Improved Gaussian Mixture Model with Background Spotter for the Extraction of Moving Objects

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Abstract: *Extraction of moving objects is a key step in a visual surveillance area. Many background models have been proposed to resolve this problem, but Gaussian Mixture Model (GMM) remains the most successful approach for background subtraction. However, the method suffers from Sensitivity (SE) to local variations; variations in the brightness and background complexity mislead the process to a false detection. In this paper, an efficient method is presented to deal with GMM problems through improvement on updating selected pixels by introducing a background spotter. First, the extracted frame is divided into several equal size regions. Each region is assigned to a spotter who will report significant environment changes based on histogram analysis. Only parts reported by spotters are considered and updated in the background model. Tests carried out on four video databases that take into account various factors, demonstrate the effectiveness of our system in real-world situations.*

Keywords: *Video surveillance, GMM, modeling the background, image processing.*

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1. Introduction

The current surveillance systems offer only the possibility to take, save and distribute videos [22] to be manually processed by experts in anomalies detection and suspicious human behavior. The most commonly used methods to solve video surveillance problems in its different levels [3, 38] are: Detection, identification and tracking of moving objects. The robustness of a video surveillance system depends heavily on an effective operation that must ensure as well as possible a good separation between background and foreground. Several studies have been conducted to improve background subtraction. Effectively, a good extraction method simplifies the subsequent treatments and allows gain in execution time and memory space.

Methods and contributions proposed by many researchers can be naively divided into two groups. The first is based on a selection of a good discriminator features to improve system performance, while the second focuses on choosing the best algorithm that will take into account all possible scenarios to separate between background and foreground. For a possible use in real-time, both approaches must also ensure a compromise between PT and memory space.

Features based on textures proposed in [9, 41] give very good results due to their invariance to brightness. However, they still require more PT and large memory space limiting their use in complex and real time environments. Features based on color spaces presented in [5, 10, 11, 15, 33, 40] consume less computing time, but remain sensitive to variations in brightness, which greatly decreases their performance. Hybrid propositions given in [2, 6] combine textures and color space features to ensure a good compromise between running time and invariance to light intensity; but the proposed system is still far from objectives. Other characteristics such as sparse [35], wavelets transformations [8, 28], cosine transformations [37], Kanade-Lucas-Tomasi features [1], spectral characteristics [26], spatio temporal characteristics [26, 36] and tensor fields [4] have been used to circumvent the paradox between quality and Processing Time (PT). But these approaches are highly dependent on assumptions made on lighting conditions for giving good results. To overcome the shortcomings of approaches based on features selection, researchers have proposed several algorithms for background modeling to build a surveillance system usable in critical conditions.

Among the proposed algorithms to model the background, we find: Scales invariant [41], region based approaches [33, 35], Markov random fields [39],

fuzzy logic [2], approaches per block [6, 36], sequential density approximation [16], median filter on several levels [20], codebook [23], Bayesian decision rule [26, 31].

Works done in [21] showed that GMM provides a good compromise between quality and execution time

compared to other methods. Unfortunately, in addition to local variations and instant changes in brightness,

background containing multiple moving objects, remains the major problem of GMM [14, 25]. The first use of GMM for modeling the background was proposed by Friedman and Russell [12]. However, Stauffer and Grimson [32] proposed the standard algorithm with efficient update equations.

Several studies have attempted to improve the performance of GMM in environments with multiple dimming and high condensation background. Initial ideas focused on substitution of using color characteristics [4]. Hybrid models such as GMM and K-means [5], GMM and fuzzy logic [10], GMM and adaptive background [9], background maintenance for GMM [34] have been proposed to overcome GMM drawbacks. Other works have focused on improving the learning speed [18, 29] through an adaptive learning rate and the execution time [40] by using real parallel operations on multiprocessor machines. Other systems use two backgrounds [11] to solve the problem of change in brightness between day and night.

