

AN IMPROVED FOREGROUND EXTRACTION TECHNIQUE IN VIDEO SURVEILLANCE SYSTEMS

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Abstract

In the current era, computer vision playing a major role in emerging research field. Mainly video surveillance systems generate huge size of data in every second. Through Video surveillance systems it is important to detect objects in order to identify the activities in the areas like tourism places, parking lots, shopping malls, highway road lines etc. In order to find the deeper insights through video surveillance cameras, it is essential to develop a system which can handle the challenges like camera Jitter, dynamic background, illumination mutations, noisy videos, shadow appeared scenes, swaying trees, camouflage, PTZ lighting camera screens etc. In order to identify the people and objects, it is essential to extract foreground while subtracting background. somehow reasonable work has been done using background subtraction which handles only few of these challenges commonly illumination variations and also various algorithms have been developed in these systems but most of them are limited in handling of static camera screens, In this paper, proposed model handles all these challenges with accurate results. Proposed model (Improved Background Subtraction - IBS method) is outperformed in handling of these challenging conditions. This methodology is more efficient in real time video surveillance applications in order to find the relevant objects used to track these objects in right path ways.

Key words: Video Surveillance. Foreground Extraction, Enhanced Segmentation (ES) method, Improved Background Subtraction (IBS) method.

Introduction

Now a days, Surveillance Cameras produces huge amount of data in every second. The advent of Big Data is introducing innovations like availability of data and computational power. Most of the surveillance systems are typically monitored by human operator but it is difficult to detect events happening in different camera feeds. The current emerging applications in this area faces various challenges like Camera Jitter, Dynamic background, video noise etc. [1]. Background subtraction is the key technique in the analysis of video surveillance systems. [2]. Many researchers have focused on detection of object of interest in video surveillance system through statistical background modeling techniques. These models are facing many challenges to recognize the objects. many of the existing techniques are using statistical modeling technique where to model background from first few frames and subtract this background from current frame. Most of the Frame differencing techniques are useful in finding foreground extraction [3]. Especially, in outdoor scenes, the images having Illumination changes and Shadow region may occur in the indoor scene that affects the performance of moving object detection. Many undesired changes such as illumination variations, branch movement, and cloud movement are caused in the outdoor scenes, which is challenging for the moving object detection method [4][5]. The false alarm rate increases when the foreground object is incomplete in video that affects the efficiency of high-level applications such as object recognition and behaviour analysis [6][7]. In [8] this model, they have used mixture of Gaussian to handle with dynamic backgrounds. [9], proposed sub space learning models based on Principle

component analysis to construct the background model based on N images to represent mean image and projection matrix with the Eigen vectors of PCA to produce the foreground segmentation. Most of the existing methodologies are performed foreground detection in order to track the objects like peoples, things and find the activities in one or two of the challenging conditions in both indoor and outdoor video frame sequences. In this paper, presented method is well performed in the most of the challenging conditions like dynamic background, camera Jitter, shadow appearance and thermal images

In this paper, the following sections are represented as, Section-I presents Dataset description Section-II Basic Methodology for Background Subtraction, Section-III Proposed method basis step, Section-IV Proposed Algorithm steps Section-V experimental results followed by Conclusion.

I. Dataset Description

Proposed model is applied on Change Detection dataset CDNET 2014 which contains both CDNET 2012 and CDNET 2014 [10]. The Changedetection.net dataset contains camera captures, which comprises in both indoor and outdoor videos. It includes the challenging category of scenes like camera Jitter, dynamic Background, noisy video frames, thermal and pan-tilt-zoom images, detailed description as follows.

Dynamic Background

The most challenging aspects while the screen state changes repeatedly are like swaying trees, water flow, moving vehicles in canoe, water fountains and moving boats. Similarly, in the dynamic background the transformation from one temporal stable to another which gives events like movement in tree leaves, it is very difficult to identify the things in all these scenarios.

Camera Jitter

In both indoor and outdoor places, the camera jitter scenes captured which are camera sway back and forth and also it causes motion in capturing frames. Due to improper position of camera, the capturing images contain noise. Sometimes wind changes also gives noise in images. Examples are games hooting, traffic monitoring and boulevard etc.

Illumination changes

Mostly, during the day and night timings, both in outdoor and indoor scenes enormous illumination changes takes place. These sudden changes occur by lighting effects due to light on and light off situations in the scene modeling. Background model should be adaptable to all such types of changes.

