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Toward Indoor and Outdoor Surveillance Using an Improved Fast Background Subtraction Algorithm

A. El Harraj, N. Raissouni

***Abstract*—**The detection of moving objects from a video image sequences is very important for object tracking, activity recognition, and behavior understanding in video surveillance.

The most used approach for moving objects detection / tracking is background subtraction algorithms. Many approaches have been suggested for background subtraction. But, these are illumination change sensitive and the solutions proposed to bypass this problem are time consuming.

In this paper, we propose a robust yet computationally efficient background subtraction approach and, mainly, focus on the ability to detect moving objects on dynamic scenes, for possible applications in complex and restricted access areas monitoring, where moving and motionless persons must be reliably detected. It consists of three main phases, establishing illumination changes invariance, background/foreground modeling and morphological analysis for noise removing.

We handle illumination changes using Contrast Limited Histogram Equalization (CLAHE), which limits the intensity of each pixel to user determined maximum. Thus, it mitigates the degradation due to scene illumination changes and improves the visibility of the video signal. Initially, the background and foreground images are extracted from the video sequence. Then, the background and foreground images are separately enhanced by applying CLAHE.

In order to form multi-modal backgrounds we model each channel of a pixel as a mixture of K Gaussians (K=5) using Gaussian Mixture Model (GMM). Finally, we post process the resulting binary foreground mask using morphological erosion and dilation transformations to remove possible noise.

For experimental test, we used a standard dataset to challenge the efficiency and accuracy of the proposed method on a diverse set of dynamic scenes.

***Keywords*—**Video surveillance, background subtraction, Contrast Limited Histogram Equalization, illumination invariance, object tracking, object detection, behavior understanding, dynamic scenes.

I. Introduction

THERE has been growing interest in the use of Background subtraction (BS) to localize moving objects in a video shot by a static camera or in a video stream [3], [11]. It is used as the first significant step in many computer vision applications, including objects tracking [11], [2], human-computer interaction [7], traffic monitoring [4], and video surveillance [7]. In this perspective many approaches have been proposed as efficient Background subtraction methods [1]-[9].

Basically, the approach proceed by detecting the moving objects from the difference between the current Video frame "foreground image" and a reference frame "background model".

Background subtraction segments foreground objects more accurately in most cases compared to other moving object detection methods, and detect foreground objects even if they are motionless. However, one weakness of traditional background subtraction methods is that they are susceptible to environmental changes like gradual or sudden illumination changes.

One reason for this drawback is that most methods assume a static background. In fact, automated surveillance systems typically use stationary sensors to monitor an environment of interest. However, the assumption of a stationary sensor does not necessarily imply a stationary background. Examples of nonstationary background are wind, ground vibrations, swaying trees or ocean ripples.

Hence we need to update the background model even if we suppose the use of stationary sensors. The update of the background model is one of the major challenges for background subtraction methods

The existing approaches vary in computational speed, memory requirements and accuracy [8].

But, robust BS techniques are supposed to be flexible enough to handle variations in lighting, moving scene clutter, multiple moving objects and other arbitrary changes to the observed scene or scenes [16]-[20].

Thus, a principal proposition in this work is to introduce the illumination invariance by CLAHE (Contrast Limited Adaptive Histogram Equalization) enhancement technique. Having an automated surveillance system that is independent of illumination changes is important for real world deployment, and we reintroduce the use of Gaussian Mixture Model to provide an accurate background model with a morphological post processing techniques to give a representation of the scene background that consistently yields high detection accuracy.

The rest of this paper is organized as follows: First we give a succinct review of the previous work in the field, second we describe promptly the basic technologies and methods used in our approach, third, we present the major finding of our research and finally we conclude our work.

A. El Harraj is with the Innovation & Telecoms Engineering, Research Group. Remote Sensing & Mobile GIS Research Unit. The National School for Applied Sciences of Tetuan. Univeristy of Abdelmalek Essaadi. BP. 2222. M'Hannech II. 93030. Tetuan. Morocco (Phone: 212 6 61 267 207, e-mail: abdeslam.elharraj@inventive-technologies.com).

N. Raissouni is with the Innovation & Telecoms Engineering, Research Group. Remote Sensing & Mobile GIS Research Unit. The National School for Applied Sciences of Tetuan. Univeristy of Abdelmalek Essaadi. BP. 2222. M'Hannech II. 93030. Tetuan. Morocco (e-mail: nraissouni@uae.ma).

