Detection And Tracking Of Moving Objects using Particle Filter

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Abstract— **Motion detection is the first essential process in the extraction of information regarding moving objects and makes use of stabilization in functional areas such as tracking, classification, recognition, and so on. In this paper, high-quality moving object detection is determined by using nonparametric modeling. The background is modeled by using the combination of chromaticity and gradients; it reduces the influence of shadows and reflected light. The foreground model combines this information and spatial information. Particle filter is introduced update the spatial information. The detection results produced by the particle filter is analysed through visual inspection and for accuracy, along with comparisons to the results produced by other state-of-the-art methods.**

Keywords- non parametric model, chromaticity, particle filter.

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INTRODUCTION

The design of an advanced automatic video surveillance system requires the application of many important functions including, motion detection[1], classification, tracking behaviour [2], activity analysis, and identification. Motion detection is one of the greatest problem areas in video surveillance as it is responsible for the extraction of moving objects, and also critical to many computer vision applications including object-based video encoding, human motion analysis, and human-machine interactions [3].The importance of moving object detection strategies, they are still far from being completely solved in complex environments. Thus, there are several problems that must be addressed, such as dynamic backgrounds (water surfaces, waving flags and trees, etc.), moving objects with areas similar to background regions, foreground objects in the training period, gradual and sudden illumination changes, or local changes such as shadows and reflected light.

In this research work, we proposed a very fast background, foreground-based nonparametric segmentation strategy, which is suitable for its application to video surveillance operating in real time either in outdoor or in indoor complex environments. Nonparametric background and foreground models are obtained by an innovative combination of chromaticity and gradients, reducing the influence of shadows and reflected light in the detections.
The detection strategy is based on a particle filter is designed to deal with an unknown and variable number of independent moving objects. Applying the nonparametric modeling over the areas, which is provided by the particle filter, combined with the result of an innovative windowed random sampling (WRS), an important reduction in computational requirements is achieved.

The spatial information is considered only for the foreground modeling, resulting in an additional improvement of the efficiency: less computational cost and less memory requirements. So, in addition to the quality of the obtained results, the achieved reductions (memory and computational costs) are high enough to justify the implementation of the proposed strategy.

In section II, we develop the nonparametric background and foreground by combination of chromaticity and gradients. In section III, particle filter is used to improve the quality of the detections and reduce the computational cost. In section IV, state-of-the-art methods is included in the performance study, our method proved to be of higher efficacy.

PROPOSED METHOD

Nonparametric Background Modeling

Let us consider, for each pixel p^n at time n, a D-dimensional vector x^n. This vector contains D different characteristics of p^n. Let x^i denote the set of corresponding D-dimensional vectors from the pixels at the same spatial position in the N_β previous images, which will be used as reference samples. The probability density function (pdf) p^n belongs to the image background, β, can be estimated non-parametrically as

$$p(\mathbf{x}^n|\beta) = \frac{1}{N_\beta}\sum_{i=1}^{N_\beta}|\Sigma_\beta|^{-1/2} K\left(\Sigma_\beta^{-1/2}\left(\mathbf{x}^n - \mathbf{x}_\beta^i\right)\right)$$

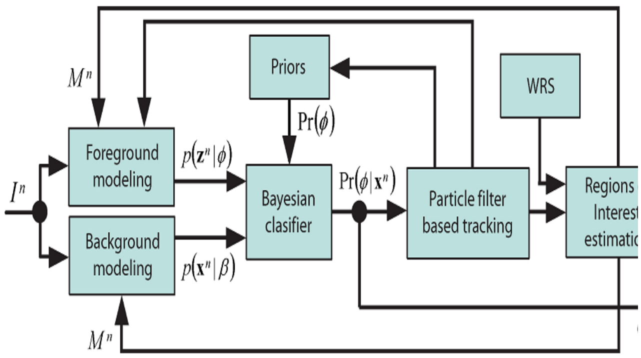
where ∑β is a symmetric positive definite D × D bandwidth matrix that specifies the "width" of the kernel, K, around each sample point.

In this way, applying Gaussian kernels, the background likelihood can be rewritten as

$$p(\mathbf{x}^n|\beta) = \frac{1}{N_\beta(2\pi)^{D/2}}\sum_{i=1}^{N_\beta}\prod_{j=1}^{D}\frac{1}{|\Sigma_\beta(j,j)|^{1/2}}$$

In Figure 1. contains two main steps: a Bayesian classifier, where the moving objects are separated from the background, and a tracking strategy, which improves the efficiency of the Bayesian modeling and reduces the area to be analyzed in the following image.