The proposed hybrid approaches led to eliminate only problems associated with background complexity. However, they increased the time required for image processing.

In this paper, we will focus on the detection of moving objects in a video surveillance through a fixed camera using an improved Gaussian Mixture Model (GMM). To cover all sections, we organized our paper as follows. Section 2 is dedicated to our contribution in which we present a description of the proposed architecture. Some experiments are discussed in section 3. We end up with a conclusion and some perspectives.

2. Proposed Approach

In this paper, we use an improved GMM to detect moving objects in video surveillance system through a fixed camera. To overcome local variation and instant change in brightness, the first extracted image from video is divided into several regions; each region is assigned to a background spotter who can detect local changes by comparing histograms. Only segments that have undergone a change are considered and updated in GMM. For better visibility, the system is organized into three stages as shown in Figure 1 as follows: acquisition, processing and detection.

2.1. Acquisition

We grouped in this block all treatments related to the acquisition and pre-processing giving a more simplified structure for the following steps:

- *Pre-Processing*: In this step, we transform the captured video in a set of frames. The extracted images from the video are in RGB mode, but this representation is not adequate because of light influence on the objects description [13]. For this reason, we made a transfer to the HSV model known to be the closest model of human perception and wherein the brightness affects only one component [13].
- *Splitting*: This operation is only used in initialization step. We divide the first frame into N equal size segment in order to minimize local variations and to simplify the background spotter task. We noticed that the number of areas greatly influences on system quality. A large number of regions lead us to the starting point (pixel based approach). In case where the number of zones is small (the size of the area is large), local variations accumulated in the same area force the system to consider the latter as an intense variation. In this way, all pixels belonging to the area will be updated. We assume that all regions are completely separate. Let A be a region of the image "I" and N is the total number of regions in the same image.

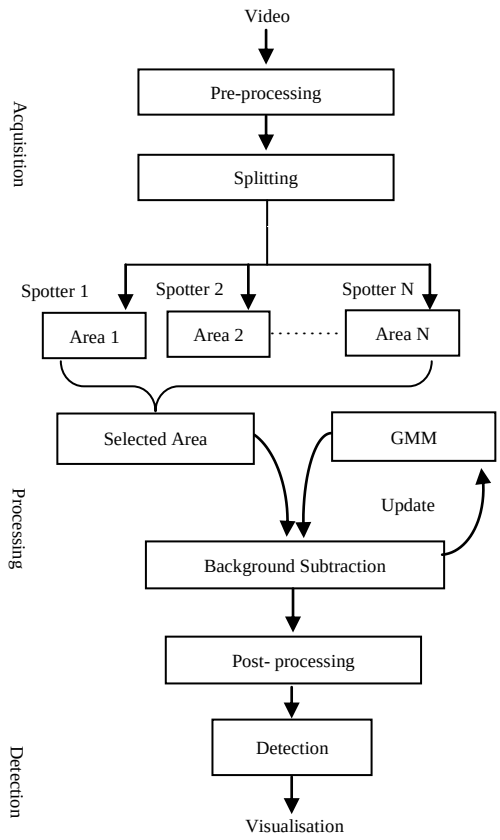

Figure 1. Proposed system

$$\forall i, j \in \{1, \dots, N\}, \text{if } A_i \in I \text{ and } A_j \in I \text{ with } i \neq j \Rightarrow A_i \cap A_j = \varphi \quad (1)$$

2.2. Processing

In this step, the collaborative work between the background spotters and GMM creates and ensures the background stability.

- *GMM*: A GMM is a statistical model that assumes the data where originates from a weighted sum of several Gaussian distributions. Stauffer and Grimson [32] presented an adaptive GMM method to model a dynamic background in image sequences. If K Gaussian distributions are used to describe the history of a pixel, the observation of the given pixel will be in one of the K states at one time [5]. K determines the multimodality of the background and the selection of K is generally based on the available memory and computing power. Stauffer and Grimson [32] proposed to set K from 3 to 5.

