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Object Activity Recognition System with Shadow Suppression Using Adaptive Gaussian Mixture Model

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Authors' contributions

This work was carried out in collaboration between all authors. Author EOO is the lead researcher, who initiated and coordinated the work. The framework was conceptualized by authors AOA and JAO while author SOO handled the mathematical analysis used for the work.

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Abstract

Moving object detection is an important step in any video surveillance system, tracking or video activity. This paper examines the result of the adaptive Gaussian Mixture Model using the Maximum A posterior (MAP) updates on video clips (dataset) obtained from Adeyemi College of Education Ondo, Nigeria. The results showed a reliable moving object detection algorithm, shadows constitute a problem, in that moving shadows can be mistaken as moving objects. The shadow was suppressed using the HSV and Phong illumination Model. The overall performance of this system was evaluated using the confusion matrix and the receiver operating characteristic (ROC), shadow detection and shadow discrimination values which showed a better result compared to existing benchmarks.

Keywords: Moving object; GMM; ROC; confusion matrix; evaluation.

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1 Introduction

Video surveillance has been an active research topic in the last few years due to the growing importance of security, law enforcement and military applications. More surveillance cameras are installed on a daily basis in security sensitive areas such as banks, train stations, highways, and borders. Object activity recognition is used in identifying the moving objects in video frame sequences [1,2]. It is easy for human beings to identify moving objects in a video clip; it is also not difficult for human beings to categorize such objects as a vehicle, a human being, a bike or a helicopter. However, it is rather a difficult task for a computer system to do the same [3-5], and due to this reason, computer vision has become an important field of study. In computer vision images are acquired, processed and analyzed to produce information. Such images can be taken from video sequences and multiple camera; the applications of computer vision in real life includes medical and automation industry. Adaptive Gaussian Mixture Model is a system that deals robustly with repetitive motion of objects, slow moving objects and introducing and removing of objects. This system works efficiently due to the fact that there are multiple distributions for each pixel i.e. if the background subtraction using Gaussian Mixture Model is used to create a distribution, the distribution is replaced by a temporary distribution which makes recovery very fast [6,7].

2 Related Works

Stauffer and Grimson [8-10] modeled the Gaussian distribution using adaptive mixture model (background subtraction and GMM), the guiding factor for this model and update procedure deploys recent history of each pixel, $\{X_1...X_t\}$. Using K Gaussian distributions. The probability of observing the current pixel is:

$$p(\mathrm{X}_t) = \sum_{i=1}^{k} \omega_{i,t} * \eta(X_t, \mu_{i.t}, \Sigma_{i,t}) \tag{2.1}$$

where

k is the number of distribution.

$\omega_{i,t}$ is the estimate weight of the ith Gaussian at time t.

$\mu_{i.t}$ is the mean of the mixture i at t.

$\Sigma_{i,t}$ is the covariance matrix of ith Gaussian at time t.

$$\eta(X_t, \mu, \Sigma) = \frac{1}{(2\pi)^{n/2} \left|\Sigma\right|^{1/2}} \exp\{-\frac{1}{2}(\mathrm{X}_t - \mu_t)^T \Sigma^{-1} (X_t - \mu_t) \tag{2.2}$$

$$\Sigma_{\mathrm{k},t} = \sigma_k^2 I \tag{2.3}$$

The prior weights of k are adjusted by:

$$\omega_{\mathrm{k},t} = (1-\alpha)\omega_{\mathrm{k},t-1} + \alpha M_{k,t} \tag{2.4}$$

$$\mu_t = (1-\rho)\mu_{t-1} + \rho X_t \tag{2.5}$$

$$\sigma_t^2 = (1-\rho)\sigma_{t-1}^2 + \rho(X_t - \mu_t)^T (X_t - \mu_t) \tag{2.6}$$

$$\rho = \alpha * \eta(X_t \setminus \mu_k, \sigma_k) \quad (2.7)$$

Where α is the learning rate, $M_{k,t} = 0$ or 1 and $1/\alpha$ is the time constant.