Shadows and reflected light are very common in video sequences and, working in a typical RGB color space, they are frequently detected wrongly as foreground [4], resulting in a source of confusion in posterior phases of analysis. To avoid this problem and discriminate between moving objects and their shadows, the chromaticity (normalized components) can be used instead of the RGB components.



Flowchart for the proposed background model

B. Nonparametric Foreground Modeling

Moving regions can show colors and gradients similar to those of the background. In these cases, object detection using only background modeling is not enough to discriminate between foreground and background [4]. To address this limitation and to improve the accuracy in the results, we propose to combine the previously presented background modeling with an efficient and novel foreground modeling strategy.

C. Bayesian Classifier

Once we have modeled both foreground and background, we can evaluate the probability of each pixel belonging to each of the two classes. Using Bayes' theorem, we can write

$$\Pr(\phi|\mathbf{x}^n) = \frac{\Pr(\phi)\,p(\mathbf{x}^n|\phi, r^n, c^n)}{\Pr(\phi)\,p(\mathbf{x}^n|\phi, r^n, c^n) + \Pr(\beta)\,p(\mathbf{x}^n|\beta)}$$

where Pr(φ) and Pr(β) are the prior probabilities for fore-ground and background, respectively.

Background has been modeled independently for each pixel location; the foreground has been modeled considering spatial information. Thus, to compare both defined models in the pixel (r^n, c^n), we shall condition our foreground model on that particular location [5]. This conditional probability can be expressed as

$$p(\mathbf{x}^n|\phi, r^n, c^n) = \frac{p(\mathbf{z}^n|\phi)}{p(r^n, c^n|\phi)}$$

where $p(r^n, c^n|\varphi)$ is the marginalization of the estimated foreground likelihood, $p(z^n|\varphi)$.

PARTICLE FILTER

Our proposed work is to update the foreground spatial information through a multi-region tracking strategy. This update allows preservation of the required quality by selecting a smaller buffer of images, N_φ, and reduced foreground spatial bandwidths, ($\sigma_{\varphi H}^2$, $\sigma_{\varphi W}^2$), achieving a significant decrease of the computational and memory requirements. For this purpose, we have used a particle filter, which is able to deal with multiple appearing and disappearing foreground regions.

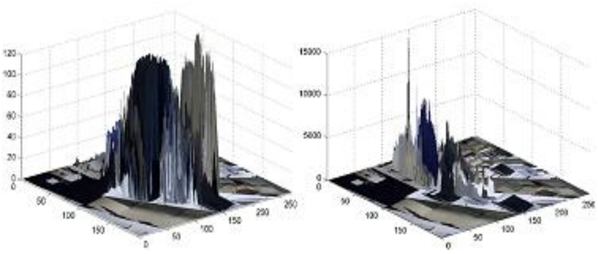
The position of predicted particles is combined with the result of a WRS to generate a mask, M^n, containing the regions to be analyzed in the following image. While the positions of the particles determine the areas where the existing moving objects are expected to appear in the future, the WRS avoids the possible misdetections of new moving objects. In this way, we reduce the number of pixels to be analyzed, achieving a very significant reduction in the computational requirements of the system.

Foreground Region Update

Let us consider a foreground region, corresponding to a moving object detected at image I^n. All the pixels of this region will be used to construct the foreground probability density function along the N_φ following images. Usually, the content of this region (color and gradient information) will maintain similar values along these N_φ next images.

Sequence	No.of Images	Duration (s)	Size(Height X Width)
Lab_001	325	13	288 x 352
Lab_002	380	15	288 x 352
Lab_003	550	22	198 x 272
Lab_004	500	20	196 x 282
Lab_005	250	10	288 x 352
Lab_006	700	28	167 x 266
Test - Set	2705	108	

Figure 2. shows some results obtained from the analysis of two video sequences: applying the conventional nonparametric foreground modeling [6] updating the coordinates of the previously detected moving objects [Figure 2.]. These results are more accurate and, consequently, the final detections provided by the proposed strategy show best quality results with more compact and better defined moving regions.