II. Related Work

Methods for background subtraction are subject of many recent researches. The simplest form of background subtraction is frame difference [17], which was used since 1979, in this approach, the current frame is subtracted from the previous one, and if the difference in pixel values for a given pixel is greater than a threshold then the pixel is considered part of the foreground [13], [14]. As a drawback of this method, there is a challenge on determining the threshold value. Thus, the result depends on threshold values and so for each different video. Early alternatives operated on the idea that the color of a pixel over time in a static scene could be modeled by a single Gaussian distribution, N(μ,σ). Karman et al. [21] and Koller et al. [22] proposed a statistical approach that used Kalman Filtering for background model updating.

In their influential work (1997), [19] modeled the color of each pixel, I(x; y), with a single 3 dimensional Gaussian, $I(x,y) \sim N(\mu(x,y), \sum(x,y))$. The mean μ(x,y) and the covariance $\sum(x,y)$, were learned from color observations in consecutive frames. Once the pixel-wise background model was derived; the likelihood of each incident pixel color could be computed and labeled as belonging to the background or not.

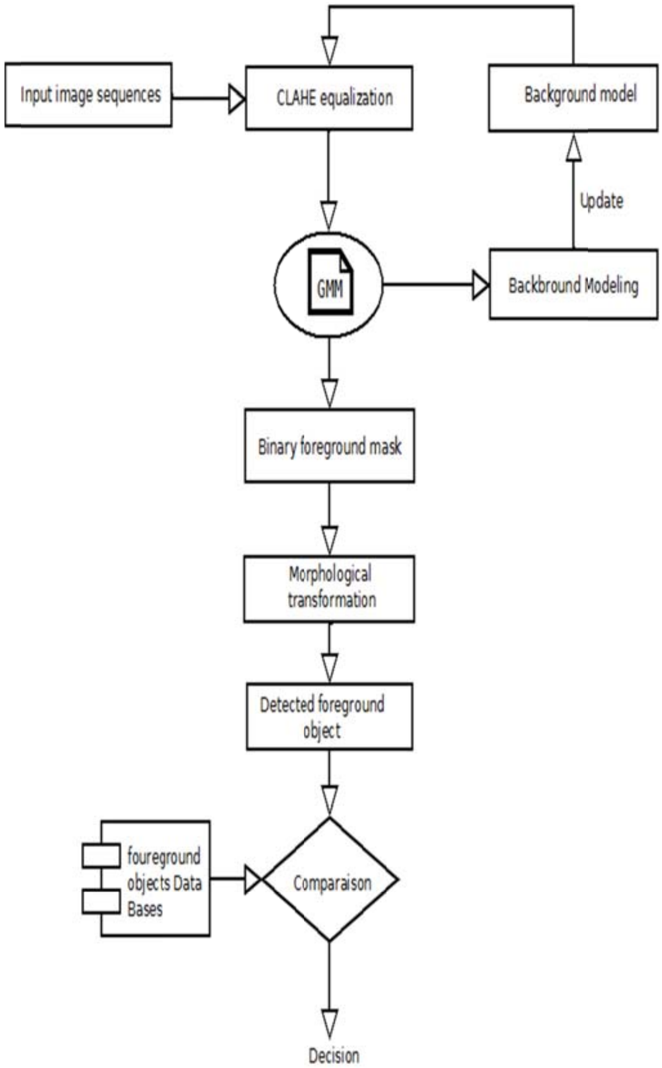


Fig. 1 Block diagram of the proposed algorithm

It was found that using Gaussian Probability Density function based approaches is not suited to most outdoor situations, since repetitive object motion, shadows or reflectance often caused multiple pixel colors to belong to the background at each pixel.

In [24] Friedman and Russell proposed modeling each pixel intensity as a mixture of Gaussians, instead, to account for the multimodality of the ‘underlying’ likelihood function of the background color. Thus, each pixel was classified depending on whether the matched distribution represented the background process. However performance notably deteriorates since dynamic textures usually do not repeat exactly. Another limitation of this approach is the need to specify the number of Gaussians (models), the K-means approximation in the case of the method that we develop in this paper.

Still, the mixture of Gaussian approach has been widely adopted, becoming something of a standard in background subtraction, as well as a basis for other approaches [11], [16], [25]

Horprasert, et al. [15] proposed a statistical approach for real-time robust background subtraction and shadow detection. This algorithm work on RGB color images, and aims to measure the distortion two RGB color pixels by breaking down the distortion into two parts, namely the brightness distortion and chromaticity distortion. By applying suitable threshold on the brightness distortion and chromatic distortion distinguish the pixels as follows: original background, if it has both brightness and chromaticity similar to those of the same pixel in the background image.