First, each pixel is characterized by its intensity in the HSV color space. Then, the probability of observing the current pixel value is given by the following equation in the multi dimensional case.

$$P(P_t) = \sum_{i=1}^{k} w_{i,t}\, \eta(P_i, \mu, \sum_{i,t}) \quad (2)$$

Where k is the number of associated Gaussians to each pixel, $W_{i,t}$ is the calculated weight, $\mu_{i,t}$ is the mean and $\sum_{i,t}$ is the covariance matrix that are respectively evaluated for the ith Gaussian at time t.

The update of the model is carried out by using K-means approximation algorithm [5, 7]. Each new pixel value is checked through the k Gaussian distributions to determine if the distance between the pixel and each Gaussian is less than 2.5 standard deviation using the following equation:

$$\frac{|P_t - \mu_j|}{\sigma_j} \quad (3)$$

If none of the distributions satisfy Equation 3, then the pixel is associated with first plan and the parameters of the least probable distribution are replaced with mean, variance and weight of the current pixel according to Equations 4, 5 and 6 described below:

$$\sigma_k^2 = \sigma^2 \quad (4)$$

$$w_k = \phi_t \quad (5)$$

$$\mu_k = P_t \quad (6)$$

The weights of the K distributions are updated according to Equation 7:

$$w_{k,t} = (1-\alpha).w_{k,t-1} + \alpha\, M_{k,t} \quad (7)$$

Where α is the learning coefficient which determines the model adaptation speed, and Mk, t is equal to 1 for the distribution which corresponds to the background and 0 for others.

After updating weights, a normalization step is carried out to ensure that the sum of the weights is always equal to 1. The other parameters are updated using the following equations:

$$\mu_{k,t} = (1-\phi_k).\mu_{k,t-1} + \phi_k P_t \quad (8)$$

$$\sigma_{k,t}^2 = (1-\phi_k).\sigma_{k,t-1}^2 + \phi_k\, (P_t - \mu_{k,t})^T (P_t - \mu_{k,t}) \quad (9)$$

With:

$$\mu = a\eta\left({P_t}/{\mu_k\ \sigma_k}\right) \quad (10)$$

To maintain background stability, we use the first 100 frames for learning mean value and variance.

2.3. Background subtraction

To decide if P_t is included in the background distributions, the distributions are ordered according to the value of $W_k, {}_t/\sigma_{k,t}$ and the first β distributions that verify the Equation 11 are selected to represent the background.

$$\beta = argmin\,(\sum_{k=1}^{b} w_{k,t} > B) \quad (11)$$

Where B determines the minimum portion of data corresponding to the background.

The threshold B represents the minimum portion of the total weight given to background model. If a small value for B is chosen, then the background becomes unimodal. If B is higher, a multi-modal distribution caused by a repetitive background motion could result from a variety of background component which allows the background to accept more than one Gaussian distribution. The use of unique threshold B for GMM implies a miss classification especially when scene contains both dynamic and static area. A higher threshold can achieve correct classifications in a dynamic background but makes incorrect detection of moving objects in stationary background.

2.4. Background Spotter

Methods based on GMM use the pixel value for detecting a probable change in the background based on the assumption that a moving object is a set of pixels in movement. This vision is very useful because it requires no a priori knowledge of objects and their trajectory. However, the natural environment is far from perfect. The presence of dust, change in brightness, rain, wind ... etc., influence on pixel value leading to a misdetection of motion.

The false pixel detection induces the system to make errors in the following steps, either by deforming moving objects or by signaling a false movement. To overcome these problems, we proposed background spotter. We have defined and assigned for each spotter, an area in an image. The spotter's role is to monitor and report the presence of activity in his area.

Upon assignment of a spotter to an area it creates and records the histogram of the latter in this memory. Thus, in each new treatment, the spotter can detect changes in area by comparing the current histogram state with the stored state. The presence of a moving objects in one or more areas triggers simultaneously and independently all the background spotters. This process will eliminate local variation, because only

areas with significant change will be considered by the system.

