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Motion detection using MoG: a parametric analysis

Detección de movimiento por medio de MoG: un análisis paramétrico

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Resumen

El proceso de sustracción de fondo localiza y etiqueta las zonas sin movimiento y las zonas en movimiento en una secuencia de imágenes. La eficiencia y rendimiento de un método determinado de sustracción de fondo depende de las variables, los parámetros del modelo y las condiciones de la escena. Este trabajo describe los efectos paramétricos en diferentes condiciones operativas para el modelo de sustracción por mezcla de gaussianas, aplicados a videos de monitoreo vial. Los parámetros analizados incluyen el tamaño de los filtros para reducir el ruido, la granularidad de la detección de movimiento y la velocidad de convergencia de la estimación del fondo. Los resultados muestran las consideraciones a tomar en la asignación de los valores a los distintos parámetros para garantizar una correcta detección de zonas en movimiento y zonas fijas, permitiendo optimizar la detección del movimiento (controlados y no controlados), por ejemplo, escenarios en exteriores (no controlado) o la detección de movimiento en líneas de producción donde es complicado controlar las variaciones de luz.

Palabras clave: Ajuste paramétrico, Mezcla de gaussianas, Sistema de vigilancia, Sustracción de fondo.

Abstract

The background subtraction process locates and labels non-moving and moving areas in an image sequence. The efficiency and performance of a given background subtraction method depends on the variables, model parameters and scene conditions. This paper describes the parametric effects under different operating conditions, for the subtraction Mixture of Gaussians model, applied to road monitoring videos. The parameters analyzed include the size of the noise reduction filters, the granularity of the motion detection and the convergence speed of the background estimation. The results show the considerations to be taken in assigning values to the different parameters, to ensure a correct detection of moving and stationary zones, allowing to optimize motion detection (controlled and uncontrolled), for example outdoor scenarios (uncontrolled) or motion detection in production lines where it is complicated to control light variations.

Key words: Background subtraction, Mixture of gaussian, Parametric fit, Surveillance system.

1. Introduction

Background Subtraction becomes used for detecting motion zones in video streams for identifying the moving objects layer (foreground) and fixed layer (background) [1, 2]. The moving information represents the input raw data of high level analysis in the video understanding process [3].

However, the performance becomes affected due to factors such as sudden changes in brightness [4], the periodic movements in cameras [5], the non-static background [6], the periodic-moving objects, the shadows effect, and different environmental conditions [7-9].

In parallel, the motion detection process has been dealt with by the Mixture of Gaussian (MoG) approach [10], becoming the most popular for background subtraction [2]; since it deals with slight changes in luminosity, periodic movements, and camera noise. However, motion detection fluctuates in real applications due to the parametric estimation method with which the user decides to work.

A mixture model is a probabilistic approach for indicating the presence of data populations within a whole data population. An observed data set should identify the sub-population to which an individual observation belongs. A Gaussian Mixture Model (GMM, or Mixture of Gaussians, MoG) is a function containing several Gaussians [11, 12], each identified by $k \in \{1, \ldots, K\}$, where K is the number of clusters of the dataset. Each Gaussian distribution in the mixture comprises the following parameters: a mean μ defining its center, σ parameters defining the sparseness of the distribution, π that defines the probability of the Gaussian function.

The Expectation Maximization (EM) algorithm [11, 13], enables parameter estimation in probabilistic models with incomplete data. The EM iteration alternates between performing an expectation (E) step, which creates a function for the expectation of the log-likelihood evaluated using the current estimate for the parameters. A maximization (M) step computes parameters maximizing the expected log-likelihood found on the E step. These parameter estimates are then used to determine the distribution of the latent variables in the next (E) step.

The EM algorithm is used to find (local) maximum likelihood parameters of a statistical

model in cases with no solution. Typically, these models involve latent variables and unknown parameters and known data observations. Either missing values exist among the data, or the model can be formulated more simply by assuming the existence of further unobserved data points.

This work presents a contribution in selecting the background parameters to efficiently detect the moving zones; due to alters in size and forms the detection of objects. Therefore, this research proposes the basis for understanding the parameters involved in the MoG approach for video sequences in surveillance systems [3, 14].

1.1. Related Work

In recent times, background approaches based on the Mixture of Gaussian (MoG) are widely used, becoming a useful approach for video surveillance systems [6, 12]. Several modifications have been proposed in the current literature to improve it [10].

Consequently, analyzing the effects on the MoG's parameters becomes essential for the effects' understanding in the motion detection process [16]. A first approach to deal with this situation is the work of Toyama *et al.* [17], which proposed a three-based system capable of discarding periodic movements. Besides, this approach is limited to scenarios with fixed lighting conditions. Subsequently, [18] built an algorithm for performing the background model based on [10]. This approach proposed a block-based algorithm. The block-based approaches encode each neighborhood as a vector binary pattern width invariant to monotonic grayscale changes; it operates in real-time under the assumption of a fixed camera with a fixed focal length. After, in their work, Lee [19] used a fixed Mixture of Gaussian, where the number of Gaussian is previously defined. It proposes a scheme to improve the convergence rate without compromising the model stability. It replaces the overall static retention factor with an adaptive processing rate calculated for each Gaussian in each image. Next, Tan *et al.* [20] proposed a modified Expectation-Maximization (EM) procedure to build an MoG with an adaptive K-component number (AKMoG). They developed a heuristic parameter selection based on the proposed model to obtain a pixel classification decision.

Paalanen *et al.* [21] studied and proposed the attributes' representation as a Gaussian mixture. The mixture approximates through maximum likelihood estimation. The classification-confidence information is offered and presents a confidence approach as an belongings process for the conditional probability density functions. Also, Teixeira and Corte-Real [22] proposed a technique that uses the Gaussian mixing algorithm to detect structural changes, including induced noise and lighting variation. The same form, Ali *et al.* [23] focused on increasing the robustness of the Gaussian mixture model for complex environments. It proposes to redefine distribution parameters, such as weight, mean, and variance, as a region-based model that eliminates the effect of noise caused by drastic changes in lighting. Other relevant work is a review and comparison of the different background models are carried out [24]. It includes the MoG approach [25], which presents a method to eliminate the presence of the background texture caused by the waves in the water and the trees shaking by the wind.

Following the trend, in the paper Zivkovic [26], the creator of MoG is mentioned; who proposed an improvement in MoG, by using the online Expectation-Maximization (EM) algorithm to initialize the parameter in the background model; like [27] created an Adaptive MoG (AMoG), to efficiently update parameters in MoG. Other relevant work is proposed by Pulgarin-Giraldo *et al.* [16], the authors developed a cost update function based

on Euclidean divergence, which provides nonlinear smoothness to the background modeling process. This aims to improve the cost function used to update Gaussian Mixture Model (GMM) weight parameters that lead to noisy masks.

Finally, at a recent time, in their work [28], the authors present a statistical review of the approaches for modeling the background layer. They express the importance of the features, properties, and implications faced by a background subtraction modeling implementation, such as those mentioned by [4-9], and the key challenges of determining the best combination of parameters that optimizes accuracy and stability in detection.

1.2. Structure

This research work becomes organized in the following chapters: in § 2 describes the materials and equipment; § 3 describes the methodology as a fundamental method for background subtraction and parameters optimization; § 4 presents the proposed parameterization criterion in conjunction with the results; § 5 the conclusions and future become reported; later in § 6 the acknowledgments; finally, in § 7 the references.

2. Materials and equipment

The techniques described in Table 1 were implemented, making different experimental variations in the input parameters. The video stream provided by the Texas Advanced Computing Center (TACC) [29] and CDnet 2014: An Expanded Change Detection Comparative Data Set [30], was used.

Table 1. Techniques and their input parameters.