PTZ (Pan-Tilt-Zoom)

Many of the background subtraction methods are applied on stationary camera images. In PTZ cameras, images cover whole view. Traditional background subtraction methods lack in detection of foreground in case of non-stationary background pixels. An efficient methodology is required to find objects in PTZ camera captures.

Shadow presence

Shadows are variant from background which is detected as background. The shadow of moving objects gives undesirable results. An effective method is required which works in dynamic background in moving camera situations that handles combination of two or more of these challenges in scenes.

Noisy videos

Generally, video signals covers noise which is caused by processing, acquisition and transmission. It leads to undesirable results in background subtraction. Mainly it disturbs scenes with artifacts, line and corners etc.

Intermittent object motion

The motion occurs when an object movement is stopped for some period of time or object in background is moving. This type of situation is interpreted as undesirable. Most of the techniques are misinterpreting such moving background objects as foreground. These types of effects are identified in the situations like sudden movement of objects and abounded objects. Some models interpret motion less foreground objects as background. Hence, a model has to handle such type of misinterpretations also.

Camouflage

Moving objects may appear as the background and some are camouflage with background. It leads to misinterpretation in differentiating foreground and background specifically when the overlap of objects occurs from foreground with background scenes such as obstructions which leads false results during background modeling. Most of the content of foreground coincides with background in that, background pixels are interpreting as foreground.

II. Basic methodology used for background subtraction

pixel based background subtraction is considered the pixels from the frame and create the probabilistic model based on first ten frames, comparison of this background model with current frame at time 't' and the similarity check is processed with the background model by comparing with the threshold value resulting in the detection of foreground if the pixels are greater than threshold 'T' otherwise background. The process is shown in the fig-1.

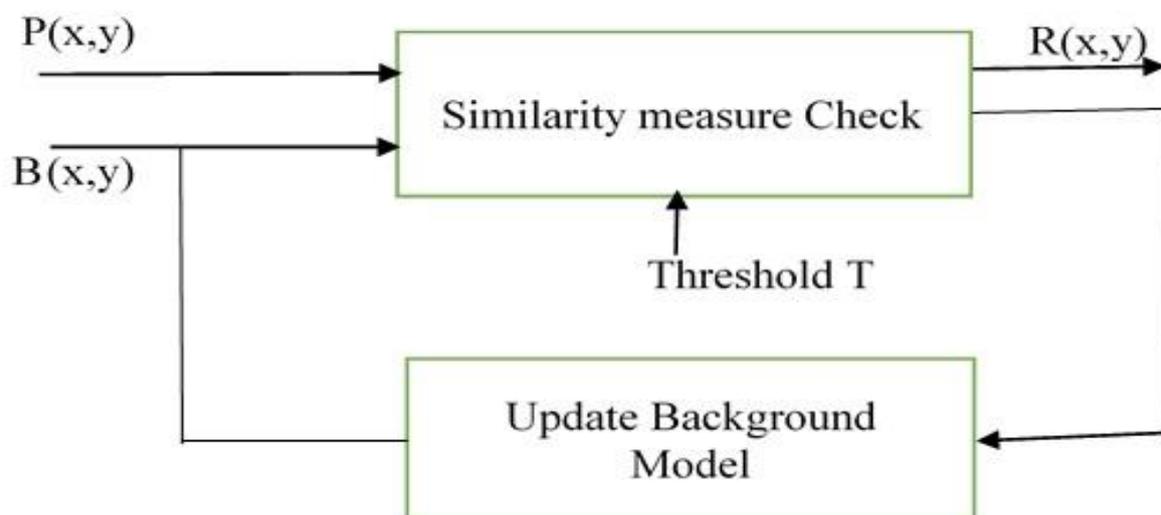


Figure 1: Background Subtraction Process

[11] The improved Gaussian Mixture model is mainly finding statistical measures and applicable for noise removal. [12] Used adaptive filtering method to find the changes in illumination variations. This is also applicable in noisy environments and motion environments. In [13] this method, authors used integrated Gaussian Mixture Model which includes three models to enhanced models for occlusion detection. Using statistical pixel wise operations on these models are used for finding objects in complex environments. [14] In this approach they used segmentation techniques for separating background from foreground frames.

[15] They developed median and MoG (Mixture of Gaussians) approach for background modeling in compressed videos. They applied this technique in DCT domain with reasonable accuracy and low complexity. [16] Uses contour analysis for detecting people in thermal images. Initially background subtraction used for region of interest after that combines region wise gradient information to contour saliency map.