In the literature, there are several methods to measure the similarity (dissimilarity) between two probability distributions *P* and *Q*, the most used are: Bhattacharyya distance [19], Kullback-Leibler and Jensen-Shannon divergence [17]. These measures are defined respectively as follows:

- *BhattacharyyaDistance*:

$$D_B(p,q) = -\ln(BC(p,q)) \quad (12)$$

With

$$BC(p,q) = \sum_{x \in X} \sqrt{p(x)q(x)} \text{ and } 0 \le BC \le 1 \quad (13)$$

- *Kullback-LeiblerDivergence*:

$$D_{K,L}(P||Q) = {}_i\sum P(i) log \frac{P(i)}{Q(i)} \quad (14)$$

- *Jensen-Shannondivergence*:

$$JSD(P \,||\, Q) = \frac{1}{2}\sum P(\log p - \log M) + \frac{1}{2}\sum P(\log p - \log M) \quad (15)$$

With:

$$M = \frac{P+Q}{2} \quad (16)$$

Notice that, in Equations 14 and 15, *P*=*Q* if and only if *Dk*, *L*(*P*//*Q*)=*JSD*(*P*//*Q*)=0, while in our case, the possibility to have equality of the two probability distributions is nearly impossible. For this reason, the use of the Bhattacharyya coefficient BC seems appropriate because we can choose a threshold value "*T*" that ranging between 0 and 1. Therefore, if the difference between *P* and *Q* is greater than *T*, the spotter triggers a signal indicating detection of a change in theregion.

In our case, Bhattacharyya coefficient calculated in frames 439 and 472 as shown in Figure 2 gives almost the same value.

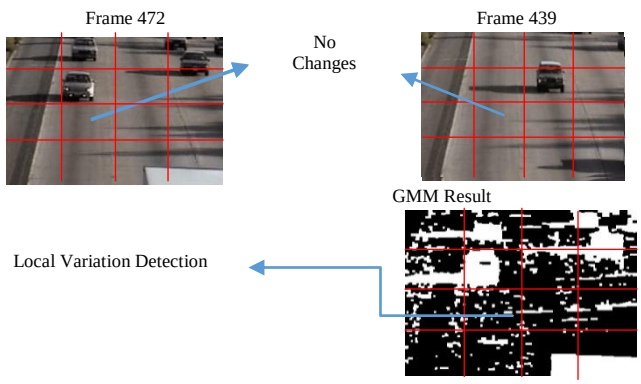

Figure 2. Impact of the local variation on GMM in highway I2.

This equality indicates to the spotter that the region had no significant changes. Therefore, disruptive pixels will not be updated and will not be considered part of a moving object. This process will not affect the GMM ability to adapt through slow changes in brightness. Indeed, any significant change will affect all of the pixel values in area, which influences on histogram shape.

2.5. Detection

2.5.1. Post-Processing

The post-processing aims to correct the mistakes made in the previous step. The background subtraction forgets a significant number of noises and holes, which influence the segmentation algorithms and system behavior. For this purpose, we have used well-known morpho-mathematical operations.

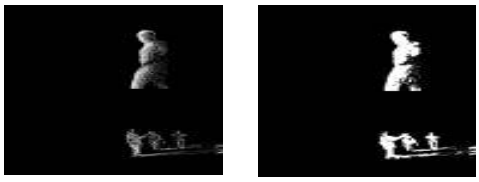

Figure 3. Result of morpho-mathematical operations.

The dilation process allows plugging the holes left inside objects, while erosion removes unwanted points generated by the presence of dust or a small change in brightness that not be detected by the background spotter. Figure 3 shows that these operations are necessary to improve the images after background subtraction for better detecting edges of objects and in order to simplify other system tasks.