Name	Parameter	Description
Gaussian Filter [34]	Filter Size	Window size of the Gaussian filter, specified as a scalar or 2-element vector of positive.
	Sigma (σ)	Standard deviation of the Gaussian distribution, specified as a positive number.
Gaussian Mixture Model [10]	Gaussians (k)	The number of Gaussian modes in the mixture model, specified as a positive integer.
	Frames (ω)	Number of initial video frames for background model, specified as an integer value.
	Variance (σ^2)	Initial mixture model variance, specified as a numeric scalar.
	Rate (ts)	Learning rate for parameter updates, specified as a numeric scalar.
	Ratio (th)	Threshold to determine background model, specified as a numeric scalar.
Morphologic Filter [36]	Size	Structuring element size measures in pixels, such that w pixels or radius as a positive integer.
	Type	Object represents a flat morphological structuring element. The most common are: square, rectangle, disk, diamond, line, octagon, cube, sphere, cuboid.

The formulation of the Mixture of Gaussian is expressed in Figure 1. This model is used to extend the background subtraction algorithm of [10] to dynamic scenes [31].

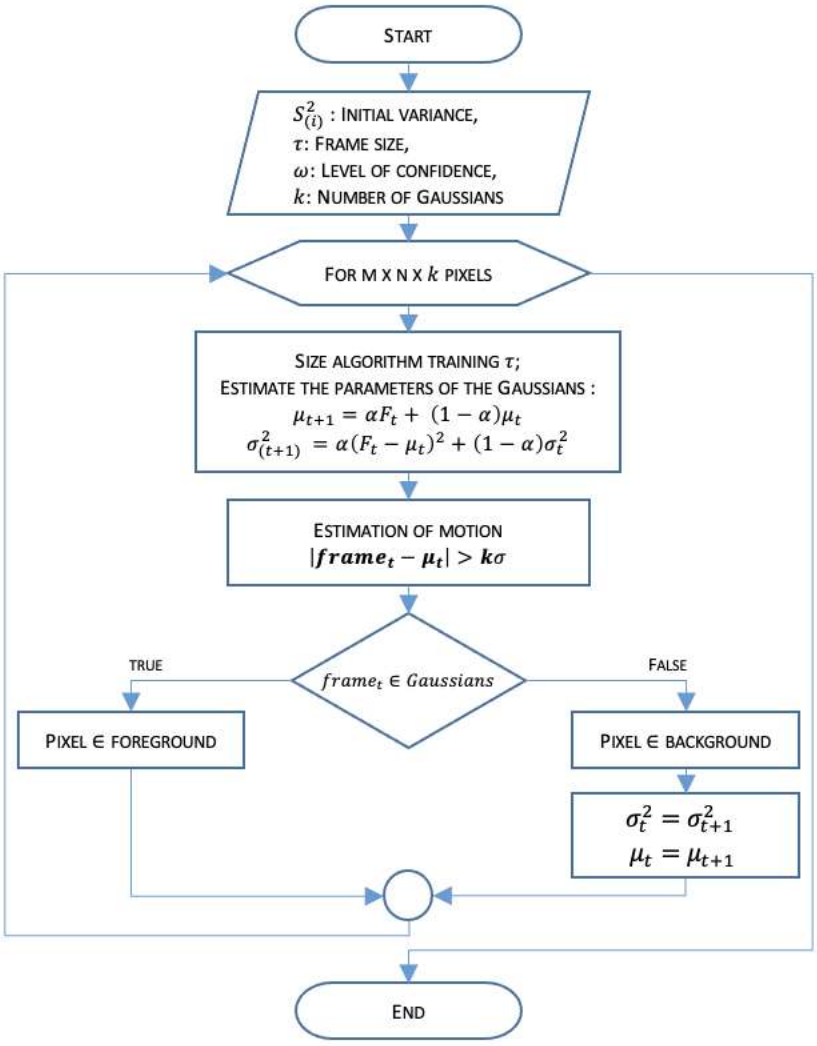


Figure 1. Overview of generalized Stauffer–Grimson [10] background subtraction in a video that has dynamic scenes.

3. Methodology

The process semantics [32] is described in Figure 1, which from a sequence of images we apply a parametric adjustment criterion following the general methodology (Figure 2).

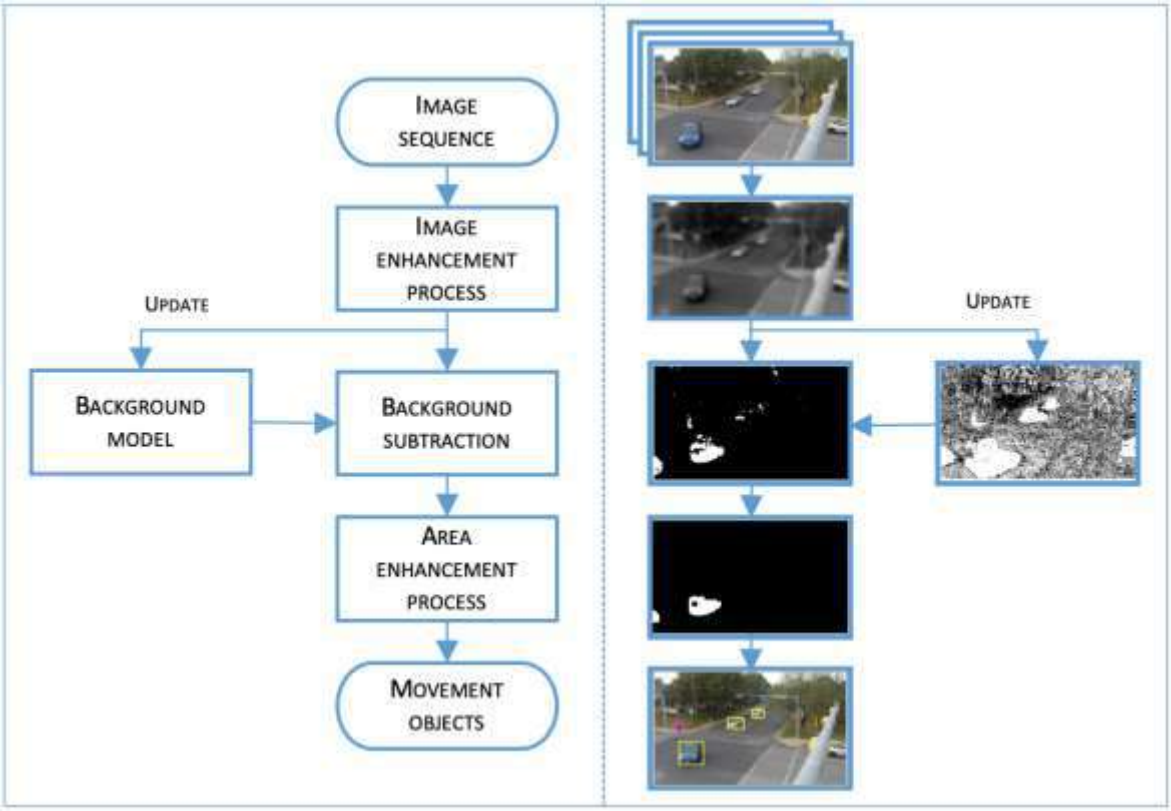


Figure 2. Process semantics illustrates the proposal for analyzing video streams. Each stage is described in the next sections.

The proposal consists of finding the effects of the parameters that make the background model fit better to detect objects [33] according to Figure 3. It also shows the impact of parameters on detection; varying values, comparing results, and according to specific situations, illustrating which combination yields the best result. As complement, in Figure 4 illustrates the methodology used.

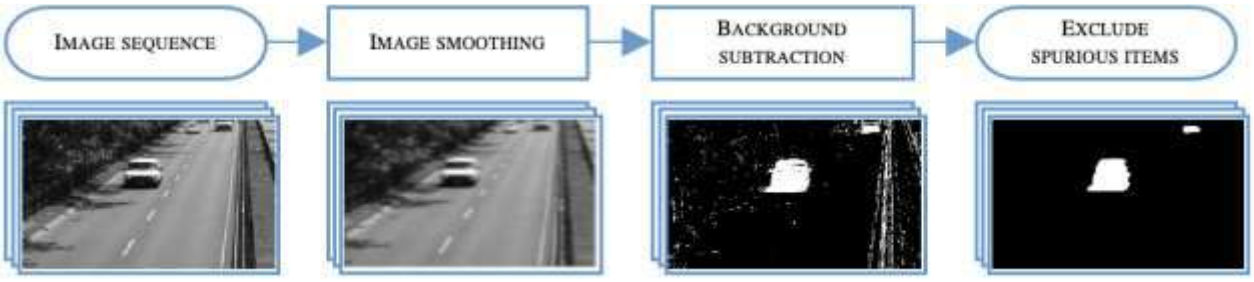


Figure 3. General scheme of the methodology.