Following some limitations (slow start and shadow removal) of the work of, [11,9] improved on those shortcomings. The guiding factor for this model and the update procedure is as follows.

The probability that a certain pixel has a value of X_N at time N can be written as

$$p(X_N) = \sum_{j=1}^{k} \omega_j \eta(X_N ; \theta_j) \quad (2.8)$$

Where ω_k is the weight parameter of the K^{th} Gaussian.

$$\eta(X : \theta_k) = \eta(X : \mu_k, \Sigma_k) = \frac{1}{(2\pi)^{d/2} \left|\Sigma_k\right|^{1/2}} e\{-\frac{1}{2}(\mathrm{x} - \mu_k)^T \Sigma^{-1} (\mathrm{x} - \mu_k) \quad (2.9)$$

Where μ_k is the mean of the kth component.

$$\Sigma_k = \sigma_k^2 I \text{ is the covariance of the kth component} \quad (2.10)$$

The online EM algorithm is updated by expected sufficient statistics using L-recent windows version [12,13]. Such that:

$$\hat{\omega}_k^{N+1} = \hat{\omega}_k^N + \frac{1}{L}(\hat{P}(\omega_k \setminus X_{N+1} - \hat{\mu}_k^N) \text{ update the weight} \quad (2.11)$$

$$\hat{\mu}_k^{N+1} = \hat{\mu}_k^N + \frac{1}{L}(\frac{\hat{P}(\omega_k \setminus X_{N+1}) X_{N+1}}{\hat{\omega}_k^{N+1}} - \hat{\mu}_k^N \text{ update the mean} \quad (2.12)$$

$$\hat{\Sigma}_k^{N+1} = \hat{\Sigma}_k^N + \frac{1}{L}(\hat{P}(\omega_k \setminus X_{N+1})(\mathrm{X}_{N+1} - \hat{\mu}_k^N)(\mathrm{X}_{N+1} - \hat{\mu}_k^N)^T - \hat{\Sigma}_k^N \text{ update the variance} \quad (2.13)$$

where

k is the number of distribution

$\hat{\omega}_k^{N+1}$ is the kth Gaussian weight

μ_k^{N+1} is the kth Gaussian mean

$\hat{\Sigma}_k^{N+1}$ is the kth Gaussian covariance

In this update equation (2.7) was cut off because there are no values for it in L- recent windows.
Despite the robustness of this work, it removed shadows in colour consistency only.

Kuralkar, Landabaso and Nirubama [14-16] modelled an Indoor surveillance tracker very close to [9] but removed shadows using an hybrid of texture and colour features of the shadow. This makes the shadow removal scheme very good. They also use morphological reconstruction [16,17] in correcting misclassifications of the shadow removal algorithm using information of the images. The shadow removal algorithm used information of the images not of shadow removed where shapes are well defined. There is need to develop an object detection system with a good speed of learning [18] and a two level (optimised) shadow removal scheme that will not detect moving shadows as moving object.

3 Design

3.1 Current state estimation

While [12] employed the L-recent windows update equations to determine the current state of the model because it allows fast convergence on a stable background model, this research work estimated the current state of the model by classifying each pixel to know how it looks when the pixel is part of a different class. Maximum a Posteriori (MAP) learnt how a Mixture of Gaussian (MOG) will view such a pixel. Like Expectation and Maximization, MAP is also a two-step estimation process: the first step is used to compute the estimate of sufficient statistics of the training data for each mixture in the prior model [19]. The second step handles the “new” sufficient statistics estimates and then combines with the “old” sufficient statistics from the prior mixture parameters [20-23]. The parameters are collectively represented by the notation [24,25].

$$\Theta = \{ w_i , \mu_i , \Sigma_i \} \tag{3.1}$$

w , μ , Σ represents the Gaussian weight, mean and covariance matrix respectively.