The authors in [17] have used Gaussian mixture model. MoG uses statistical measures covariant matrix, average and probability of each of the Gaussians. For each pixel, the probability density function is considered. The

variants MoG uses adaptive background mixture model. Initially, background model is constructed BG (x,y) and maintained at pixel P(x,y) at time 't' and later, it finds similarity measure between BG(x,y) and p(x,y), then it classifies as either foreground or background. This model is updated by adopting changes in the scene. [18] Uses adaptive density feature for measuring the probability. However, no ghost technique is used for background subtraction.

III. Proposed Method - Basis Step

In the proposed method the basis step is used from [19], where Enhanced Background subtraction (ES) is uses pattern descriptors with corresponding threshold and computed d_{min} for each pixel. Computed the similarity measure for every pixel with updated value of BSP(X,Y) then compared the values with threshold R(X,Y) and finding the suitable segmentation map as foreground or background.

In the Enhanced Segmentation block wise pixel values, the pixel located at block center is B(x,y). If the texture at point (x,y) is obtained by using local neighborhood radius R, the ES(x,y) of center point is measured using similarity check between central point value(i_c) and neighborhood point value (i_p). At this point, we set the threshold 0 .01 and model replacement rate as 0.001 such that, it gives $S(i_p, i_c)$ is zero if $|i_p - i_c| \leq \text{Threshold}$ (or) otherwise.

$$S(i_p, i_c) = \begin{cases} 0 & \text{if } |(i_p - i_c)| \leq T \\ 1 & \text{otherwise} \end{cases} \quad (1)$$

IV. Proposed Approach - (Improved Background Subtraction Method)

In this method, along with Enhanced Segmentation we have used parametric Integrated Background subtraction (IBS) and is applied for faster moving objects detection over the background. This methodology is based on the rate of wave distortion amplitude and wave speed from the frame sequences. It uses the parameters like wave length distortion, wave speed and the rate of fast object over the background.

We have set the values of the parameters in the Integrated Background subtraction (IBS) as Wave length=20, amplitude of 2 and wave speed of 6.0 with 2.0 rate of object movement. Through these parameters, object instance is obtained from the foreground. The comparison of this method with state- of-the art methods proves best results in all the quality measures. The experimental results are compared using the metrics like precision, recall, accuracy, F1 measure, MSE, FPR, FNR, PSNR, and PWC.

Precision is the positive detection that gives percentage of true positives (TP) detected are compared to total number of detected ones that is true positives (TP) and false positives (FP), the standard value of precision is close to 1, and the formula is,

$$\text{Precision} = \frac{TP}{TP+FP} \quad (6)$$

Recall is the rate of detection which is the percentage of true positives (TP) detected with total number of true positives (TP) of the ground truth and total number of false negatives (FN), the standard value of recall is close to 1 without compromising precision value and the formula is

$$\text{Recall} = \frac{TP}{TP+FN} \quad (7)$$

F1 measure is the measure of segmentation accuracy by balance the precision and recall, the formula is

$$\text{F1 Measure} = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (8)$$

Specificity is the percentage of true negatives (TN) as compared to true negatives and false positives, the formula is

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (9)$$

False Positive Rate (FPR) is the percentage of false positives as compared with false positives and true negatives, the formula is

$$\text{False Positive Rate} = \frac{FP}{FP+TN} \quad (10)$$

False Negative Rate (FNR) is the percentage of false negatives as compared with true positives and false negatives, the formula is

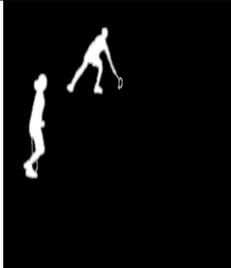
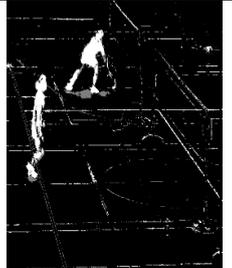
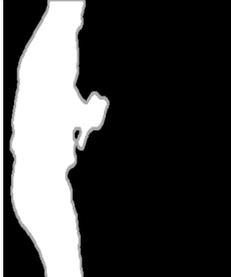
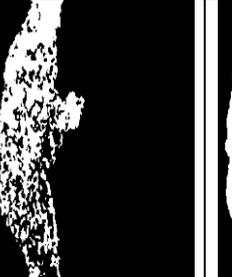
$$\text{False Negative Rate} = \frac{FN}{TP+FN} \quad (11)$$