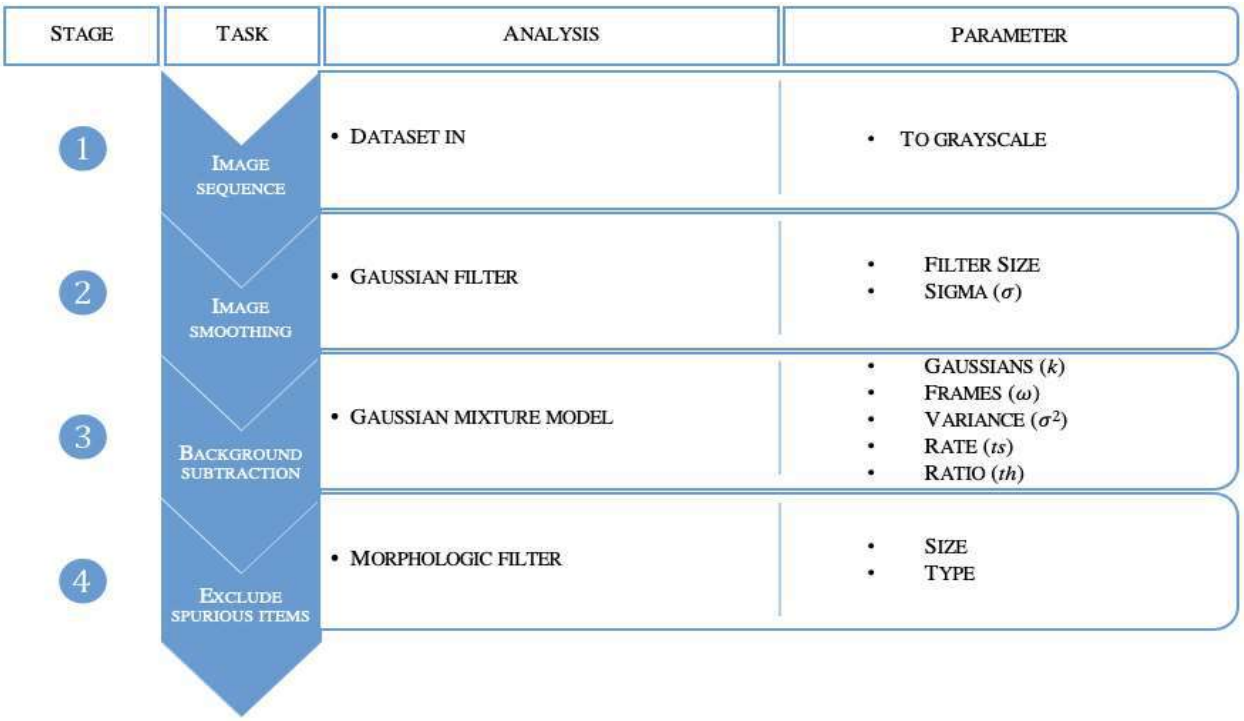


Figure 4. Task, analysis and parameters.

The methodology described in Figure 4, is summing up in the following steps.

1. Import the image sequence from the dataset and load into the memory.
2. Enhance each frame dismissing the noise acquisition effects through a Gaussian filter.
3. Compute the foreground using a MoG subtraction approach.
4. Enhance the motion detection map by the use of area filters.

In further paragraphs each step becomes explained.

1. The first step is to import the dataset for reading the sequence.
2. The next step is to enhance the image by applying a Gaussian filter in the frequency domain to smooth the image and reduce the intensity variations between neighboring pixels.
3. In this step, background subtraction is applied, using a MoG to separate the background (marked as zero) from the objects of interest (marked as one).
4. Finally, a technique is applied to filter and enhance the image to allow easy interpretation of its content, highlighting the structure of the objects, sharpening, contrasting certain aspects of the image and also to eliminate unwanted effects, such as noise while preserving all its characteristics. This technique is known as spurious element exclusion using a morphological filter that implements morphological operations to process the binary image based on the shape of its objects of interest.

The tasks of each step, the parameters considered and the possible analyses are described below.

3.1. Image smoothing

There are several approaches in the literature to dismiss noise effects. The most known are related to the frequency domain. However, approaches based on convolution might become useful because they use the analysis of

a spatial neighborhood to dismiss noise effects [34, 35].

A general-purpose filter is the Gaussian filter based on convolution approach. This filter approach to a Gaussian distribution, where the maximum value of one appears in the center of the hood, and its value begins to decrease according to an exponential function; whose dispersion or aperture is given by the sigma parameter, defined by the cutting frequency (Eq. (1)). The result in the frequency spectrum will be a set of values between zero and one.

$$G(\mu,\sigma) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\left(\frac{x-\mu}{2\sigma}\right)^2} \qquad \textbf{(Eq. 1)}$$

The result of the first criterion is shown in Figure 5. These results refer to applying a low-pass filter based on Gaussian distribution, which contributes to a noise reduction, therefore, a value for σ is chosen experimentally, to make the Gaussian smaller than the characteristic. For example, for a filter size of 15×15, you get a value of 4σ.