A Gaussian Mixture Model of M component Gaussian density is given by

$$P(x \setminus \Theta) = \sum_{i=1}^{M} \omega_i g(x \setminus \mu_i \sum_i) \tag{3.2}$$

X is a D- dimensional continuous valued data vector

ω_i is the mixture weight, i=1,…M

$g(x \setminus \mu_i \sum_i) =$ Component Gaussian density

i=1…M

D -Variate Gaussian function

$$g(x \setminus \mu_i \sum_i) = \frac{1}{(2\pi)^{D/2} \left|\Sigma\right|^{1/2}} \exp\{\frac{-1}{2}(x-\mu_i)^T \textstyle\sum_i^{-1}(x-\mu_i)\} \tag{3.3}$$

where

μ_i is the mean vector

$\sum_i$ is the covariance matrix and

$\sum_{i=1}^{M} \omega_i = 1$ (must be satisfied)

$\Theta = \{\omega_i, \mu_i, \sum_i\}$ i=1,… M
M is the number of the distributions
M=5

The Posteriori probability for component i is given by:

$$\text{Pr}\ (i \setminus x_t, \Theta) = \frac{w_i\ \text{g}(x_t \setminus \mu_i, \Sigma_i)}{\sum_{i=1}^{\text{M}} w_k g(x_t \setminus \mu_k, \Sigma_k)} \tag{3.4}$$

Given a prior model and training vectors from a class:

$$x = \{x_1, ..., x_{\text{T}}\} \tag{3.5}$$

The sufficient statistics for:

$$\text{Weight,}\ \ \text{N}_i = \sum_{t=1}^{\text{T}} \text{Pr}(i \setminus x_t, \Theta_{\text{prior}}) \tag{3.6}$$

$$\text{Mean,}\ \ \text{E}_i(x) = \frac{1}{\text{N}_i} \sum_{t=1}^{\text{T}} (\text{Pr}(i \setminus x_t, \Theta_{\text{prior}}) x_t \tag{3.7}$$

$$\text{Variance,}\ \ \text{E}_i(x^2) = \frac{1}{\text{N}_i} \sum_{t=1}^{\text{T}} (\text{Pr}(i \setminus x_t, \Theta_{\text{prior}}) x_t^2 \tag{3.8}$$

Equations (3.6) …(3.8) are the same as Expectation in EM algorithm.

The M distributions are ordered based on the fitness value w_i / σ_i and the first B distributions are used as model of the background of the scene where B is estimated as:

$$B = \arg_b \min \left[\sum_{i=1}^{b} w_i > T \right] \tag{3.9}$$

The threshold T is the minimum fraction of the background model, it is the minimum prior probability that the background is in the scene. Background subtraction is performed by marking a pixel foreground if it is more than 2.5 standard deviation away from any of the B distributions [26,27].

The above new sufficient statistics from the training data are used to update the priors sufficient statistics for mixture *i* to create adapted parameters for mixture *i* having the following equations will update the Gaussian:

$$w_i = \{\alpha_i^w N_i / \hat{T} + (1 - \alpha_i^w)\}\omega_i\}\gamma \tag{3.10}$$

$$\hat{\mu}_i = \{\alpha_i^m \mu_i + (1 - \alpha_i^m)\mu_i\} \tag{3.11}$$

$$\hat{\sigma}_i^2 = \alpha_i^v \sigma_i^2 + (1 - \alpha_i^v)(\sigma_i^2 + \mu_i^2) - \mu_i^2 \tag{3.12}$$

where

α_i^w is for the mixture weights.

α_i^m is for the mixture means.

α_i^v is for the mixture variances.

γ is the scale factor, which is ensured sum to unity for all adapted mixture weight.