2.6. Detection of Moving Objects

Our system can detect multiple moving objects. To locate each object separately, we perform segmentation into connected components. Conventional methods such as region growing segmentation cannot detect partially overlap objects. Objects are located by analyzing horizontal and vertical projection histograms with an iterative process. In each step, the image is segmented into parts according to the number of peaks between two minima of the histogram. This process is applied successively to each part until it can no longer be segmented. Each peak between two minima represents a moving object.

3. Experiments and Results

3.1. Settings

The system presented in this paper is implemented in Java on a computer with an Intel Core i5 2.67GHz and a 4GB memory capacity.

In this section, we present experimental results obtained from tests performed on video databases taken from different contexts taking into account fluctuations of light intensity, richness with objects, number and type of people, movements caused by nature elements, such as: clouds, dust, noise and finally camera movements.

To evaluate system performance, we used in addition to our databases three public databases. The first one DBA contains six videos labeled A1, A2, … A6 taken in four environments representing respectively: A campus, a highway (I, I2 and II), an intelligent room and a laboratory [30]. The second DBB is constituted of nine videos labeled B1, B2, … B9 representing respectively a bootstrap, a campus, a curtain, an escalator, a fountain, a hall, a lobby, a shopping mall and a water surface [27].The third DBC contains two videos labeled C1, C2 representing respectively a highway and a hallway [24]. Our database DBD is constituted of four environments labeled D1, D2, …D4 representing respectively a campus, a hallway, a highway and a public park where each environment is taken with three videos. Table 1 shows some details about the used videos in the test.

3.2.Performance Evaluation

To ensure system stability during performance tests, the number Gaussians K, the learning rate α, and the minimum portion measure B were empirically chosen and set respectively to 5, 0.001 and 0.3. Note that, the system uses the same settings for all used videos in the experiment.

For evaluating performance we also used four criteria: Sensitivity (*SE*), Accuracy (*AC*), Specificity (*SP*), and *PT*.

$$SE = \frac{number\ of\ Pixels\ detected\ as\ foreground\ in\ our\ system}{number\ of\ pixels\ in\ the\ frame} \quad (17)$$

$$AC = \frac{number\ of\ pixels\ detected\ as\ foreground\ in\ our\ system\ number}{number\ of\ pixels\ detected\ as\ foreground\ in\ a\ simple\ GMM} \quad (18)$$

$$SP = \frac{number\ of\ frame\ correctly\ treated}{Total\ number\ of\ frame} \quad (19)$$

The algorithms proposed in the literature and that we had the opportunity to study do not specify explicitly the treatment of the local variation problem in GMM but they suggested improvements in the algorithm itself. Some proposals have increased the quality of results compared to the simple GMM but on the other hand, they also increased computational complexity which produces a slow executions compared to the base model. Among the GMM problems treated in the literature we find:

- The adaptation speed of the model,
- The number predetermined of Gaussians,
- The need for good initializations,
- The dependence of the results on the true distribution law which can benon-Gaussian,
- The needs for a series of training frames absent of moving objects,
- The amount of memory required.

For this reason, we implemented the simple GMM proposed by Stauffer and Grimson [32] which will be used as a reference method. Both methods are tested with the same parameters and on the same machine (More credible results).

Table 1. Description of used databases

Data Base	Video Name	Number of Frame	Resolution	Length (mn)	Frame Rate	Environment
DBA	A1	1178	352 x	01:57	10	Campus
	A2	439	320 x	00:29	10	Highway I
	A3	439	320 x	00:29	14	Highway I2
	A4	499	320 x	00:33	14	Highway II
	A5	299	320 x	00:30	10	Intelligent
	A6	886	320 x	01:28	10	Laboratory
DBB	B1	3054	160 x	/	/	Bootstrap
	B2	2438	160 x	/	/	Campus
	B3	23963	160 x	/	/	Curtain
	B4	4814	160 x	/	/	Escalator
	B5	1522	160 x	/	/	Fountain
	B6	4583	176 x	/	/	Hall
	B7	2545	160 x	/	/	Lobby
	B8	2285	320 x	/	/	Shopping
	B9	1632	160 x	/	/	Water surface
DBC	C1	1799	320 x	03:00	10	Hallway
	C2	2055	320 x	03:42	10	Highway III
DBD	D1	526 896 896	320 x	00:17 01:30 02:38	30	Campus
	D2	616 893 382	640 x	00:20 00:29 00:12	29	Hallway
	D3	1210 420 896	640 x	00:40 00:14 00:29	29	Highway
	D4	559 585 555	640 x	00:18 00:19 00:18	29	Public Park