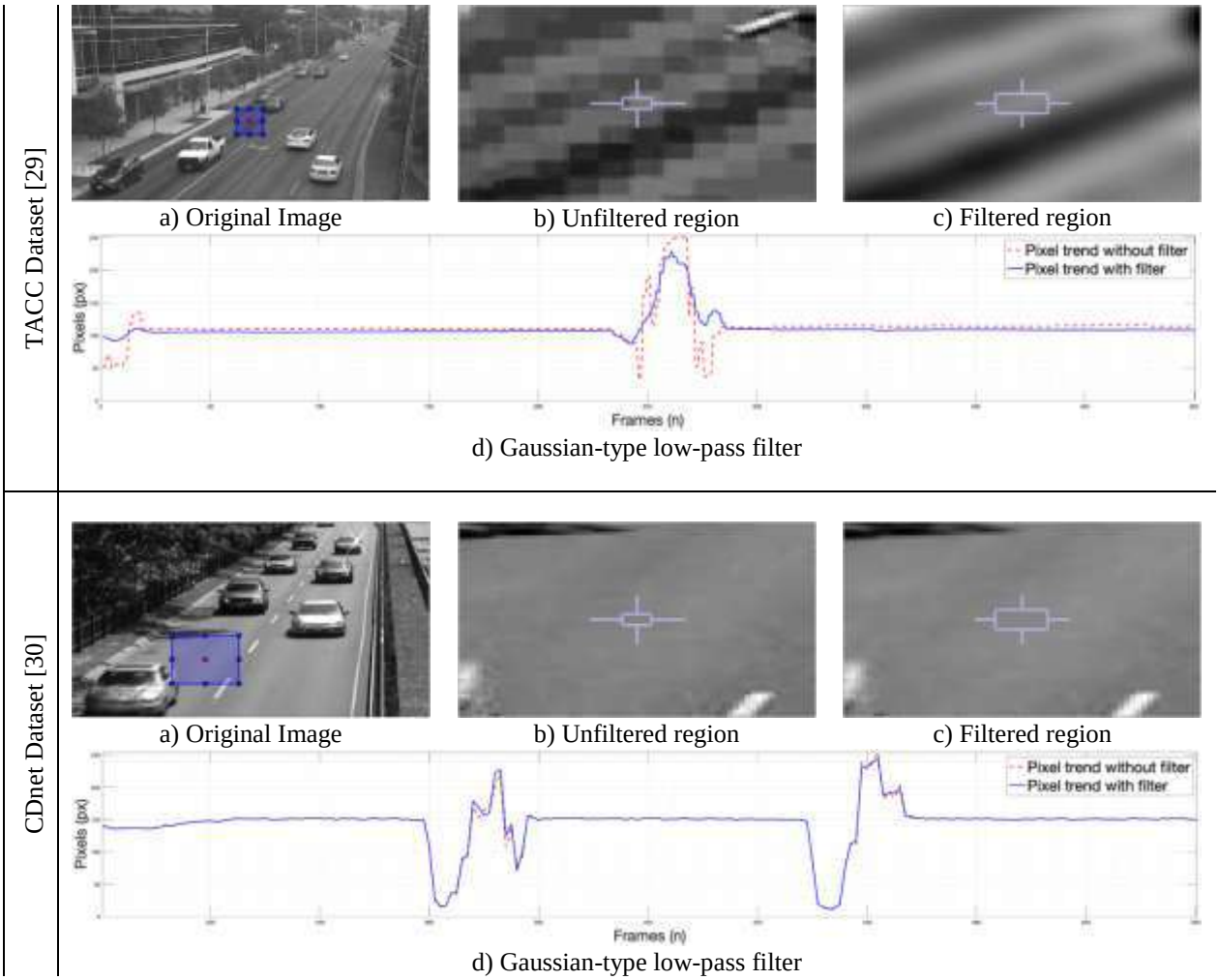


Figure 5. Effect of Gaussian-type pass-low filter. The effect of Gaussian-type as noise reduction with the user predefined parameters: The Figure 5 (a) is the original; Figure 5 (b) is a zoomed region and Figure 5 (c) the resulting under applies the gaussian filter. The parameters of the filter are a neighborhood of $\mathbf{15 \times 15}$, with a $\boldsymbol{\sigma = 4}$. The Figure 5 (d), the graph that represents the trend of the filtered and unfiltered pixel values.

3.2. Background subtraction

A common problem with the MoG approach is to achieve an acceptable parameterization as expressed [10]. This method is based on a probability function (Eq. (2)), which uses a Gaussians mixture for each individual pixel. These mixtures represent from 3 to 5 Gaussians to model the variance values. The initial values for the μ_0 and σ_0 are computed by the mean pixel intensities for a given position. Similarly, the standard deviation for σ_0.

Then, iteratively the rest of the gaussian is computed with the EM algorithm. In general terms, the mixture of gaussian distribution models the pixel intensity variability, for which the probability to achieve a concrete value are expressed as follows.

$$P(X^t|\theta^t) = \sum_{i=1}^{k} \omega_i^t \, G(X^t|\mu_i^t, \Sigma_i^t) \quad \textbf{(Eq. 2)}$$

Where ω_i represents the probability of the Gaussian for the mixture, and Σ_i the covariance matrix for the mixture.

The result shows in Figure 6 and according to Eq. (2), the experimentally controlled parameters are as follows: the number of Gaussians $k = 5$, which allows multiple background behaviors to be modeled; $\omega = 500$, the learning set, which represents the number of initial video images to be processed; $ts = 0.005$ the processing rate that controls how quickly the model adapts to changing conditions, such as lighting; $\sigma^2 = 48^2$ initial variance (we assume that each MoG is independent); and the threshold $\mathrm{th} = 0.84$, to represent the minimum possibility of pixels being considered part of the background.

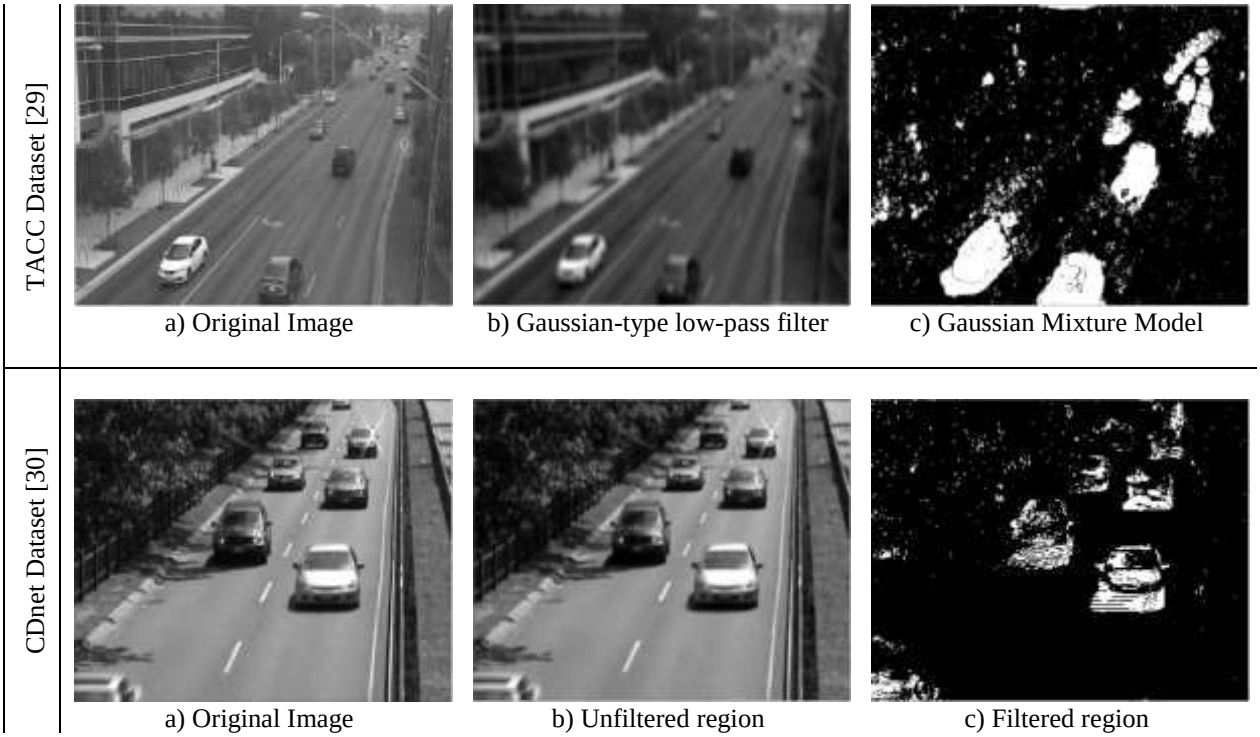


Figure 6. Application of the GMM background model. The results for the video sequence image show from the left to right image, background subtraction using Gaussian Mixing Model, applying parameters equivalent to $\boldsymbol{k = 5}$, $\boldsymbol{\omega = 500}$, $\boldsymbol{ts = 0.005}$, $\boldsymbol{\sigma^2 = 48^2}$ $\boldsymbol{y}$ $\boldsymbol{th = 0.84}$.

It is essential to mention that when applying the background model, there is a disturbance in the result, this disturbance is a type of intrinsic noise derived from the process.

3.3. Exclude spurious items

Morphology in terms of image processing is the study of the structure of objects from their respective images to describe their own form. The morphological operations allow us to obtain a description of the geometric structures of objects [36], such as contours, holes, corners, cracks, among others. The basic operations are dilation and erosion, and their combination between them defines filters such as opening and closing. The erode (expressed by the symbol $\ominus$ [37]) of a set f by the structural element E, denoted by $f \ominus E$, applies to enlarge the regions of the image with a value equal to 1 and white. The dilations (expressed by the symbol $\oplus$ [37]) of an f element by a structural element E, denoted by $f \oplus E$, reduce the regions of the image with a value equal to 0 and black. The opening of a set f by a structural element E, denoted by $(f \ominus E) \oplus E$, resulting from a combination of applying the erosion operation and then the expansion, the effect is to eliminate the points or fine elements. The closing f structural element E, denoted by $(f \oplus E) \ominus E$, applies expansion and then erosion, its effect is to fill in the black holes of a certain size.