3.2 Shadow removal technique

The technique employed is a two level approach that removed shadows optimally in outdoor situations; this research work used the HSV suppression and the Phong reflection model, since each of the approaches suffers its own weaknesses. For example, a pixel is said to be a shadow if and only if the results of both removal techniques agrees. Phong reflection model, an illumination model widely used in 3D computer graphics was employed to remove shadows from video streams, Phong reflection model helped to prove the local coherence (over a pixel neighbourhood) of intensity reduction ratio used in texture verification. Phong model exploited the chromaticity, texture and intensity reduction [28,29]. According to Phong illumination model, a surface point is lit by three types of lights: Ambient light i_a, diffuse light i_d, and specular light i_s. The point of luminance in the image is described by:

$$I=k_a\, i_a+ k_d\,(L.N)i_d +k_s(R.V)^{\alpha}\, i_s \tag{3.13}$$

Where k_a is the ambient reflection constant, k_d is the diffuse reflection constant, k_s is the specular reflection constant, L is the direction vector from the point on the surface towards the light source, N is the normal at this point on the surface, R is the direction that a perfectly reflected ray of light (represented as a vector) would take from this point of the surface, V is the direction towards the viewer, α is a constant (.) is the dot product operation. Since this work is modeled in two dimensions and R directions are eliminated from (3.14) Having $k_d = k_a = k$ then the equation above will become:

$$I \ = k(i_a + (\mathrm{L\,.\,N})\,\mathrm{i}_d) \tag{3.14}$$

Relevance is the RGB colour space that becomes:

$$I^j = k^j(i_a^j + (\mathrm{L\,.\,N})\,\mathrm{i}_a^j) \tag{3.15}$$

where index j corresponds to red, green and blue.

A shadow occurs when light power from the light source to a surface is partially or completely blocked by an object. Then the point of luminance becomes:

$$I_{shadow}^j = k^j(i_a^j + \beta(\mathrm{L\,.\,N})\,\mathrm{i}_d^j) \tag{3.16}$$

where β ε [0,1] indicating how much diffused light has been blocked.

After that HSV suppression will be applied since the Phong reflection model works well in indoor environments.

4 Implementation

The video recordings were captured mainly in environments where human, human group and vehicles were freely moving; the experiment also captured video images that involve shadows so as to remove them using the modified algorithm.

4.1 Test cases

The test cases involved in this research work are to detect moving regions in a video frame, these regions could be human, human group and to optimally remove shadowed regions using a combination of HSV suppression and Phong's Model.

4.1.1 Moving object detection results

The developed algorithm was implemented on the Matlab (2010a), different human motions subjected to assess how well the algorithm can detect moving regions in outdoor scenes using fixed-camera situations. In video surveillance, motion detection refers to the capability of the surveillance system to detect motion and capture the events. Motion detection is usually a software-based monitoring algorithm which will signal the surveillance camera to begin capturing the event when it detects motions. This is also called activity detection. In this experiment, a camera fixed to its base has been placed and is set with an observer at the outdoor scene, while recoding is chosen from time to time. Any small movement with a level of tolerance is picked and detected as motion.

5 Evaluation

5.1 Detection experimental results

At this stage, moving objects detection rate is be evaluated for Human and Vehicles. Using the following human actions: Walking (W), Running (R), Boxing (B), Kicking (K), Hand Waiving (HW), Clapping (C) and Occlusion (O). The confusion matrix generated as the results of the tests is shown in Table 1. from Figs. 4.1, 4.2, 4.3 and 4.4. The Receiver Operating Characteristic curve Fig. 1.0 is generated from the 7x7 confusion matrix of Table 1., where True Positives TP values are 48, 21, 16, 8, 12, 8 and 15 for Walking (W), Running (R), Boxing (B), Kicking (K), Hand Waiving (HW),Clapping (C) and Occlusion (O) respectively. False positive FP and False negative FN values for each True positive are estimated from the adjourning rows and columns. Each video stream generated its own ROC [26] but Statistical Package for Social Sciences version 15.0 (SPSS) was used in generating the reported ROC curves. Similarly, the 3x3 confusion matrix of Table 2. is generated by Figs. 4.5, 4.6, and 4.7 where: Trucks(T), Cars(C), and Bikes(B) in Table 2. have True Positives values 12,13 and 15 respectively for vehicle motion detection.