Shadow, if it has similar chromaticity but lower brightness than those of the same pixel in the background image.

This approach is also sensitive to threshold values.

More recently, the problem of dynamic backgrounds was treated by Pless et al. [26] and Mittal et al. [27]. Pless et al. proposed several pixel-wise models based on the distributions of the image intensities and spatio-temporal derivatives. Mittal et al. proposed an adaptive kernel density estimation scheme with a joint pixel-wise model of color (for a normalized color space), and optical flow at each pixel.

Yaser et al. [20] propose a model of the background as a single probability density and use a model for the foreground to augment the detection of objects (without explicit tracking).

In context of earlier work (in particular [23], [30] and [11]), our approach is included in the category of methods that employ Gaussian mixture model to update background models

III. Proposed Method

The proposed work has essentially three novel contributions.

First, to establish illumination changes invariance we enhance the contrast of an image by locally applying Contrast Limited Histogram Adaptive Equalization (CLAHE) [10] on small data regions called tiles. The resulting neighboring tiles are then stitched back seamlessly using bilinear interpolation. The contrast in the homogeneous region can be limited so that noise amplification can be avoided.

Secondly, we model each background pixel using a Gaussian Mixture-based Background/Foreground Segmentation and an online approximation to update the model [9]. In this model, based on the persistence and the variance of each Gaussian of the mixture, it is determined which Gaussian may correspond to background colors. Pixel values that do not fit the background distributions are considered foreground [11].

Thirdly, we use morphological transformation to erode and dilate [12] the resulting foreground binary mask to get rid of the noise that may affect the binary mask.

Finally, for experimental validation we use the standard dataset used in [20] and available online [32].

A. Contract Limited Adaptive Histogram Equalisation (CLAHE)

To enhance the performance and ensure the illumination changes invariance of our approach we use Contrast limited adaptive histogram equalization (CLAHE) to makes hidden features of the image more visible.

Originally developed for medical imaging, CLAHE is a generalization of Adaptive Histogram Equalization (AHE), developed to prevent the over amplification of noise that AHE can give rise to [10], [28]. CLAHE enhance the contrast of an image by locally applying Contrast Limited Histogram Equalization on small data regions called tiles rather than the entire image. The resulting neighboring tiles are then stitched back seamlessly using bilinear interpolation. The contrast in the homogeneous region can be limited so that noise amplification can be avoided (Fig. 2).

As illustrated in (Fig. 3), first, the input RGB image is converted to 16-bit grayscale image (can be obtained from an 8-bit grayscale image by multiplying pixel values by 255). This conversion aims to improve the effectiveness of the histogram equalization step.

Second, we apply Contrast-limited adaptive histogram equalization (CLAHE) to the converted 16-bit grayscale image.

CLAHE establishes a maximum value to clip the histogram and redistributes the clipped pixels equally to each gray level.

It can limit the noise whereas enhancing the contrast [29].

Suprijanto et al. [28] showed that Rayleigh distribution of CLAHE produce better image quality.

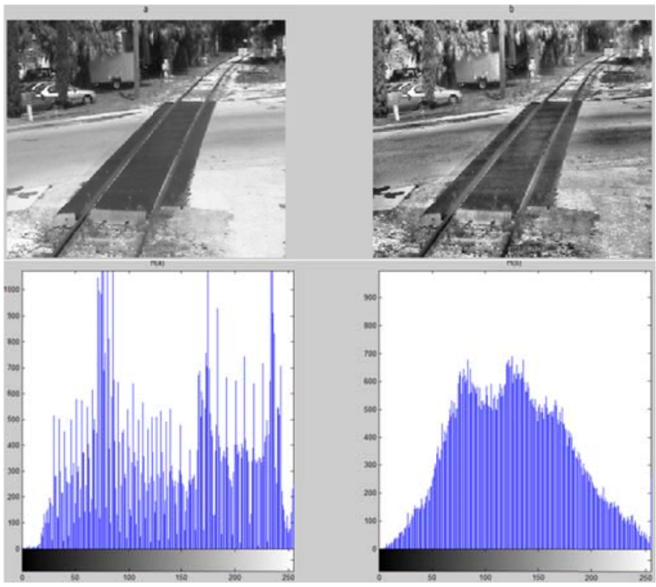
In our case we use a Rayleigh distribution with a clip limit of 99.99%. (Fig. 2) shows an example of the produced enhanced grayscale image after the whole preprocessing steps described previously.