Considering mathematical morphology, morphological filters arise to represent the local transformation of geometric characteristics, satisfying the property of invariability to translation [35, 36], typically applied to binary images for the removal of unwanted elements in the image. Filters use a parameter called a structuring element of a certain size and shape type, it is chosen a priori, according to the morphology on which it is to be applied and depending on the obtaining of the shapes that you want to extract.

From the morphological operators, post-background model processing is carried out (Figure 7), using the composite opening and closing filters, to exclude the spur values contained in the image.

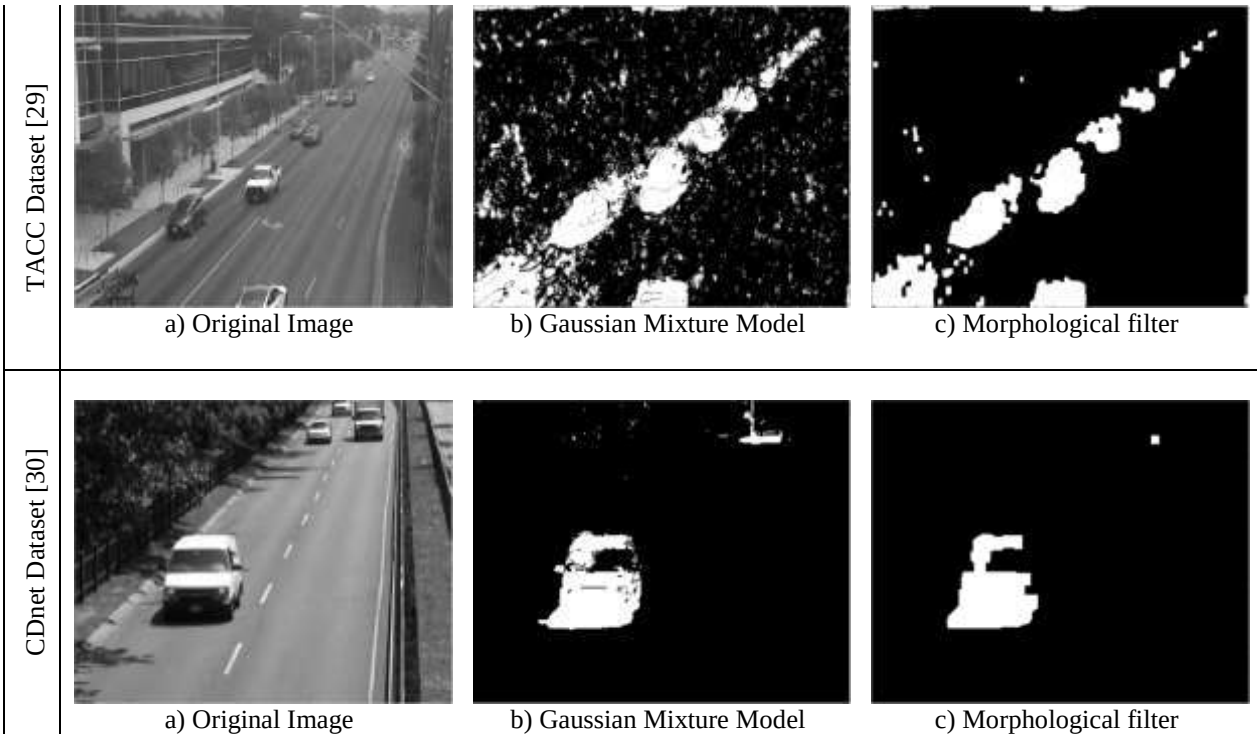


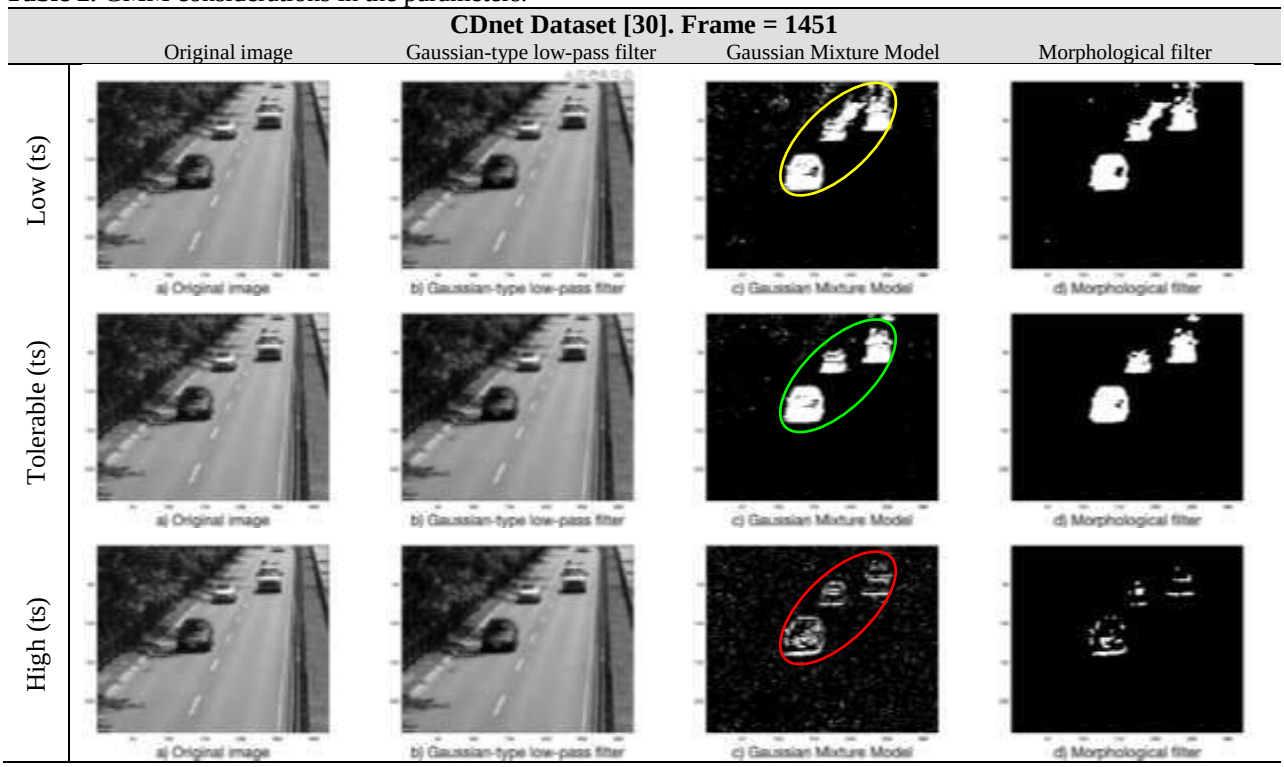
Figure 7. Remotion of spur elements. Image of the background model, left, and right image, result of applying the morphological filters of opening and closing, using a structuring element of size = 7 pixels and the type = square.

3.4. Parameterization criterion

The parameterization criterion is based on analyzing the techniques for detecting external factors to the movement (Table 3). For example, to smooth the image and attenuate noise, it is recommended to vary the filter size based on the value of the standard deviation of the Gaussian distribution, thus reducing abrupt changes in the lighting presented in each iteration. To variate the Gaussian mixture model parameters, it is suggested to make variations in the number of Gaussian, decrease the value only if the background is static. On the other hand, increasing the value helps when the background is not constant. For example, when there is a movement of the leaves of the trees, set a considerably acceptable value for the number of processing frames; vary the processing rate (ts), and control how quickly the background model adapts to lighting changes.

If (ts) it is too high, slowly moving objects can become part of the background. If it is too low, the background model will not be able to adapt to lighting changes (Table 2); set a minimum threshold to determine the background model, and thus get pixels to be considered background values; and define a value for the mixing model variance.

Table 2. GMM considerations in the parameters.



Finally, adjust the spurious element removal filter parameter, make variations to the structuring element's value, and set the 2D shape for the element. The most common are square, rectangle, disk, diamond, line, octagon, cube, sphere and cuboid.