$$\text{Recall} = \text{Sensitivity} = \frac{TP}{TP+FN} \tag{5.1}$$

$$\text{Specificity} = \frac{TN}{TN+FP} \tag{5.2}$$

Table 1. The confusion matrix of the human motion detection

	W	R	B	K	HW	C	O	%
W	48	0	0	0	0	0	0	100
R	0	21	0	0	0	0	0	100
B	1	0	16	0	0	0	0	94
K	1	0	0	8	0	0	0	88
HW	0	0	0	1	12	0	0	92
C	0	0	0	0	0	8	0	100
O	0	0	0	0	0	0	15	100

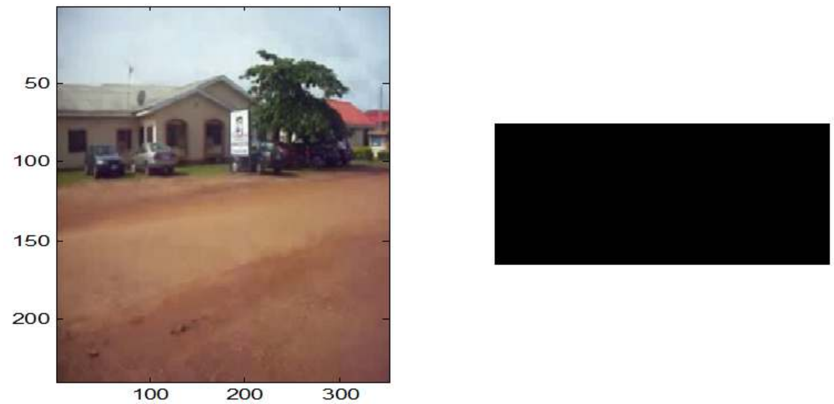

Fig. 4.1. The background model

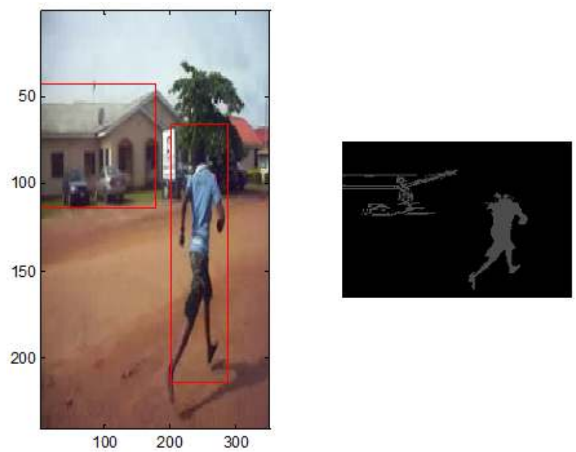

Fig. 4.2. Detected moving object (Running) with shadow and foreground

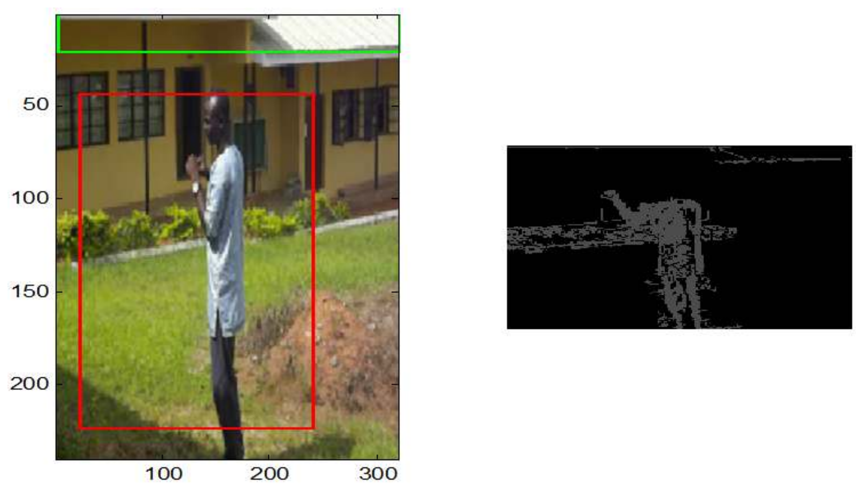

Fig. 4.3. Detected moving object (Boxing) with shadow and foreground

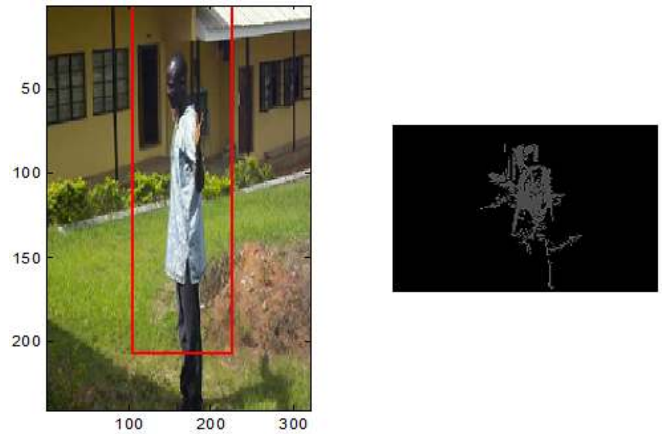

Fig. 4.4. Detected moving object (Clapping) with shadow and foreground

