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Comparative Study of Statistical background Modeling and Subtraction

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Abstract

Background subtraction methods are widely exploited for moving object detection in videos in many computer vision applications, such as traffic monitoring, human motion capture and video surveillance. The two most distinguishing and challenging aspects of such approaches in this application field are how to build correctly and efficiently the background model and how to prevent the false detection between; (1) moving background pixels and moving objects, (2) shadows pixel and moving objects. In this paper we present a new method for image segmentation using background subtraction. We propose an effective scheme for modelling and updating a background adaptively in dynamic scenes focus on statistical learning. We also introduce a method to detect sudden illumination changes and segment moving objects during these changes. Unlike the traditional color levels provided by RGB sensor and Gaussian distribution aren't the best solution to overcome noted problem, for this reason we propose a recursive algorithm that contributes to select very significant color space. Experimental results show significant improvements in moving object detection in dynamic scenes such as waving tree leaves and sudden illumination change, and it has a much lower computational cost compared to Gaussian mixture model.

Keywords*: moving object detection; gaussian mixture model; color component; background modelling; Rayleigh distribution*

1. Introduction

Background modeling and subtraction is a fundamental subject in many applications, in fact image segmentation is an important research field, and it has increased dramatically over the last decade. One of very active research topic is visual surveillance in the last years due to the great importance for security in industrial field and public applications [1]. A typical automated visual surveillance system consists of semantic description [2], activity and gesture recognition [3], object classification [4], tracking [5], event, fire detection [6], and video retrieval [7]. Moving object detection is the mainly task for many computer vision application like visual surveillance system, video indexing and human machine interaction. Since these processes are greatly dependent on the results of this step, it is important that the classified foreground pixels accurately correspond to the moving objects of interests. A background subtraction segment foreground objects more accurately in most cases compared to other common moving object detection methods, and detects foreground objects even if they are motionless. However, one disadvantage of background subtraction methods is that they are susceptible to environmental changes, for example, gradual or sudden illumination changes and in addition the second source of problems are caused by camera shake or by the presence of moving objects in every image. In these cases the moving background pixels are assumed as a foreground pixels then it won't be subtracted and figures in the segmented image. The reason for this disadvantage is that most methods assume a static background, and hence one needs to update the background model for dynamic backgrounds. The update of the background model is one of the major challenges for background subtraction methods. W. Dong et al. [8] propose an approach for moving object detection mixed with adaptive iterative block and interval frame difference method in the Gaussian Mixture Model. Another authors use two learning rates for the background update, one in the initial part of the sequence and a different rate for the rest of the sequence using a Gaussian mixture model (GMM) for the background.

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They estimate the GMM using the Expectation-Maximization (EM) algorithm by for the initial part and then switch to L-recent window version for the rest of the sequence. Using this method, the GMM learns faster and more accurately at the beginning, it does not improve the convergence rate of the background model if the background changes at normal phase. This work proposes an efficient method based on Rayleigh distribution which incorporates statistical theory for modeling each pixel with a learning data base set and color information for both good exhibition of various distributions and overcome the confusion between dynamic background, moving objects and shadow pixels.

Like [9] we try in this paper to introduce a method to detect sudden illumination changes and segment moving objects during these changes in one hand and recursive algorithm to select relevant color space that allowing to effective background subtraction and object detection in other hand. In fact sudden illumination change is still a very challenging problem for foreground segmentation. Another contribution of this paper is to introduce a method to detect sudden illumination changes and segment moving objects during these changes in one hand and recursive algorithm to select relevant color space that allowing to effective background subtraction and object detection in other hand. In fact sudden illumination change is still a very challenging problem for foreground segmentation.

This paper is organized as follows. We talk about related works of this approach in section 2. Section 3 describes our background model with the Rayleigh method, foreground detection and shadows subtraction. Extensive evaluation experiments are shown in section 4. Finally section 5 concludes the paper.