The clip limit can be obtained by: β [28].

$$\beta = \frac{M}{N}\left(1 + \frac{\alpha}{100}(S_{\max} - 1)\right) \tag{1}$$

where α is clip limit factor, M region size, and N is grayscale value. The maximum clip limit is obtained for α=100.

Once the background and foreground images are separately enhanced by applying CLAHE, we apply our background modeling procedure using the Gaussian mixture model (GMM) [9]



(a) (b)

Fig. 2 (a) original colored image, (b) 16-bit grayscale enhanced with CLAHE (Distribution = Rayhleigh , clipLimit=0.9999), H(a)- classical histogram image for original 8-bit grayscale image and H(b)- CLAHE histogram for the transformed image

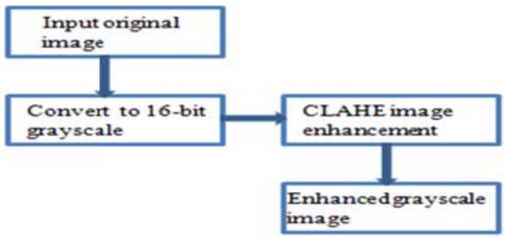


Fig. 3 Block diagram of CLAHE integration: the original image is converted to a 16-bit grayscale level, than processed with a CLAHE histogram with a Rayleigh distribution and a clipLimit=99.99%, to produce the enhanced grayscale image used for as input for the proposed algorithm space

B. Gaussian Mixture Model

In our work we use the background model suggested by [11]. Rather than explicitly modeling the values of all the pixels as one particular type of distribution, Stauffer et al. simply model the values of a particular pixel as a mixture of Gaussians. Based on the persistence and the variance of each of the Gaussians of the mixture, they determine which Gaussians may correspond to background colors. Pixel values that do not fit the background distributions are considered foreground until there is a Gaussian that includes them with sufficient, consistent evidence supporting it [11].

In this model, each pixel is modeled as a mixture of Gaussian and an online approximation to update the model. The values of a particular pixel are modeled as a mixture of Gaussians rather than modeling it as one particular type of distribution. Based on the persistence and the variance of each Gaussian of the mixture, it is determined which Gaussian may correspond to background colors. Pixel values that do not fit the background distributions are considered foreground. The online update process of this method is as follows:

Consider a pixel (x_0, y_0) at any time t with its history

$$\{X_1, X_2, \dots X_t\}$$

where

$$X_i = \{I(x_0, y_0, i): 1 \le i \le t\} \quad (2)$$

where I is the image sequence.

A mixture of K Gaussian distribution is used to model the recent history of each pixel, $\{X_1, X_2, \dots X_t\}$. The probability of observing the current pixel value is:

$$P(X_t) = \sum_{i=1}^{K} w_{i,t} * \eta(X_t, \mu_{i,t}, \sigma_{i,t}) \quad (3)$$

where K is the number of distributions and is usually chosen between 3 to 5, $w_{i,t}$ is an estimate of the weight of the i^{th}Gaussian in the mixture at time t , $\mu_{i,t}$ is the mean value of the ith Gaussian in the mixture at time t, $\sigma_{i,t}$ is the covariance matrix of the i^{th} Gaussian in the mixture at time t, and where η is a Gaussian probability density function

$$\eta(X_t, \mu, \sigma) = \frac{1}{(2\pi)^{\frac{n}{2}} |\sigma|^{\frac{1}{2}}} e^{-\frac{1}{2}(X_t - \mu_t)^T \sigma^{-1} (X_t - \mu_t)} \quad (4)$$

The co-variance matrix is a 3X3 matrix and is a diagonal matrix because R, G, B values are assumed to be independent.

$$\sigma_{k,t} = \sigma_k^2 I \quad (5)$$

A new pixel value is, in general, represented by one of the major components of the mixture model and is used to update the model. A match is defined as a pixel value within 2.5 standard deviations of a distribution. If none of the K distributions match the current pixel value, the least probable distribution is replaced with a distribution with the current value as its mean value, an initially high variance, and low prior weight. The prior weights of the K distributions at time t, $w_{k,t}$, are adjusted as

$$w_{k,t} = (1 - \alpha) w_{k,t-1} + \alpha(M_{k,t}) \quad (6)$$

where α is the learning rate and $M_{k,t}$ is 1 for the model which matched and 0 for the remaining models. $\frac{1}{\alpha}$ defines the time constant which determines the speed at which the distribution parameters change.