PWC (Percentage of Wrong Classification) is the measure to produce wrong classification score, the formula is

$$\text{PWC} = \frac{100 \cdot (FN+FP)}{TP+FN+FP+TN} \quad (12)$$

V Experimental Results

In this section, we have provided the results of background subtraction methodologies with comparison of MoG, ES and IBS method are shown in the Table-1 to Table-4. ES method produces reasonable results in these challenging conditioned frames like baseline and camera Jitter challenges. whereas the proposed IBS method outperforms all the challenging environments like baseline, camera jitter, thermal and shadow environments. Specifically, thermal category of images foreground extraction is difficult in real-time environments. The proposed method proved best not only in challenging environments but also in real-time scene changes. The below section Figure 1, Figure 2 and Table 1 shows that the results for the category of baseline pedestrian images which consists of pedestrians crossing roads in challenging environment. In this experimentation, the proposed model produces high precision value compared to other methods.

Input Image	Ground Truth	MoG	ES	IBS Method
				
				

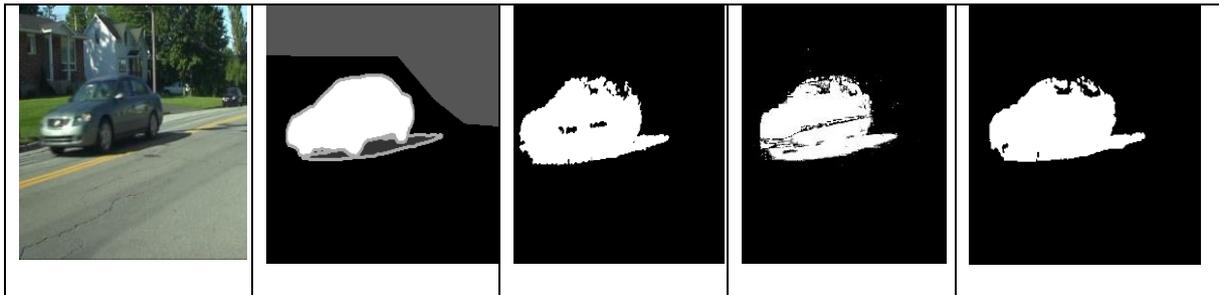


Figure 2: Camera Jitter/Thermal/Shadow category of images from CDNET 2014

Table 1. The Experimental Evaluation Precision Graph On These Three Methods

Precision			
Challenges/Methods	MoG	ES	IBS
Baseline	0.8754	0.9767	0.9765
Camerajitter	0.4555	0.6115	0.9064
Thermal	0.964	0.999	0.9999
Shadow	0.8967	0.8946	0.906

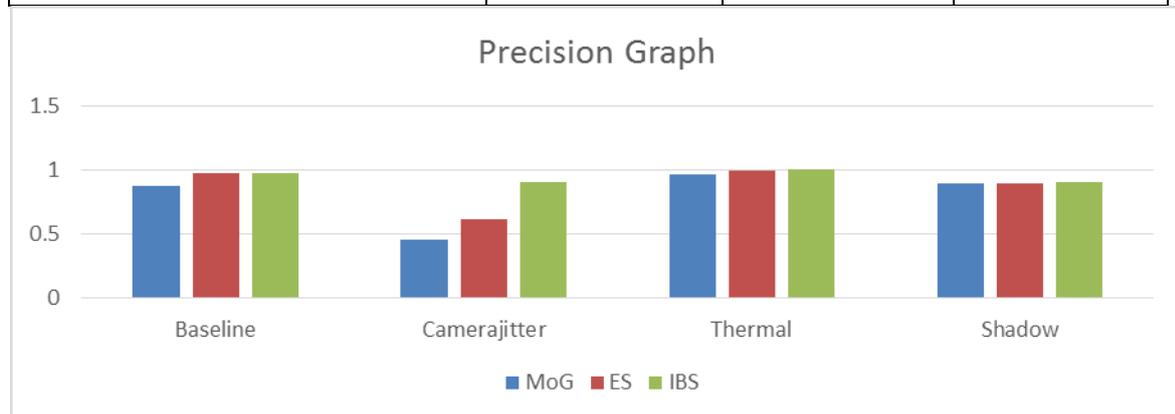


Figure 3: Precision Graph on MoG, ES and IBS methods

Table 2. The Experimental Evaluation Recall Graph On These Three Methods

Recall			
Challenges/Methods	MoG	ES	IBS
Baseline	0.8799	0.7178	0.8337
Camerajitter	0.7958	0.4956	0.8149
Thermal	0.5229	0.6172	0.9478
Shadow	0.8986	0.8859	0.9045