2. Gaussian Mixture Model

2.1. Introduction

We present a statistical background modelling and foreground detection method to extract objects for future analysis like object tracking and classification. The statistical background modeling algorithm consists to generate a representation of an image using density functions [10]. Given a sequence of images issued by a RGB sensor, the intensity of each pixel is considered to follows a stochastic distribution. A mixture of densities is commonly used to represent the distribution of the intensity of a pixel, like Cauchy, Gamma, Chi-2 and Gaussian Mixture Model (GMM) that represents the many studied one in both theoretical and practical ways. A prominent previous works uses GMM to create background model, and specify the belonging of each pixel and this model is easily for updating. The use of GMM are commensurate with a single Gaussian, this model was extended to GMM model by T. Elguebaly et al. [11]. Foreground is then readily extracted by searching the suitable mixture with a new input frame. This approach leads us to incorporate an Expectation-Maximisation algorithm estimating the parameters of the GMM process. In [12], [13], the authors establish an online EM algorithm to reach optimal coefficient values related to the GMM background. Image sequences are usually coded in RGB color space. GMM uses different Gaussian densities to describe events that may occur at the same pixel, providing multiple possibilities for each pixel in the background model. In fact each pixel of background model is evaluated by several Gaussian distributions is formed to represent each pixel. The choice of cluster number emphasise the repartition of the intensities pixel, the weight of a Gaussian is denoted by W_j, which reflects the ability of the j^{th} member to take over the mixture. The mean vector of a member is defined as $\mu j = \left[\mu j,R,\mu j,G,\mu j,B\right]^T$ which represents statistical means of RGB color intensities, and a 3×3 covariance matrix C_j representing the deviations. Let K be the total number of distributions in the mixture; the parameters are represented by a vector; $\theta = \left[w1,...,wk,\mu 1,...,\mu k,C1,...,Ck\right]^T$.

Let $y_i = \left[y_i,R,y_i,G,y_i,B\right]^T \in \mathrm{Y}_{1:n}$ as a sample vector contains intensities of a pixel at a given time t. Then the membership probability of y being generated from the j^{th} mixture is given by “(1)”:

$$p_j = \left(y \mid \theta_j\right) = \mathcal{N}\left(y \mid \mu_j, C_j\right) = \frac{1}{(2\pi)^{3/2}\left|C_j\right|^{1/2}} \exp\left[-\frac{1}{2}\left(y-\mu_j\right)^T C_j^{-1}\left(y-\mu_j\right)\right] \quad (1)$$

Where $\mathcal{N}(y|\mu_j, C_j)$ designates a three dimensional Gaussian distribution. The conditional probability of y at θ is given by equation (2):

$$g(y|\theta) = \sum_{j=1}^{k} w_j\, p_j(y|\theta_j) \tag{2}$$

Where $g(y|\theta)$ is the statistical representation of the GMM under probabilistic constraint, $\sum_{j=1}^{k} w_j = 1$, as shown in equation (3) the posterior probability that observation y is generated by the j^{th} probability is calculated by Bayes rule:

$$h_j(\theta|y) = \frac{w_j\, p_j(y|\theta_j)}{\sum_{j=1}^{k} w_j\, p_j(y|\theta_j)} \tag{3}$$

Finally the determination of key parameters by EM algorithm achieves the background modeling stage, which will be used later for foreground extraction.

2.2. Estimate Parameters using EM Algorithm

The classical EM algorithm for an observation data and its limits are proposed in many works. It is a recursive approach that uses incomplete data to evaluate the potential parameters. EM is the most flexible algorithm for establishing Maximum Likelihood Estimation (MLE) of parameters in GMM models. A played role by EM algorithm is the computation of two stages. The "E" step computes the expected value of conditional probability of incomplete or underlying parameters given the observed data at the present parameter setting. The "M" stage then maximizes the log-likelihood of the complete data on the basis of the result from the former stage. In a GMM model, the expectation phase Q is constructed in the "E" as:

$$Q(Y_{1:n}|\theta) = \frac{1}{n}\sum_{i=1}^{n} \mathrm{E}_{j\,|\,\theta}\left[\mathbf{log}\, p_j(y|\theta_j)\right] \tag{4}$$

The "M" step then maximizes $Q(Y_{1:n}|\theta)$ to estimate vector θ representing the mixture containing *k* distribution. The two stages will be repeated until convergence or a maximum iteration number is reached in our case the stop condition is evaluated by the ε coefficient that represent the difference between two consecutive values of Q. The three recursive equations for updating the parameters of the GMM are represented by following expression.

$$w_j^{(k+1)} = \frac{\sum_{i=1}^{n} h_j\left(\theta_j^{(k)}|y_i\right)}{n}$$

$$\mu_j^{(k+1)} = \frac{\sum_{i=1}^{n} h_j\left(\theta_j^{(k)}|y_i\right) y_i}{\sum_{i=1}^{n} h_j\left(\theta_j^{(k)}|y_i\right)}$$

$$C_j^{(k+1)} = \frac{\sum_{i=1}^{n} h_j\left(\theta_j^{(k)}|y_i\right)\left[y_i - \mu_j^{(k)}\right]\left[y_i - \mu_j^{(k)}\right]^T}{\sum_{i=1}^{n} h_j(\theta_j^{(k)}|y_i)}$$