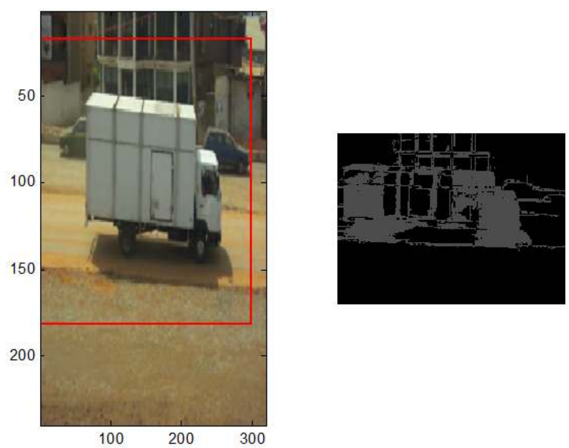

Fig. 4.5. Detected moving object (Truck) with shadow and foreground

Fig. 4.6. Detected moving object (Car) with shadow and foreground

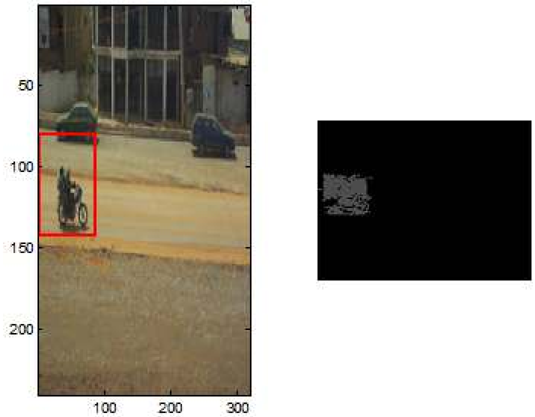

Fig. 4.7. Detected moving object (Bike) with shadow and foreground

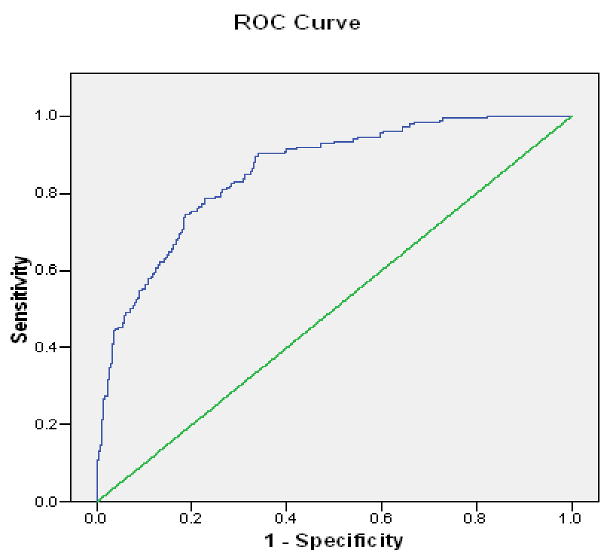

Fig. 1.0. The ROC curve for the human motion detection
PCC=96.28%; AUC =0.76

Table 2. The confusion matrix of the vehicles motion detection

	T	B	C	
T	12	0	0	100
B	1	13	0	92
C	0	0	15	100

5.2 Shadow removal technique

The performance of any shadow detection and removal technique can be tested using two metrics proposed by [29], namely shadow detection rate (η) and shadow discrimination rate (ξ):