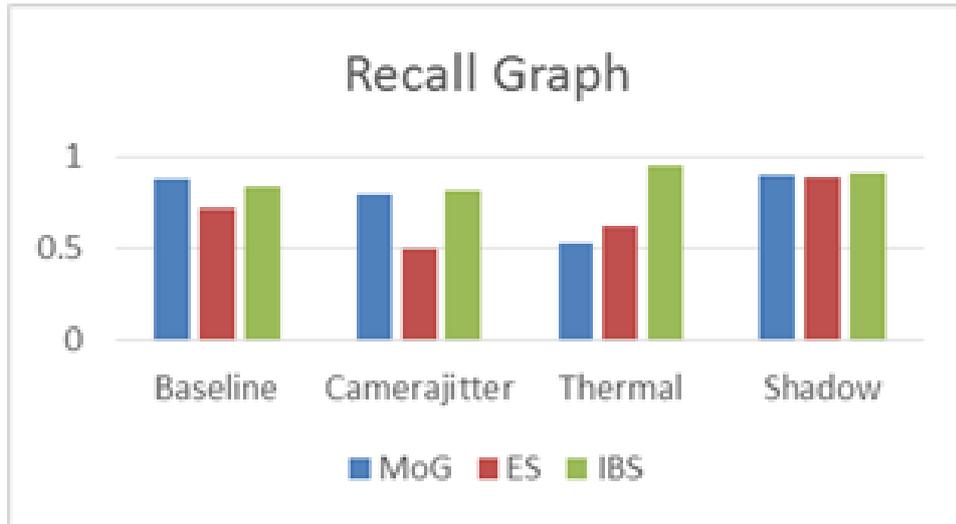


Figure 4: Recall Graph of MoG, ES and IBS methods

Table 3. The experimental evaluation F1_score Graph on these three methods

F1_score			
Challenges/Methods	MoG	ES	IBS
Baseline	0.8777	0.8274	0.8995
Camera jitter	0.5794	0.5475	0.8901
Thermal	0.6781	0.763	0.9731
Shadow	0.89766	0.8902	0.9742

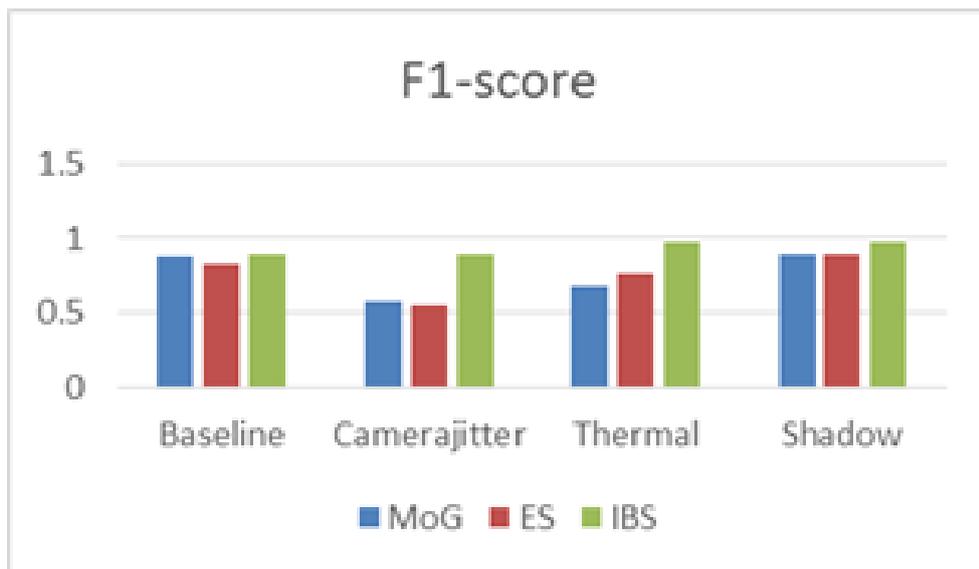


FIGURE 5: F1_Score Graph of MoG, ES and IBS methods

Table 4. The experimental evaluation Accuracy Graph on these three methods

Accuracy			
Challenges/Methods	MOG	ES	IBS
Baseline	0.9945	0.9933	0.9929
Camerajitter	0.9602	0.9718	0.9926
Thermal	0.8721	0.9012	0.9865
Shadow	0.9721	0.9703	0.9742