Equations (5)–(7) are evaluated when the assumption that all observations are available and will not change in estimation is true. Therefore, in this study we are applying the EM algorithm suggested by [14] to the Gaussian mixture model, which is based on the argument that the complete data likelihood function of the model belongs to the exponential family. Updating background model consists of re-computation to these equations after each new observed data sample. A Kronecker vector $\delta = [\delta_1, ..., \delta_k]^T$, that contains one element among several and the others are 0, is defined to form the complete-data likelihood. If element δ_j equals 1, then the current observation vector y is actually produced by the j^{th} Gaussian of that mixture. The incorporation of incomplete data y and δ gives the complete data vector x. assume that the missing-data density given in equation 3, a complete data density function is formulated as "(5)":

$$f(x \mid \theta) = \prod_{j=1}^{k} \left[w_j p_j (y \mid \theta_j) \right]^{\delta_j} \tag{5}$$

The previous evaluated parameters are the final recursive updating equations used in background learning step. Each parameter is re-calculated by the contribution of parameters values estimated in the last observation and the posterior probability of the current observation.

2.3. Foreground Detection

A statistical foreground extraction step is carried out on each new input frame to extract foregrounds. The probability of a pixel belonging to background is given by the theorem of total probability "(6)":

$$p(B \mid y) = \sum_{i=1}^{k} p(B \mid N_j)\, p(N_j \mid y) \tag{6}$$

Where B is the background, and because in real time recursion the assumption of Equation 4 is not everywhere satisfied, the ability of a Gaussian distribution represent the background is given by:

$$p(B \mid N_j) = \frac{w_j}{\sum_{i=1}^{k} w_j} \tag{7}$$

Where $p(N_j \mid y)$ represents the relationship between the input pixel and the j^{th} Gaussian. A cylindrical method in RGB space is applied to make all or nothing purpose probability (i.e. 1 or 0). Finally $p(B \mid y)$ is compared with a threshold; if the probability is lower, the pixel is classified as a background pixel; otherwise, it is a foreground pixel. A clean background image without moving foreground can also be reconstructed from the learned background model. The intensity of a pixel in the background image is estimated as the weighted average of the means of normal densities in the mixture as:

$$y_{background} = \sum_{j=1}^{k} \mu_j \; p(N_j \mid B) = \frac{\sum_{j=1}^{k} \mu_j \, w_j \, p(B \mid N_j)}{\sum_{j=1}^{k} w_j \, p(B \mid N_j)} \tag{8}$$

3. Statistical Background Subtraction

3.1. Introduction

Intensity pixels of static and quasi-static background can be modeled by statistical distribution such as Gaussian, Cauchy and Chi-2. Indeed the model can adapt to changes due to several circumstances affecting an image by recursive algorithm updating the model in critical situation. Our method is based on Rayleigh distribution for designing pixels intensities. Let $x_i = x_1, x_2, ..., x_N$ is N dimension sample of intensities values of one pixel. From this sample, we can approximate the density of probability $p(x)$ when a pixel will have x_t intensity value at a given time t, it can be estimated by a non-parametric function using the kernel estimator [34] given by:

$$P(x_t) = \frac{1}{N}\sum_{i=1}^{N} K(x_t - x_i) \tag{9}$$

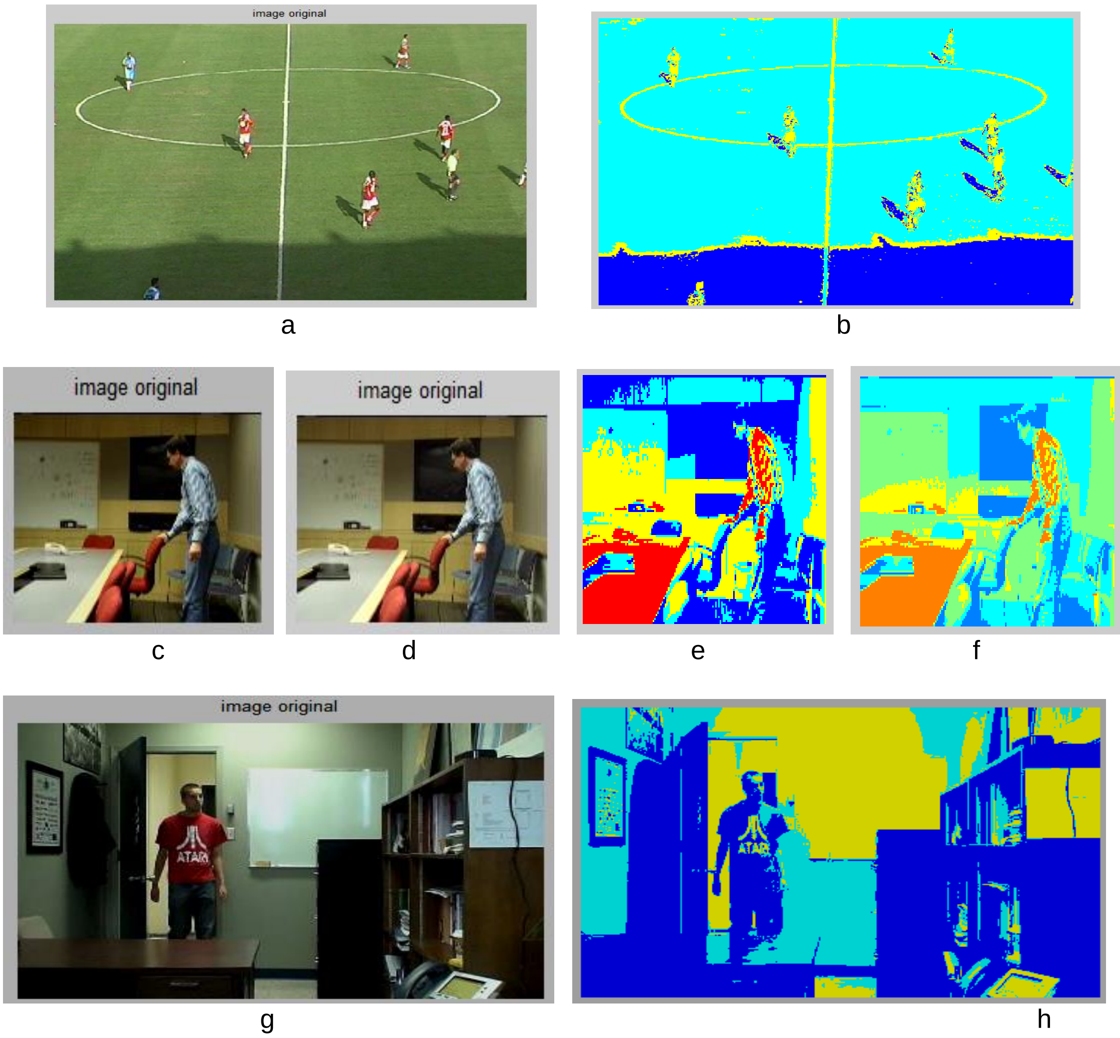


Figure 1. Experimental results: (a), (c), (d) and (g) original image, (b) segmented image with (k=3), (e) and (h) segmented image with (k=4), (f) segmented image with (k=5)

3.2. Learning Step

a) Estimation of background features: In our approach kernel estimator is the Rayleigh distribution characterized by standard deviation σ. Given N independent variables of Rayleigh distribution that having the same bandwidth density σ, the maximum likelihood estimator for standard deviation is defined by:

$$\sigma = \sqrt{\frac{1}{2N}\sum_{i=1}^{N} x_i^2} \tag{10}$$

The deviation intensity of each I_{cand} pixel around the same model pixel plays a crucial role both, (1) in the contribution of decision maker of membership of this pixel and (2) in updating the background model.

b) Modeling and updating background: the main purpose of this technique contains two steps, in this subsection we describe the first one where it consists to make model for each pixel that constitutes the image, in other terms we consider a set of 50 images that represent only the background pixels, we specify the features of each distribution in various color components. We can evaluate the bandwidth parameters σ of probabilities density related to intensities values of one background pixel, this density can be estimated by following equation:

$$F(x,\sigma)= \frac{x}{\sigma^2}\exp\left(\frac{-x^2}{2\sigma^2}\right) \tag{11}$$

So for each background and given the history of its intensity values, we have to estimate the bandwidth parameters of Each Rayleigh distribution and this procedure for three colour levels To eliminate possible disturbances that may occur either in the acquisition system or in the scene, we can use a recursive filter to update recursively the background model when the variation of intensity value is significant.

$$B_{t+1} = B_t(1-\alpha) + I_t\,\alpha \tag{12}$$

Where B_{t+1} and B_t represent the intensities values of successive background pixel, α is the adaptation coefficient $\alpha \in [0,1]$.

