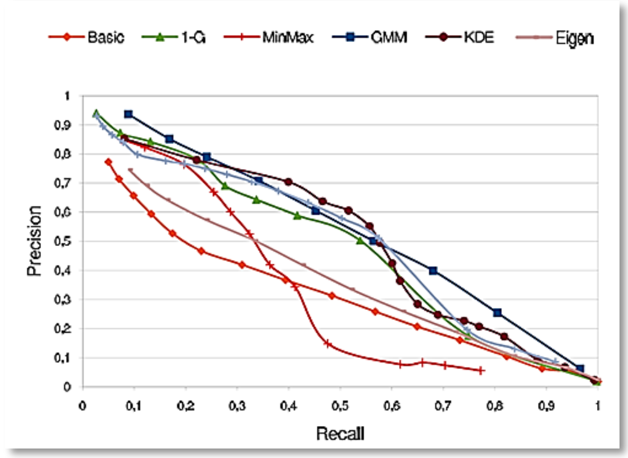

Fig. 8. Precision/Recall curves for videos with multimodal backgrounds (Benezeth *et al.*, 2010)

Fig. 8 illustrates the results obtained from Basic and GMM which shows barely any differences. Every method fails in detecting regions for the moving objects whose their color is similar or same to the background. This is a camouflage effect and no background subtraction method is able to dealing with it. Fig. 9 represents the Basic and GMM methods on the static background.

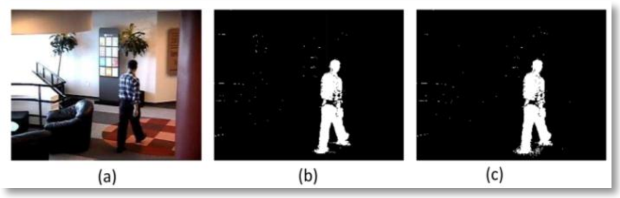

Fig. 9. (a) Input video with static background and large signal-to-noise ratio (b) motion mask with Basic (c) motion mask with GMM. (Benezeth *et al.*, 2010)

The MinMax approach is not suite in noisy videos as Fig. 10 shows that. The MinMax threshold depends on the maximum inter frame difference. This amount is large in a noisy video, so it causes to generate false positives. The global threshold of the Basic method penalizes significantly the performance factor. Statistical methods such as KDE, 1-G, GMM, or CBRGB showed better results, especially GMM method.

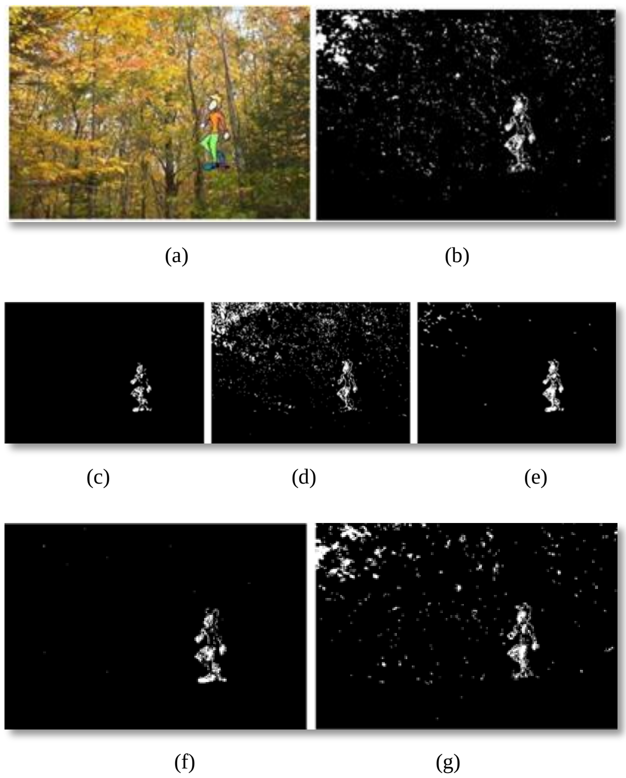

Fig. 10. Motion masks obtained with a video containing a multimodal background, (a) original image, (b) basic, (c) 1-G, (d) MinMax, (e) GMM, (f) KDE, (g) Eigen (Benezeth *et al.*, 2010)

Considering the curves, the global variable between the mentioned techniques is decreased compared to those in Fig. 7 and Fig. 8. Two factors are considered here. Firstly, some of the videos used in order to test a large signal-to-noise ratio with an accurate fixed background. Since all background subtraction approaches have high performance on these videos, the variation between those is smaller on the dataset. The second factor is related to the post processing step. The post processing stage reduces the number of false negatives and false positives that simple

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techniques provide on noisy or multimodal videos. Consequently, a combination of these factors can remove the gap between simple approaches like Basic, MinMax, or 1-G and some sophisticated ones like GMM, and KDE. The curves demonstrate that Basic, MinMax, and Eigen methods commonly underperform while 1-G, GMM, CBRGB, and KDE are more robust. Table 1 shows the memory requirements of the methods

Table 1
Classification of Methods in memory requirement

Memory requirement		
Low	Intermediate	High
Running average Basic: 3 1-G :6 MinMax: 3	Mixture of Gaussians: K*5 that K is the number of Gaussians in the mixture (between 3 and 5) Eigen backgrounds: M*3+3, M is the number of Eigenvectors kept (typically 20)	Average median KDE: N*3+3, N is the number of frames in the buffer (between 100 and 200) Mean-shift

Between the reviewed methods, simple techniques like the median filter or running Gaussian average represent reasonable accuracy. It has high frame rate while this method needs to limited memory requirement. Table 2 demonstrates a comparison of speed and accuracy rate between the methods.

Table 2
Average Relative Computation Time and accuracy

Speed	Slow	Standard mean-shift
	Intermediate	Computation time (CT) of the Mixture of Gaussian is 4.91 KDE: CT = 13.80 Eigen backgrounds: CT = 11.98 SKDA, optimized mean- shift
	Fast	Basic: CT = 1 1-G: CT = 1.32 MinMax: CT = 1.47 average, median, running average
Accuracy	Acceptable	Running average, Standard average, median
	Good	Mean-shift, KDE, Mixture of Gaussians Eigen backgrounds , SKDA

The KDE and Mixture of Gaussians show very good accuracy. KDE needs to a high memory requirement. This is a problem during the implementation on low memory devices. The Eigen background presents a good accuracy against memory complexity and reasonable time.

5. Conclusion

In this paper, we presented a comparative study of implementing background subtraction methods. Some of these techniques have a simple structure like Basic, One Gaussian, MinMax, while the other methods are significantly more sophisticated like Eigen, KDE, and GMM. These methods according to their computation time and memory requirements were compared together. Furthermore, their capability in correct detecting motion of a video in the indoor environments and moving backgrounds were investigated and an overall summary has been concluded. Some techniques on grayscale videos such as MinMax were less accurate than color videos. The complex methods did not provide more accurate results, especially in the videos with little background motion and large signal-to-noise ratio. Likewise, some techniques such as KDE and GMM presented better results only when the level of the noise got significantly large or the background was unstable. The GMM, KDE and Eigen were not suitable for real-time applications because of their memory requirement.

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