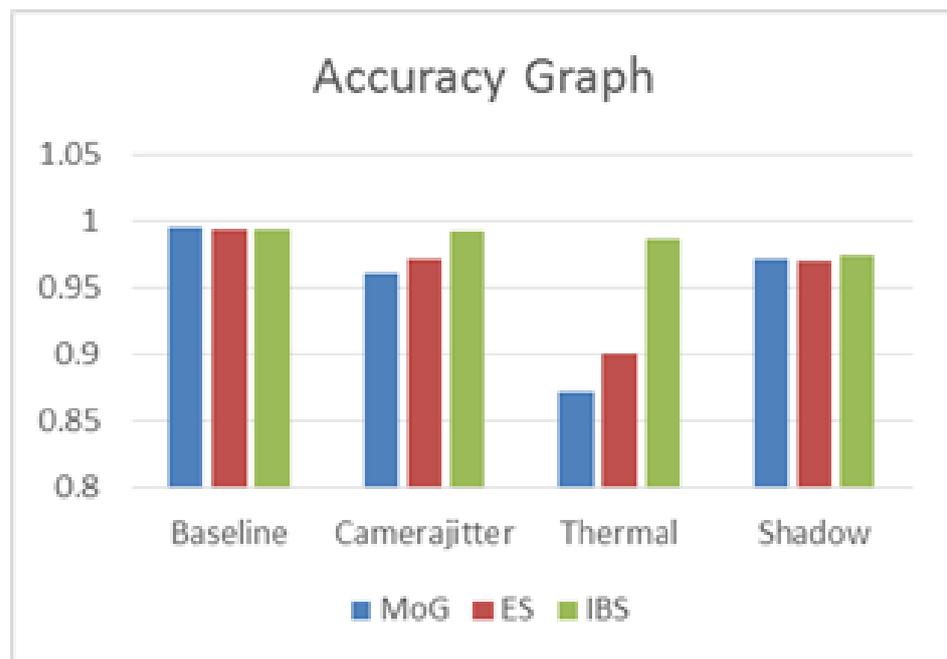


Figure 6: Accuracy Graph of MoG, ES and IBS methods

The below section Table-5 and Figure - 7 & Figure - 8 shows results for the all the mentioned category of images which consists various challenging environments. The proposed model Integrated Background subtraction (IBS) method compared with latest methods both parametric and non-parametric and outperforms in real-world scenes.