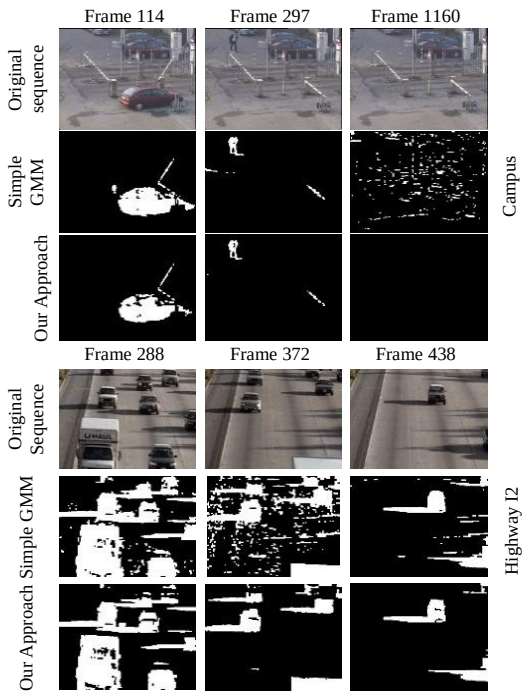

Figure 4. Results of the background subtraction in DBA database using outdoor environment videos.

Figure 4 clearly shows that the proposed approach gives better results compared to a simple GMM. It shows that our system is able to greatly reduce the noise caused by the instantaneous variation of brightness and keep an acceptable quality in stable environments. Figure 4 shows the effectiveness of the proposed system in an environment with multiple

moving objects. It also shows the weak influence of the dust effect caused by moving cars.

Figure 5 shows the effectiveness of a system with a low brightness source.

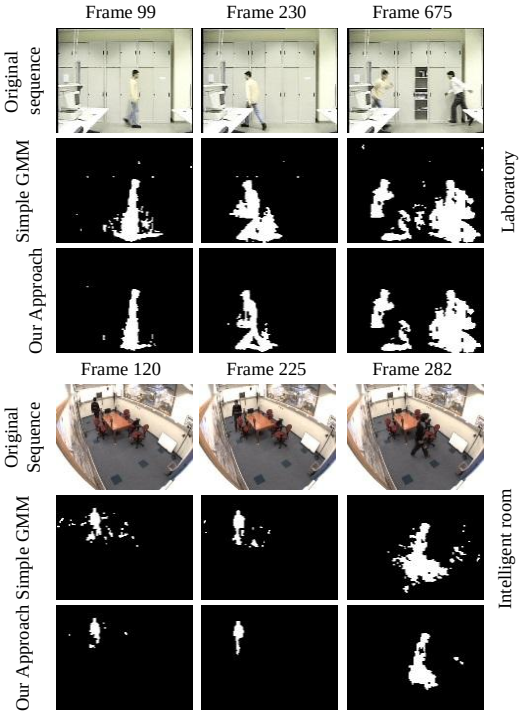

Figure 5. Results of the background subtraction in DBA database using indoor environment videos.

Figure 6 shows that the proposed system performs a slight correction compared to a simple GMM in environments with low dimming.

In Figure 7, we can clearly see the contribution of our approach in the videos taken randomly and without any constraint in a complex environment. The first part of Figure 7 (campus) is taken in unstable weather conditions when the passage of clouds in a sunny day allows an instant brightness change. The frame 196 shows the undesirable effect caused by this variation in simple GMM while our system has reduced considerably this disturbance.