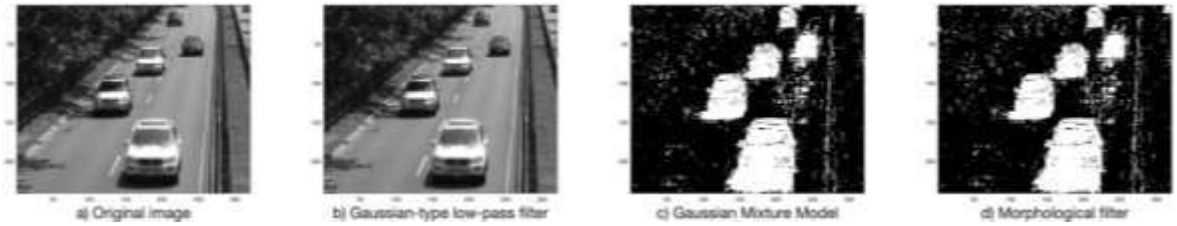
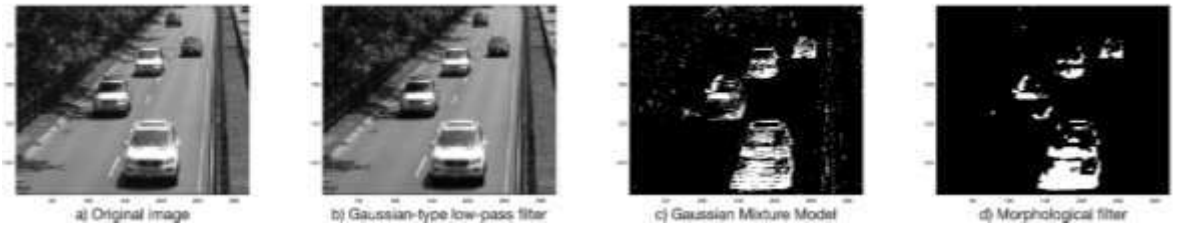
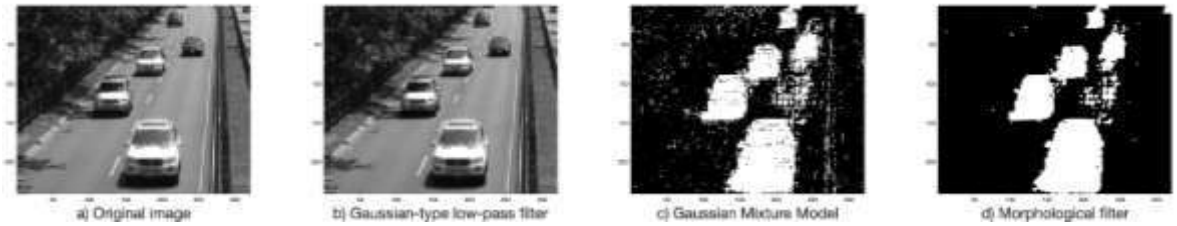
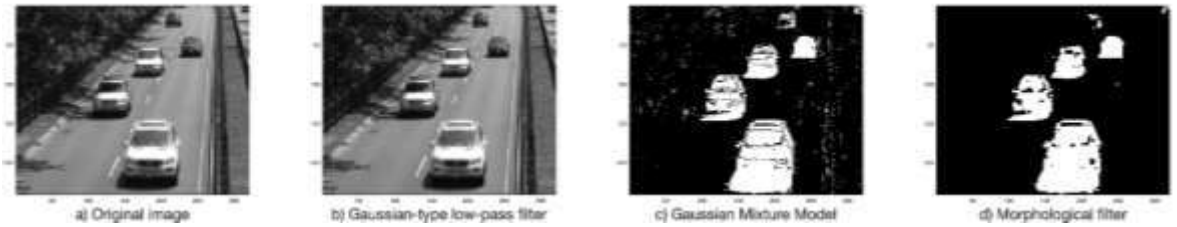
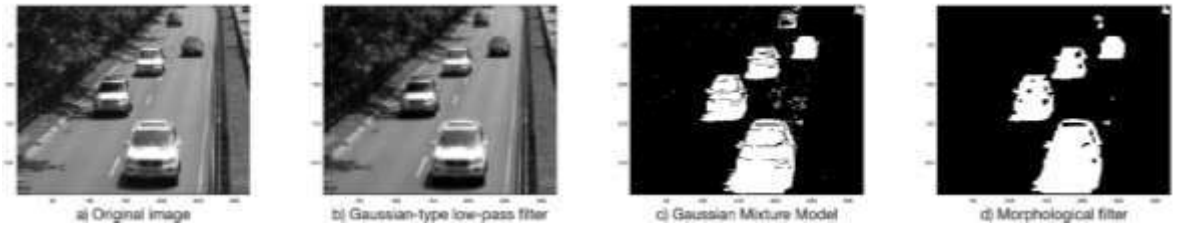
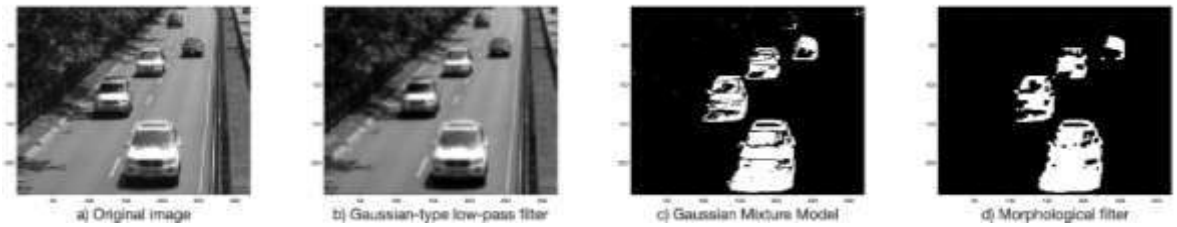
Table 3. Adjustment parameters for each technique.

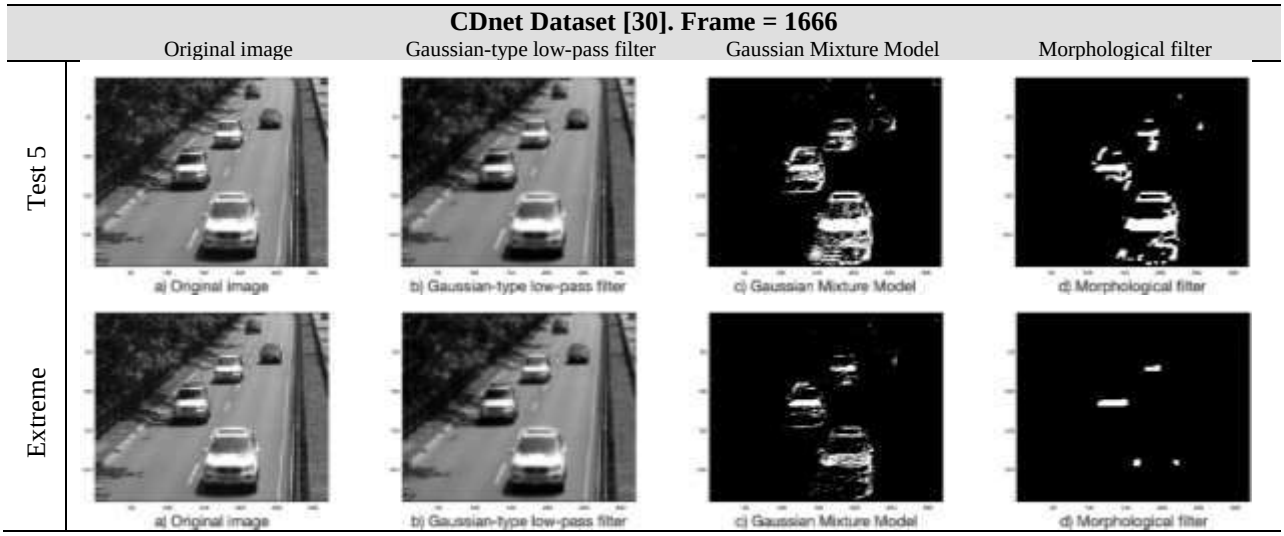
Name	Parameter	Basic	Default	Test1	Test2	Test3	Test4	Test5	Extreme
Gaussian Filter	Filter Size	[3 3]	[3 3]	[3 3]	[3 3]	[7 7]	[9 9]	[9 9]	[9 9]
	Sigma (σ)	0.100	0.500	0.333	0.333	0.777	0.999	0.999	0.999
Gaussian Mixture Model	Gaussians (k)	2	3	2	3	3	4	5	6
	Frames (ω)	10	150	150	150	450	500	750	1000
	Variance (σ2)	10 x 10	30 x 30	10 x 10	15 x 15	25 x 25	30 x 30	35 x 35	48 x 48
	Rate (ts)	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005
	Ratio (th)	0.500	0.700	0.700	0.750	0.845	0.850	0.855	0.900
Morphologic Filter	Size	1px radius	4px radius	4px radius	4px radius	10px width	10px width	10px width	15px width
	Type	Disk	Disk	Disk	Disk	Square	Square	Square	Square