Input Image	Ground Truth	MoG_Foreground	ES	IBS Foreground

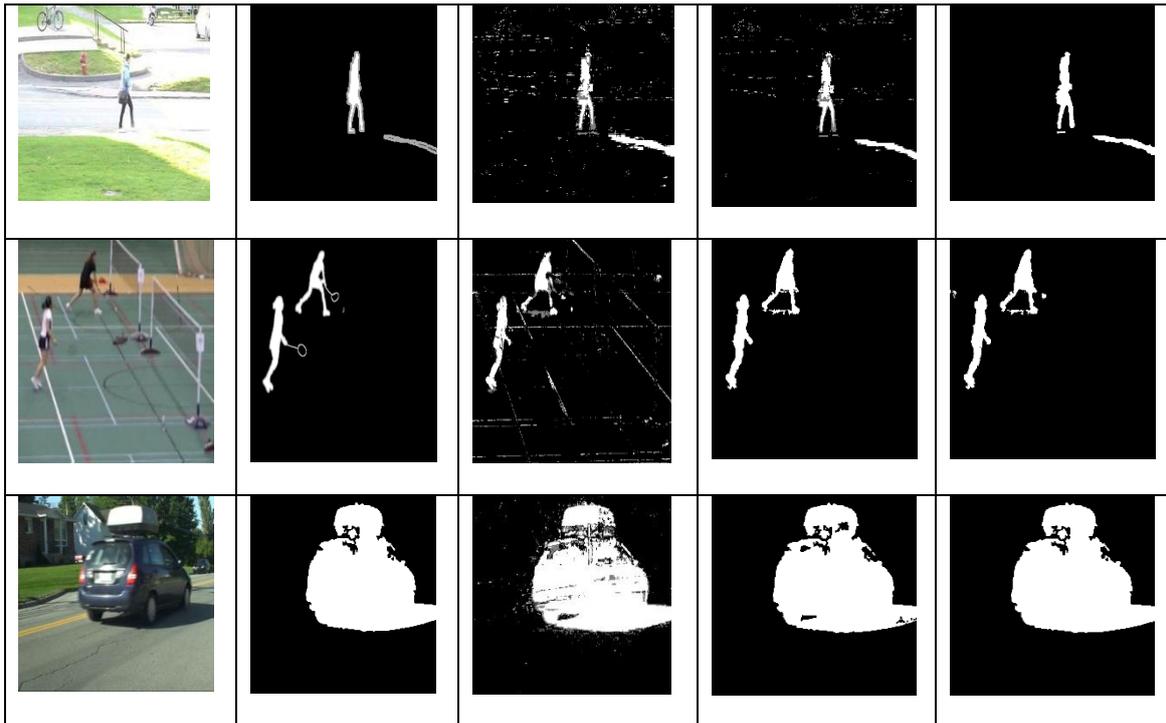


Figure 8: Baseline office & Pedestrians/Camera Jitter/Shadow category of images from CDNET 2014

Results Description

The above results shown are with input category of images having challenges baseline office, baseline pedestrians, camera jitter badminton, shadow bungalows of Dataset CDNET2014 with 150 consecutive frames of each category have produced the best results than the existing state-of-the-art methods. In this paper, we have presented the quality measure values in tabular format and in graphical representation also. The proposed method outperforms than the existing techniques.

Table 5. Results Comparison table proposed method with State-of-the-art methods

Methods	Precision	Recall	F1_score
GMM	0.7108	0.7012	0.6623
KDE	0.7442	0.6843	0.6719
SOBS	0.7882	0.7179	0.7159
VIBE	0.6821	0.7357	0.6683
SUBSENSE	0.828	0.858	0.826
PBAS	0.784	0.816	0.7532
ES Method	0.8704	0.6791	0.757
Proposed method (IBS)	0.9742	0.8752	0.9342

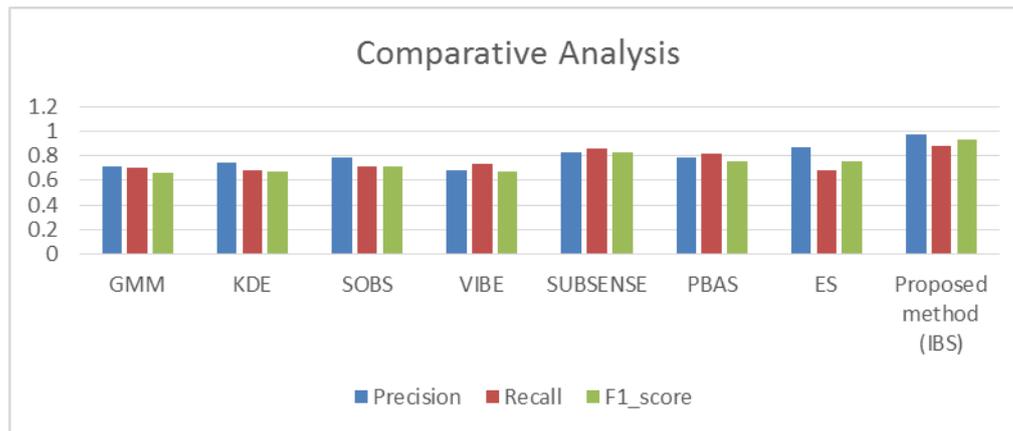


Figure 8: Results Comparison Graph of proposed method with state-of-the art methods

Conclusion

In this paper, we proposed enhanced and improved background segmentation method to handle the real time challenging conditions in intelligent surveillance systems. The proposed model used Integrated Background Subtraction (IBS) method for effective background subtraction in camera jitter, thermal and shadow images. The experimental results are outperformed through this method which yields improved and efficient results than the state-of-the art methods. This work is assessed qualitatively and quantitatively using the standard measures. The obtained precision, recall, accuracy and f1-measure values are clearly indicating that, the proposed method outperforms than the state-of-the-art methods. The value of F1_score is maximum indicating that, the proposed method is accurate and efficient and much more suitable in the real world scenarios. In future work, there is a need for developing a machine learning model for updated values of background model for accurate foreground extraction in large set of frames.

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