$$\eta = \frac{TP_S}{TP_S + FN_S} \tag{5.3}$$

$$\xi = \frac{TP_F}{TP_F + FN_F} \tag{5.4}$$

Where TP and FN stand for true positive and false negative pixels with respectively to either Shadows(S) or foreground objects (F). The shadow detection rate is concerned with labeling the maximum number of cast shadow pixels as shadows. The shadow discrimination rate is concerned with maintaining the pixels that belong to the moving object as foreground.

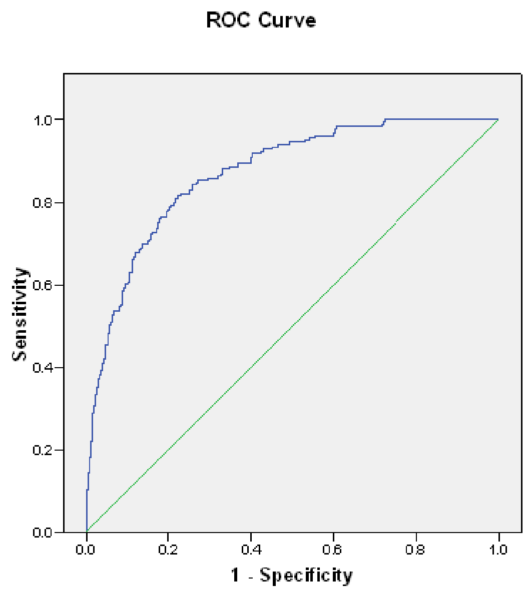

Fig. 2.0. The ROC of the vehicles motion detection
PCC=97.33%; AUC=0.78

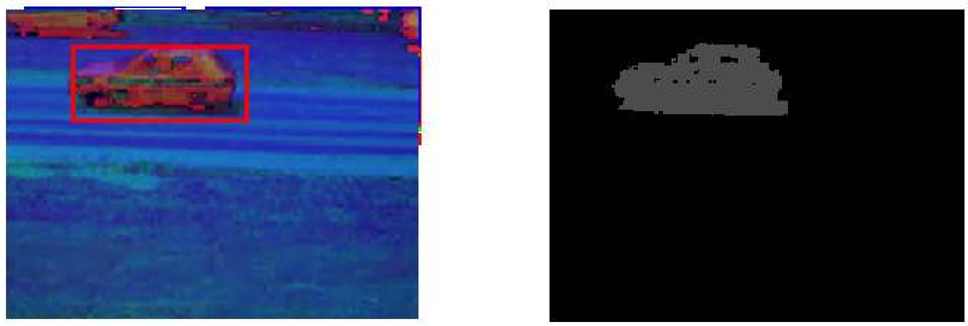

Fig. 4.8. Correct vehicle classification with partial shadow removal (HSV suppression only)
PCC=98%; AUC=0.8