Suggested value Moderate value Not favorable value

We can see below the results of applying the default parameters that each technique has (Table 4). It is observed that the morphological filter yields small elements that should not be considered objects. On the other hand, when the parameters are modified experimentally to remove the spur objects, it is observed that some objects decrease in their size, and even others are linked to each other. This phenomenon is due to a configuration of erroneous parameters.

Table 4. Apply the test parameters. The first image represents: a) the original image, the second image b) the result of applying the low-step filter, the third image c) shows the result of the background model, and finally in the last image d) the moving objects are illustrated after applying a morphological filter.

CDnet Dataset [30]. Frame = 1666				
	Original image	Gaussian-type low-pass filter	Gaussian Mixture Model	Morphological filter
Basic				
Default				
Test 1				
Test 2				
Test 3				
Test 4				



Based on the experimentation, the values of the parameters that improve or worsen the performance of the MoG are explained below.

The basic test line shows the result of applying the parameters according to the Table 3, and it is observed that in item c of the MoG model there are small white dots that could be interpreted as noise caused by the mismatch in the parameter k of the Gaussian, as well as in the morphological filter image, item d, it can be seen how the size and shape parameter of the disk-type structuring element in the morphological filter could not blur the pixels catalogued as spurious objects, giving unfavorable results in the background subtraction.

The following line displays the image as a result of the default parameters test, the values of the parameters stipulated in Table 3 are increased. In the MoG model item c, the value of k improved slightly, but spurious objects continue to appear. On the other hand, in the image of item d, it can be seen how the size and shape parameter of the disk type structuring element in the morphological filter, managed to blur the pixels cataloged as spurious objects, but also deformed the objects that are considered as movement.

Subsequently, the image is presented as result of the parameters of the first test, where again the values of the parameters stipulated in Table 3 are modified. In the MoG model item c, the shape of the objects improved slightly, but spurious objects still appear. On the other hand, in the image of item d it can be seen how the size and shape parameter of the structuring element of disk type in the morphological filter, managed to blur the pixels catalogued as spurious objects, with the difference that now the objects that are considered as movement maintain their shape, but there are still spurious elements.

The following experiment shows the image as a result of the second test, with parameter values proposed in Table 3. In the MoG model item c, it can be seen that the shape of the objects improved slightly, but spurious objects still appear. On the other hand, in the image of item d, it can be seen how the size and shape parameter of the structuring element of disk type in the morphological filter, managed to blur the pixels cataloged as spurious objects, with the difference that now the objects that are considered as movement slightly lose their shape.

In the image of the third experiment, with parameter values proposed in Table 3. In item

c of the MoG model it can be seen that the shape of the objects improved remarkably, on the other hand, in the image of item d, it can be seen how the size and shape parameter of the structuring element of square type in the morphological filter managed to blur the pixels catalogued as spurious objects, showing a clean result and being able to appreciate the objects in movement.

Now, in the image of the fourth test, with parameter values proposed in Table 3. On the other hand, in the image of item d, it can be seen how the size and shape parameter of the structuring element of square type in the morphological filter manages to blur the pixels cataloged as spurious objects, giving a clean result, with the drawback that the moving objects are slightly deformed.

For the case of the fifth test and the test with extreme parameters proposed in Table 3, in both images the value of k in the MoG model item c deforms the shape of the objects; on the other hand, in the image of item d, it can be seen how the size and shape parameter of the square type structuring element in the morphological filter manages to blur the pixels catalogued as spurious objects, only that the objects in movement are deformed and even disappear from the scene.

Therefore, it is summarized in that the space or variation of the parameters is between the noisiest and the most filtered that deform the objects. That is why there is an average which are the parameters that do not deform and remove the noise, third experiment of the Table 3.

The implementation of the algorithm is elaborated in "*.m" code and is implemented according to the following pseudo-code (Algorithm 1).

Algorithm 1. Shows the implementation of parametric adjustment.

Algorithm 1: parametric adjustment

Input: image sequence I^t
Output: $\hat{B}$, *Labels*
Initialize filter Size, σ, k, ω, σ^2, ts, th, size, type.
While *you have a sequence* I^t **do**
  get $frame_{(i)}$
  to gray(frame)
  $G(\mu,\sigma) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\left(\frac{x-\mu}{2\sigma}\right)^2}$ // Apply gaussian filter
  $P(X^t|\theta^t) = \sum_{i=1}^{k} \omega_i^t \, G(X^t|\mu_i^t, \Sigma_i^t)$ // Estimate GMM
  $(f \circ E) = (f \ominus E) \oplus E$ // Apply open morphological filter
  $(f \cdot E) = (f \oplus E) \ominus E$ // Apply close morphological filter
End

4. Results discussing

The techniques described in § 2 and § 3 were implemented making different experimental variations in the input parameters (Table 3). Once the parameters for each technique are set, the objects are discovered, obtaining the results described in Table 4.

As can be seen, the proposed criterion adapts quickly to drastic changes in lighting and dynamic backgrounds to detect real moving objects. It is important to note that this proposal blurs low frequency background noise due to movement caused by wind gusts and heatwaves.

In general, the results are good for the following reasons:

1. The inclusion of a low-pass filter eliminates drastic lighting changes.
2. It was confirmed that wind gusts, camera movements, and the sun and trees' movement greatly affect the methods of background subtraction.
3. Applying a criterion of higher intensities to a given pixel value and applying a morphological process to the Gaussian mixture result also helps obtain better results.

This proposal's most important feature is that this criterion can be adapted for any background modeling application. For example: road monitoring, defect detection, shape recognition, quality criteria in the development and manufacture of the products, motion detection in production lines.

The trend of the percentage error is shown below (Figure 8), from the calculations performed on the sample data estimated by the dataset [30], this calculation is root-mean-square error (RMSE), which is the difference between the sample values estimated by the dataset and the values observed as a result of each test (Table 3). It is observed that the trend of "test3" is the one that has the best performance of 17.74% with respect to the other tests (Table 5).