The second part of Figure 7 is taken in a dark hallway with a window. It shows the effectiveness of our system with respect to very large variations in light intensity.

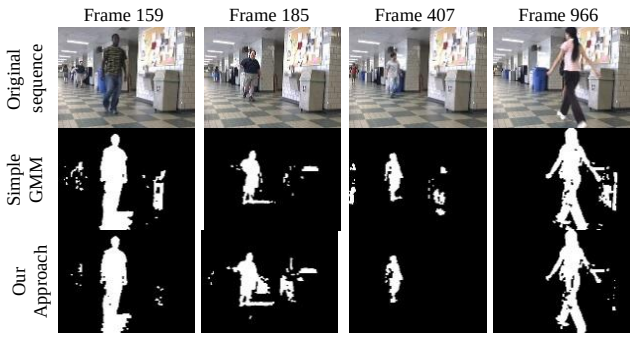

Figure 6. Results of the background subtraction in DBB using indoor environment videos.

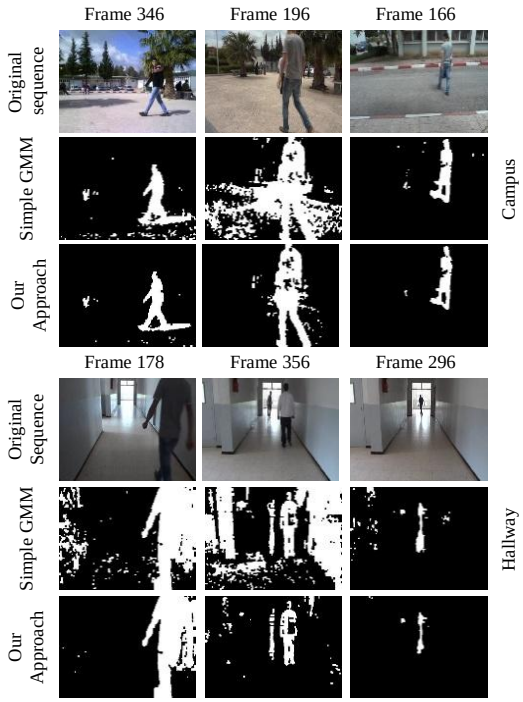

Figure 7. Results of the background subtraction in DBD database using indoor and outdoor environments.

Figure 8 shows the stability of our system in a dusty environment caused mostly by wind.

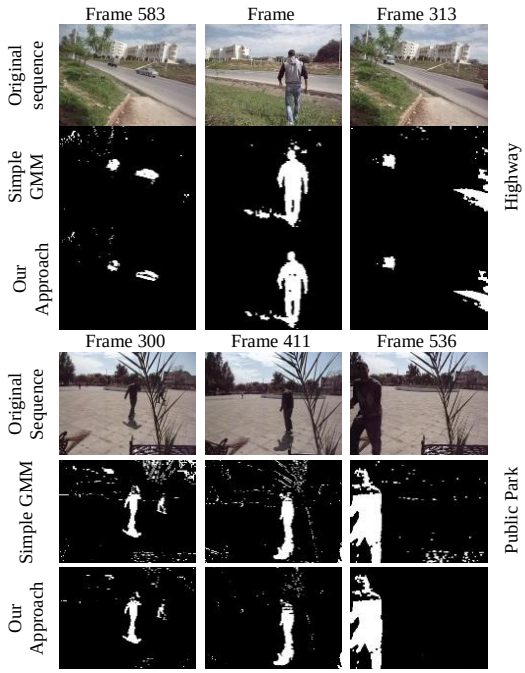

Figure 8. Results of the background subtraction in DBD database using random conditions.