μ and σ parameters for unmatched distributions remain the same. The parameters of the distribution which matches the new observation are updated as

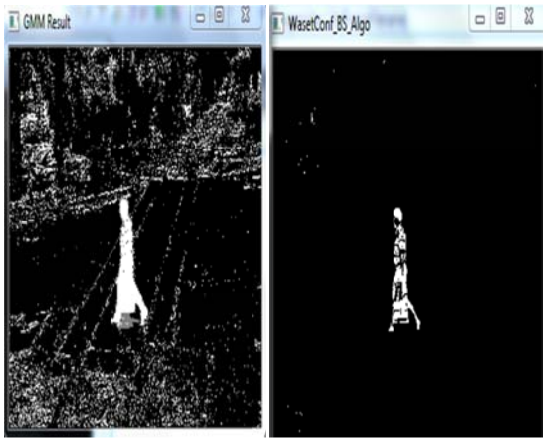
$$\mu_t = (1 - \beta)\mu_{t-1} + \beta(X_t) \quad (7)$$

$$\sigma_t^2 = (1 - \beta)\sigma_{t-1}^2 + \beta(X_t - \mu_t)^T (X_t - \mu_t) \quad (8)$$

$$\beta = \frac{\alpha}{w_t} \quad (9)$$

(a) (b)

Fig. 4 (a) The image used as a background model for test, (b): the image used as to test the approach for foreground binary mask extraction



(R1) (R2)

Fig. 5 Using the image presented in (Fig. 4). (R1): is the result returned the classical GMM and (R2) is the result returned by the proposed approach

One of the significant advantages of this method is when something is allowed to become part of the background, it doesn’t destroy the existing model of the background. The original background color remains in the mixture until it becomes the K^{th}most probable and a new color is observed. Therefore, if an object is stationary just long enough to become part of the background and then it moves, the distribution describing the previous background still exists with the same μ and σ^2, but a lower ω and will be quickly reincorporated into the background. At the end of the approach we have a binary foreground mask that can be noisy, so we have to remove this noise by morphological transformation.

C. Noise Removal: Erosion and Dilation Morphological Transformation

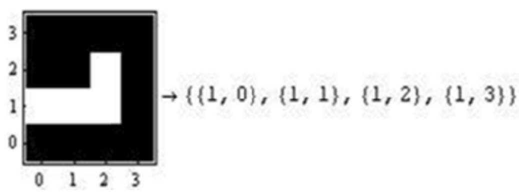


Fig. 6 Binary image and its set description

The definitions of dilation and erosion are typically formulated using the concept of a set translation and a set reflection. The translation of a set a by a point (or vector) x, denoted a_x, is defined by [12]:

$$a_x = \{a + x: a \in x\} \tag{10}$$

The reflection of a set σ, denoted $\overline{\alpha}$, is defined

$$\breve{\alpha} = \{-a: a \in \alpha\} \tag{11}$$

Binary dilation of set α by set β, denoted here $\alpha + \beta$, is the set union of all translations of set α by elements of set β or equivalently the set of all positions of the reflected set $\breve{\beta}$ for which it intersects with, set α. The set β is commonly called the structuring element and plays a similar role to a finite impulse response filter in linear signals and systems theory.

$$\alpha + \beta = \cup_{b\epsilon\beta}\, \alpha_b = \{x: \breve{\beta_x} \cap \alpha \neq 0\} \tag{12}$$

Grayscale morphology extends the morphological operators to the domain of integer or real-valued signals defined on a Cartesian grid. The definitions of binary morphology extend naturally to the domain of digital grayscale signals with translation, reflection, and inversion defined as in linear processing while intersection and union become point-wise minimum and maximum operators, respectively. Therefore we have the following definition of grayscale dilation [31].

$$f + s = \vee_{x \in D_s} f_x \tag{13}$$

where the symbol $\vee$ denotes a point-wise maximum. Thus the dilation of a grayscale signal or image is a point-wise maximum of a series of translations defined by the shape of the structuring element. This definition implies a flat structuring element.

Erosion and dilation operators are seldom used by themselves. Two well-known combinations of the operators result in the so-called open (○) and close (●) operators [12].