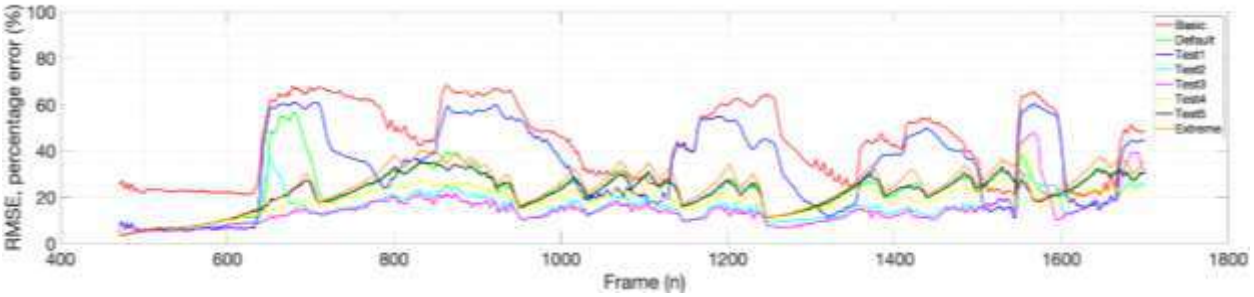


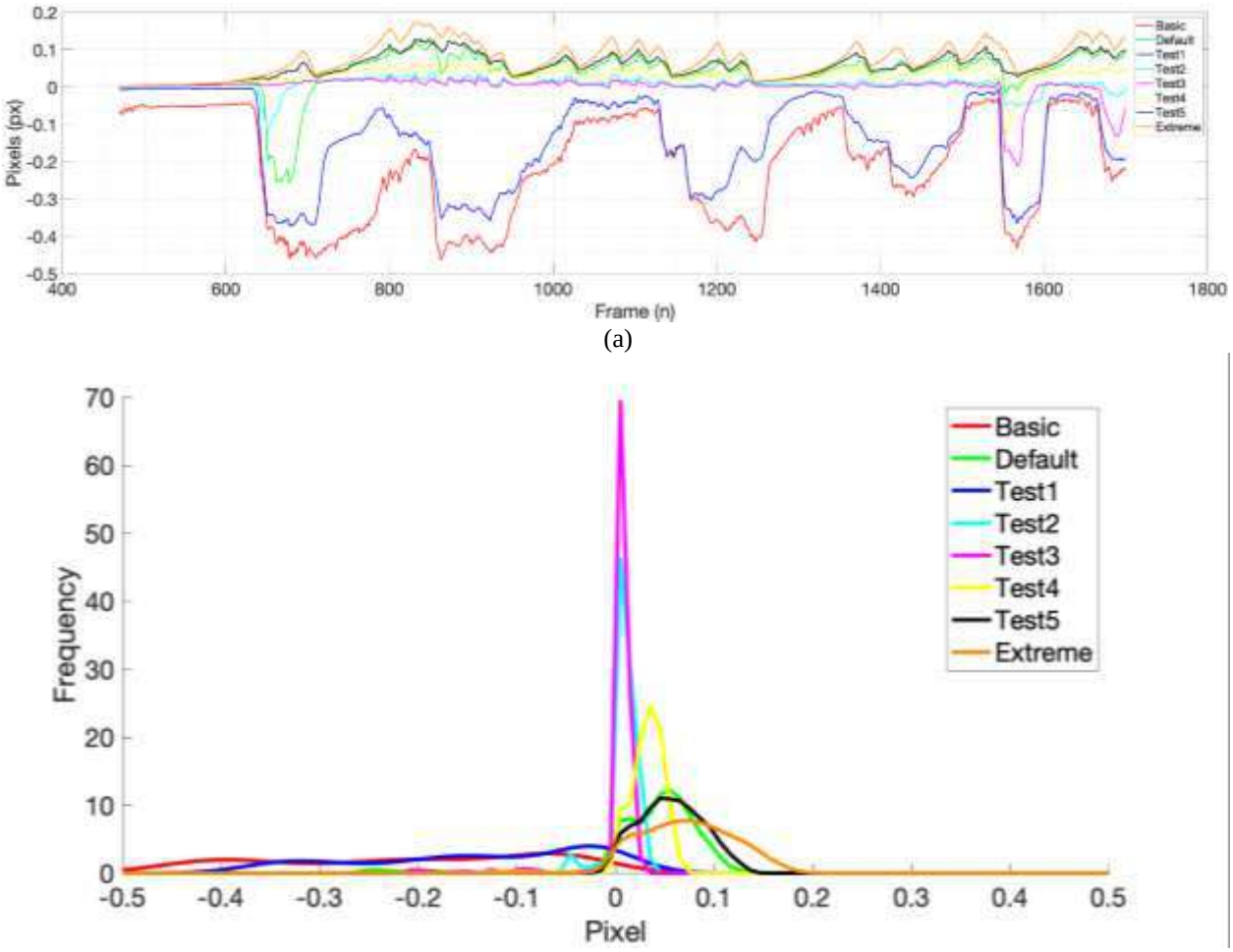
Figure 8. RMSE, percentage error trend.

Accuracy is measured using the RMSE which indicates the difference between the ground truth and the detected movement.

Table 5. RMSE, average percentage of error against the groundtruth.

Test name	Basic	Default	Test1	Test2	Test3	Test4	Test5	Extreme
Result	53.72 %	28.88 %	40.98 %	19.06 %	17.74 %	22.99 %	27.26 %	29.99 %

The Figure 9 shows the bias of the error on the data set, where the experimental results indicate how the background model adjusts to the test scenario. Note that the error change refers to the dynamic changes of the scenario. It reflects the inclusion of density of moving objects and some effects such as reflection and shadows. The basic test and smaller parametric values have a low impact on performance, indicating that the parameters become insufficient to catch the pixel dynamic of the scenario. Then, aggressive parametric values affect adding motion noise, but with the advantage that it adapts better to the background. These situations become better illustrated in (b), where the best parametric combinations correspond to the second test and third test; such as they become a more centered bias distribution.



(a)

(b)

Figure 9. Bias Error: (a) shows the error trend over time for each frame; (b) distribution of Bias.

Summing up, the parameter affectation's influence is described as follows: The Gaussian Filter has a significant impact because it homogenizes and dismisses those situations where the camera catches noise data. The noise data becomes observable in the borders or isolated regions affected by reflections. The Gaussian filter ignores the abrupt data changes; however, using a bigger filter decreases the image information that affects the border recognition of objects detected. The number of images used to approximate the initial background might affect whenever it takes a few frames, this is, as long as the camera frame rate ratio and the amount of frame used to approximate the initial background are small, the initial movement will be affected by spurious objects. After that, the variance used to estimate the model affects the operation because it is related to the convergence of the EM step in the background updating. Suppose the variance is close to the mean. In that case, the variability becomes higher, causing that the gaussian mean does not reach a convergence, prescribing suddenly spurious regions in consecutive frames, even, there are no intensities variations. The conclusions become a higher value and dependable on the number of gaussians used in the training step. An empirical rule [38] to follow is: $\sigma_0 = \frac{R}{\sigma \times N_g}$, where, $R = 2^8$ is the rank of the sensor, $9\sigma_0$ is the width of a gaussian with the 95 of significance and N_g the number of maximum

of gaussian to model a pixel, which for the case of 5 Gaussians and 8 bit depth, the initial σ_0 be $\frac{255}{9\times5} \approx 6$, which refers to $\sigma_0^2 = 36$.

Finally, the morphological filter becomes useful as a generalized area filter that helps to complete blobs (by eliminating holes) or dismiss small artifacts representing spurious objects. The filter size becomes related to the image perspective and image dimensions. This situation makes that for specific scenarios dimension at the center of the image, artifacts' noise ratio area is more precise in its detection. Instead of regions with high perspective levels, the objects become deformed.

We will consider the study of the perspective effects in the parameter estimation for morphological filters for further works because it assumes a fixed front parallel perspective.

Other disturbance affectations include color invariances in reflecting surfaces and color variations disturbances in outdoors environments.

5. Conclusion and future work

The results of this work allow to optimize motion detection (controlled and uncontrolled) this includes for example outdoor scenarios (uncontrolled) or motion detection in production lines where it is complicated to control light variations.

The method of background subtraction based on a mixture of Gaussian performs its task efficiently, although it exhibits some deficiencies in its parameterization. This work proposes a brief parameter review that improves the current results reported in the literature. This work leaves open the possibility of continuing to experiment with the parameters for these methods and determining and applying a more objective way for their evaluation and comparison. Finally, adding a technique for detecting and removing shadows to increase the robustness in the background model.

The objective is to analyze the parameters and the effects they have on motion detection. The contribution is the proper search of the parameters (Table 3), so that the background model performs better (Table 4).

Another advantage of this study is that many of the researchers use background models but have not delved into an analysis of the parameters and how they affect motion detection. In general terms, they do not express what are the values of their parameters/variables that integrate their algorithms, only formulas and/or equations are defined, showing only the percentage of effectiveness (score) [39] and its comparison with other algorithms.

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