3.3. Image Segmentation

a) Background Subtraction: Second step is based on Bayes rule to bring out the membership decision of each pixel when we proceed with validation data base. Indeed each pixel must be compared with the same one in the made model. The effectiveness of such method can be concluded in the choice of background model and its color space where it will be exploited. Let x_t is the intensity value of such pixel at a given time t, its membership probability $p(x_t)$ can be expressed by:

$$P(x_t)=\frac{1}{N}\sum_{i=1}^{N}\prod_{j=1}^{d}\left[\frac{(x_{tj}-x_{ij})}{\sigma^2{}_j}\exp\left(-\frac{(x_{tj}-x_{ij})^2}{2\sigma^2{}_j}\right)\right] \tag{13}$$

Where N is the dimension of learning sample, d is the dimension of color space, commonly constituted by three relevant components and being suitable with the considered application. According the probability value $p(x_t)$ we can classify each pixel either a background pixel or a foreground one.

b) Shadows Suppression: Detection of shadow pixels as moving objects is a major biggest problem faced in image and video segmentation. The color information is a useful resource to overcome the confusion between object and its shadow. We carry out segmentation results in a space of hybrid attributes in which the normalized RGB space has been used to weaken lightness and eliminate intensive set of pixel. Indeed the use of color allows separating the chrominance component that represents the important information of the luminance information. Many studies have been made and prove that the normalized components rgb have a uniform aspect where it was able to weakness the intensive pixel. Consider the case where background pixels model are static, each pixel was characterized by (r,g,s) coordinates, suppose that at a given time t this pixel will be covered by the shadow it will have a new coordinate like (r_t,g_t,s_t), this pixel is classified as foreground if the ratio of luminance component s_t and s satisfy the following condition

$\alpha \le \frac{St}{S} \le \beta$, where α et α are two empirical thresholds, suitably chosen for all segmented image, beyond this interval, the pixel will be classified as background pixel. Nevertheless, the use of normalized components cannot always the best component that leaded to subtract shadow, despite their compactness power to improve various distribution associated to each pixel.

3.4. Experimental Results

We will begin this discussion by evaluating the two curves that represent the probability density function of the pixel intensity belonging to the background. In fact it is clear that the Rayleigh distribution is more compactness than the Gaussian one. Statistical algorithm for background modeling and subtraction by the Rayleigh distribution is applied in soccer shots for the contribution to the moving pixel classification. The efficiency of proposed method is proved by experimental results, indeed Rayleigh distribution it's more compactness allowing to reduce the overlapping between histograms of each cluster in the scene.

The computation of false ratio detection (FRD) prove that this ratio decreases when we have applied Rayleigh distribution for modeling background, the reached values for Gaussian and Rayleigh are respectively 33.71 and 18.08 for the first image, 44.16 and 20.93 for the second image. This method returns relevant segmented image. Indeed from a number of detected pixels (PN) we can calculate FRD and so it will be consider as an appreciating criterion. The False Ratio Detection (FRD) is expressed by:

$$FRD = \left(\frac{theoritical\ Detection}{ideal\ Detection} - 1\right) * 100 \tag{14}$$

If the FRD increases the segmentation results are poor. According the denoted results our approach optimizes segmented image and reduce the processing time because Rayleigh distribution is faster than the Gaussian. Figure 4 shows segmentation results with Rayleigh distribution and proves our choice and effectiveness of the proposed technique.