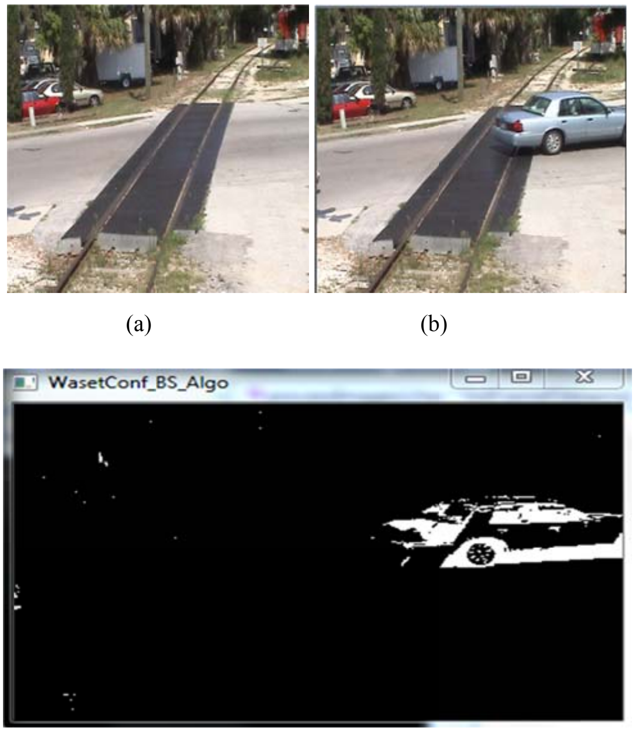
Openings and closings are typically used to suppress structures that cannot contain the structuring element, peaks in the case of openings and valleys in the case of closings.

In our case we use erosion and dilation as an opening operation for noise removal.

IV. Results

All images used in our tests was used in [20] and are available online as a standard dataset on [32]

We find significant improvement combining CLAHE enhancement, background subtraction and morphological transformations (Fig. 5). The results reflect the benefits of having an adapting background model along with a fast and efficient adaptive contrast enhancement CLAHE. GMM based background subtraction image incorporates a lots of errors induced due to many factors varying to switching on/off of light sources to noise presence in the frame due to highly illuminated scene capture by the sensor. The GMM based model adapts slowly to the changes occurring to the background. So when a light is switched on/off, the region affected by this change gets classified as foreground. But the fast new established model rejects that region of change immediately unless that light source is repetitive in natural or has motion associated with it. Since the proposed approach is invariant to illumination changes and remove possible binary foreground mask, it switches to buffered region of activity image for help. The introduced model doesn't affect the adaptive nature of the GMM. It's a tool to get rid of the unnecessary errors incorporated in the background subtraction results from the GMM method.



(a) (b)

(c)

Fig. 7 Using the same scene (a) and the tested image (b) The proposed approach was able to detect the car object (c)

V. Conclusion

This paper introduced an improved probabilistic illumination invariant approach for background subtraction that can be used in automated video surveillance in both indoor and outdoor. It involves modeling each pixel as a separate mixture model as done with GMM. We used the real-time approximate method for GMM which is stable and robust.

The proposed method deals with slow and fast lighting changes by using an efficient adaptive contrast enhancement approach and adapting the values of the Gaussians. It also deals with multi-modal distributions caused by shadows, specularities, swaying branches and computer monitors as suggested for GMM based background subtraction models. As future work, we aim to improve our approach by using an adaptive model for both background and foreground, and to test exhaustively our approach on a standard dataset along with the corresponding ground truth data.

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El Harraj Abdeslam received his MS degree in Telecommunications and Network engineering from the National School of Applied Sciences, Tangier, Morocco in 2008 and an MS degree in Entreprise management from University of Perpignan, French in 2010. Since 2012 he is a PhD. Student in computer vision with University Abdelmalek Essaâdi, Tangier-Tetuan, Morocco. From 2008 to 2012, he was a Programmer Engineer with Creargie Maroc Company, Casablanca, Morocco. Currently, he is heading the Research and Development Department in the Company INVENTIVE Technologies, Casablanca, Morocco and also a member of Remote-Sensing & Mobile-GIS Unit/Telecoms Innovation & Engineering Research group.

Raissouni Naoufal received the M.S., and Ph.D. degrees in physics from the University of Valencia, Spain, in 1997, and 1999, respectively. He has been a Professor of physics and remote sensing at the National Engineering School for Applied Sciences of the University Abdelmalek Essaadi (UAE) of Tetuan, since 2003. He is also heading the Innovation & Telecoms Engineering research group at the UAE, responsible of the Remote Sensing & Mobile GIS unit. His research interests include atmospheric correction in visible and infrared domains, the retrieval of emissivity and surface temperature from satellite image, huge remote sensing computations, Mobile GIS, Adhoc networks and the development of remote sensing methods for land cover dynamic monitoring.