In Table 2, *SE* criterion shows that the proposed approach has a low *SE* to noise compared to a simple GMM in all used databases with an average gap of 6.36%, while *AC* criterion shows a better quality with an average rate of 68%. The *SP* criterion shows that our system has a delay of3.05%.

Table 2. SE, AC, SP and PT criteria.

	Average of Criteria for each Video						
	SE		AC	SP %		PT(S)	
	Our App	RGB GMM		Our App	RGB GMM	Our App	RGB GMM
A1	2.49	4.34	0.57	8.66	12.4	0.46	0.92
A2	16.5	21.7	0.76	8.15	12.7	0.41	0.89
A3	15.0	20.2	0.74	8.09	11.8	0.38	0.87
A4	5.13	5.76	0.89	8.14	12.3	0.38	0.87
A5	1.77	3.28	0.54	8.34	12.0	0.41	0.89
A6	8.12	10.1	0.80	8.69	12.5	0.41	0.89
B1	19.1	24.6	0.78	14.5	18.6	0.31	0.45
B2	24.2	34.1	0.71	15.1	18.3	0.31	0.45
B3	21.8	32.5	0.67	15.4	17.1	0.31	0.45
B4	14.5	29.1	0.50	15.0	17.5	0.31	0.46
B5	13.6	24.7	0.55	15.4	18.4	0.32	0.46
B6	28.2	35.3	0.80	15.5	17.8	0.34	0.48
B7	19.7	34.0	0.58	15.2	17.7	0.32	0.46
B8	13.7	21.1	0.65	14.4	17.8	0.42	0.91
B9	24.2	35.6	0.68	15.6	18.6	0.32	0.45
C1	8.04	9.28	0.87	21.4	21.8	0.44	1.19
C2	7.5	9.06	0.83	21.5	21.8	0.43	1.17
D1	6.93	13.0	0.53	8.12	11.8	0.41	0.89
D2	8.75	22.2	0.39	8.04	11.5	0.57	1.46
D3	3.82	4.81	0.79	8.18	12.0	0.54	1.43
D4	6.04	7.6	0.79	8.92	11.4	0.57	1.48
AV	**12.8**	**19.9**	**0.68**	**12.5**	**15.5**	**0.39**	**0.83**

This is mainly due to the non-triggering of background spotters responsible for certain regions. Indeed, background observers could not be started because the shape of the histogram has not undergone any significant change. This error is due to the use of HSV model which sometimes gives certain equivalence after a transfer from RGB to HSV color space. The PT criterion shows that despite the addition of some operations, the computation time of our system is much lower compared to a simple GMM with an average gap of 0.44 seconds. This performance gain is due to the selective tripping of updates in the background model. The majority of the proposed work to improve GMM performance used personal video databases (for very specific application) which make the comparison task difficult and sometimes impossible. The lack of unified outcome measure and the absence of source code for the other methods are also problems for situate our work relative to other methods.

4. Conclusions

In this paper we proposed a background subtraction system for image sequences extracted from fixed camera using GMMs and background spotters. To overcome the brightness and local variation we first made a transition from RGB to HSV space. Then we divided the image into *N* areas and assigned to each region a background spotter that allows selecting regions with a very large change using color histogram analysis. Transfer to HSV color space has significantly decreased light effect on the system behavior through accumulating all brightness variations in a single component (V). While segmenting the image into regions and the use of background spotters have eliminated local variations caused mainly by the presence of dust. GMM is a pixel based method. This means that any variation in pixel value will directly influence the behavior of GMM. The presence of some disruptive pixels generates no problem. However, the pixels cloud caused by local variations will induce the system in error. Because it can be considered, even after the post-treatment steps, as a moving object. For performance evaluation, we used four video databases. Tests conducted on databases show that our system has a good sensitivity, more *AC* and less computational resources than a simple GMM but less *SP*. This improvement is very important for implementation in video surveillance system or real-time embedded systems. In future work, our algorithm will be adjusted by dividing the image into homogenous regions and solving the problem of shadow and color similarity between moving objects and background.

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