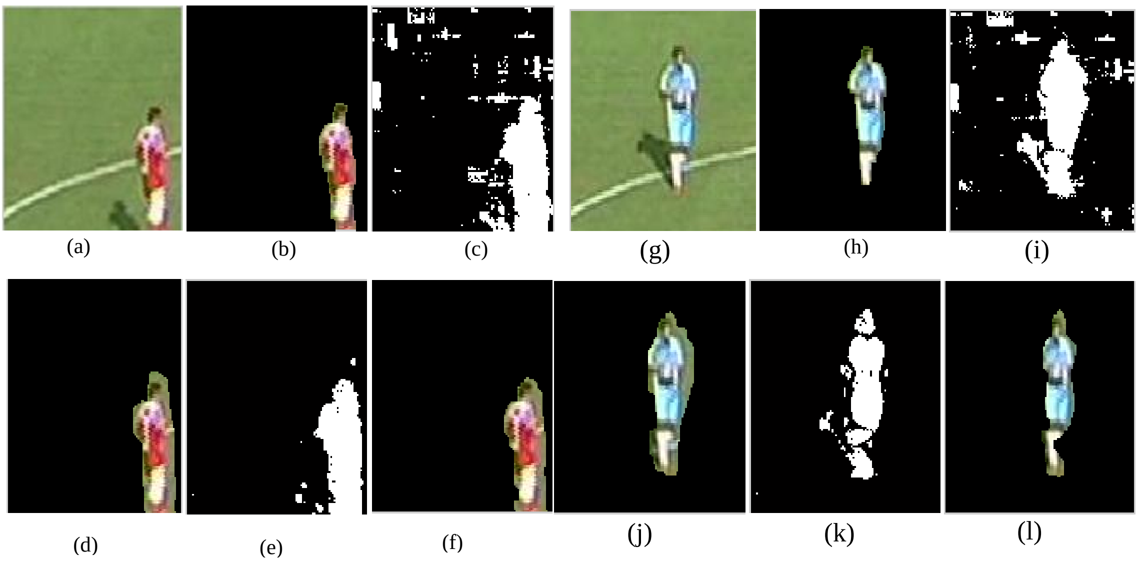
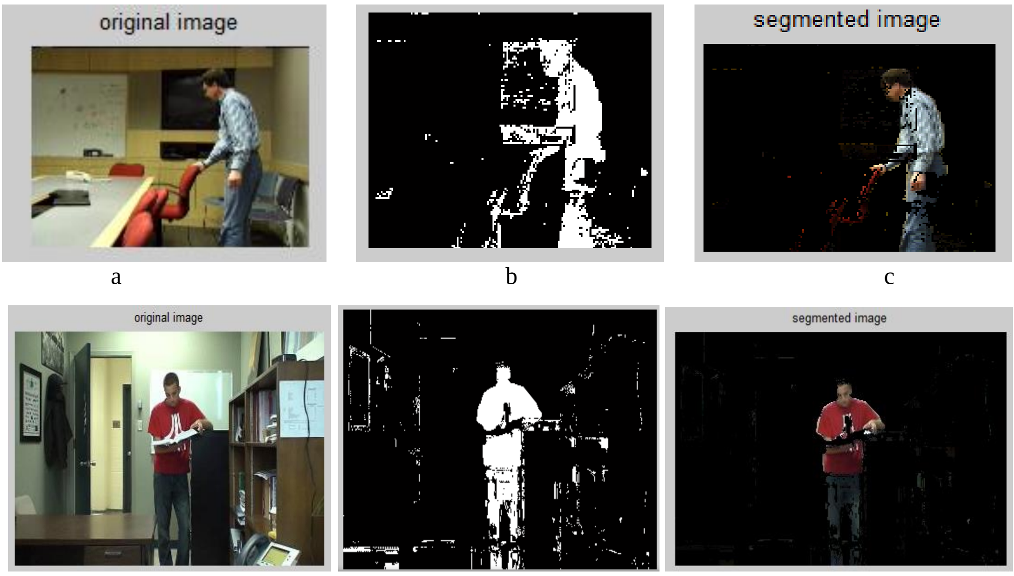


Figure 3. Exprimental Results. (a), (g) Original image. (b), (h) Reference objects. (c), (i) Segmented image with Gaussian model (binary image). (d), (j) Segmented image after post-treatment (Gaussian model). (e), (k) Segmented image with Rayleigh model (binary image). (f), (l) Segmented image after post-treatment (Rayleigh model)



a b c

d e f

Figure 5. Experimental Results. (a), (d) Original image. (b), (e) mask of extracted object with Rayleigh model. (f), (c) Segmented image

4. Conclusion

In this paper we have presented an improved segmentation method based on statistical modeling of background, the new technique uses the Rayleigh distribution to model the probability density of background pixel compared with GMM algorithm. Our algorithm has been used for different color image aim to realize segmentation task, in soccer field and other type of image. The experimental results show that our new algorithm provides an improvement in the segmentation of moving objects compared with classical model based on Gaussian distribution.

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