Fig. 4.9. Correct human classification and shadows completely removed

5.3 Shadow removal based on shadow position

In most cases, shadow suppression in HSV colour space seems effective, this method is not reliable when the background brightness is low or the background has the similar chrominance with foreground pixels. Once the brightness of background is low, it is very difficult to distinguish all the shadows from the background because its brightness will change a little when shadows cover on the background as shown in Fig. 4.8. Meanwhile, some pixel points inside the moving object may be eliminated as shadow points. To overcome this shortcoming of HSV suppression, this research work will optimally eliminate shadows by combining HSV suppression with a chromaticity based approach to get a better performance.

5.4 Shadow removal using the Phong’s Model

The HSV suppression is a chromaticity based method having its own shortcomings as discussed, this work introduces Phong’s Model to compensate for those shortcomings. Mostly the chromaticity consistency constraint used to detect shadows is valid only if the ambient light chromaticity is not different from the chromaticity of diffuse light. The Phong’s model exploits chromaticity consistency and texture consistency in the outdoor scene. Phong’s reflection model is a 3D shadow removal model used in graphics and indoor shadow detection and removal, this work will remove shadows from the affected video scenes so that the system will not to wrongly classify the moving shadow as moving human, human group or vehicle.

5.4.1 Shadow removal experimental results

This research work measured the shadow detection performance at both stages of implementation, i.e at the HSV suppression stage and after the Phong’s Model stage measuring the shadow detection rate (η) and shadow discrimination rate (ξ), Fig. 4.8 showed the stage of HSV suppression while Fig. 4.9 showed the result after Phong’s removal. Table 3.0 showed the shadow detection rate (η) and shadow discrimination rate (ξ) at each stage. The result showed an improvement after Phong’s has been employed in shadow removal.

Table 3. Table showing the discrimination rate and detection rate at each stage of the shadow removal

	Shadow detection rate	Shadow discrimination rate
HSV	0.482	0.786
HSV & Phong	0.695	0.895

Table 3.1. Comparison of Simulation results of the designed system and Some Existing works

Author	Approach	Slow start	Shadow removal scheme	Segmentation
Stauffer and grimson	Online E-M	7^{th} frame	None	Good
Kaewtrakulpong and Bowden	L-recent windows	5^{th} frame	Colour consistency	Very good
Developed	MAP	5^{th} frame	Colour and texture consistency	Very good

6 Conclusion

This research work employed the modified adaptive background mixture model method in detecting human and vehicular motions in video images, the Maximum A posterior (MAP) was used to update the Gaussian to: Detect moving region as Human or Vehicles and remove shadowed regions in the video scene optimally using the combination of HSV suppression and the Phong's illumination Model (Chromaticity and Texture constraints only).

The system performed well in detection of moving images (Human or vehicles), but fails when a group of people are walking or running at the same speed in the same direction; this type of motion confuses the system giving this set of people the variance of a car or a truck, the system also classifies moving objects in its view to Human and Vehicles. The system performs well in classification, creating a bounding boxes on the target objects correctly even when more that one object is in its view, The sensitivity of this system was tested against the target presence with percentage of correct classification PCC and the Receiver Operating Characteristic ROC, which showed that the detection of moving objects (Human) has PCC of 96.28% and Area Under Curve AUC 0.76; Vehicle has PCC OF 97.33% and AUC 0.78.

The system removed shadows optimally from the video streams, so that moving shadows will not be detected as moving objects. The removal of shadows are in two phases: HSV suppression and Phong Reflection model, this approach is novel in that each shadow removal technique has their shortcoming, combining the colour and texture consistencies removes the shadow optimally.

Competing Interests

Authors have declared that no competing interests exist.

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