Updating the spatial position of previously detected foreground regions

RESULTS

To evaluate the proposed strategy, quality of the results has been analyzed. Then, the system has been tested in several indoor and outdoor environments containing critical situations, such as dynamic backgrounds, shadows, illumination changes, and multiple moving objects with significant gray areas and similar to background regions.

We have used a set of six sequences, described in Table I, extracted from our lab database [7]). These sequences cover the required challenging scenarios (indoor and outdoor), contain a different number of moving objects with different sizes, and having several background environments. In addition, we have considered the union of all these sequences (labeled as *Test-Set*) to provide an overall result for some analysis stages.

Computational analysis

Applying typical processing values [6], Table II presents the background computational comparison at pixel level, between our method and the above-mentioned nonparametric strategies.

DESCRIPTION OF THE TEST SEQUENCES

This comparison shows that background modeling without a spatial modeling allows us to reduce four or five orders of magnitude the number of operations, depending on the image sizes. As this reduction is proportional to the size of the images, the computational savings are greater for larger images.

The total computational reduction, obtained for all the test sequences, is shown in Table II. The fifth column (labeled as Reduction 1) shows the computational reduction resulting from the application of the background modeling without spatial information. This result allows us to appreciate that the proposed strategy, by updating the previously detected moving objects and to significantly reduce the computational cost provided by other nonparametric modeling strategies.

Finally, we have analyzed the computational cost in each stage of the proposed system. The summary of the results is shown in Table III. These results show that the foreground modeling is responsible for the main computational cost. The cost of the background modeling is proportional to the size of the images, and the cost of the foreground heavily depends on the percentage of moving objects in each sequence.

B. Quality Analysis

The conventional *recall* and *precision* evaluation parameters have been used to provide an objective measure of the performance of the algorithm

$$\text{Recall} = 100\frac{CD}{CD + ND}\%\,,\quad \text{Precision} = 100\frac{CD}{CD + FD}\%$$

where CD is the number of correctly detected foreground pixels, ND is the number of non detected foreground pixels, and FD is the number of false detections.

Additionally, the *F* measure [8] has been used to evaluate the call and the precision as follows:

$$F = \frac{2 \times \text{recall} \times \text{presision}}{\text{recall} + \text{precision}}\%.$$

COMPUTATIONAL REDUCTION PERCENTAGES

Sequence	Foreground Pixels	No. of moving objects	Computed Pixels	Reduction 1
Lab_ 001	1.00%	1	14.08 %	77.60%
Lab_ 002	2.47%	2	23.61%	71.90%
Lab_ 003	2.72%	1	15.86%	82.98%
Lab_ 004	2.79%	1	17.73%	69.32%
Lab_ 005	0.94%	2	15.44%	81.94%
Lab_ 006	5.25%	1	33.94%	65.81%

COMPUTATIONAL ANALYSIS IN EACH STAGE OF THE PROPOSED SYSTEM

	Background Modeling	Foreground Modeling	Particle Filter	Other
Percentage of cost	23.7%	61.2%	13.9%	1.29%
Mean processing time	56 ms	144 ms	33 ms	3 ms

First, we have analyzed (using RGB color components) the quality of the detections by combining the proposed background–foreground modeling and the estimated prior probabilities.

On the one hand, these results show that combining background and foreground the recall is higher (moving objects are better detected). In addition, this increase in recall is even greater when the estimated prior probability is added.

The achieved precision decreases by incorporating the foreground modeling and the prior probabilities. By adding this information, we achieved the moving objects, shadows and the light they reflect are detected better. Thus, the amount of false detections also increases (especially on sequences with more shadows and reflected light).

Table IV presents the final obtained results, compared to the results provided by the color-space-based nonparametric background–foreground modeling strategy in [6]. These results show that we are able to obtain higher recall percentages than [6] in all the analyzed sequences, except in those where the moving objects remain static a prolonged period (e.g., *Lab_ 006)*

EXPERIMENTAL RESULTS

Sequence	Nonparametric Modeling			Proposed strategy estimation		
	Recall	Precision	*F*	Recall	Precision	*F*
Lab_ 001	**88.14**	**47.06**	**61.36**	**95.20**	**88.36**	**91.66**

Lab_002	**87.20**	**71.48**	**78.56**	**93.35**	**86.85**	**89.98**
Lab_003	**62.72**	**77.58**	**69.36**	**74.64**	**86.92**	**80.32**
Lab_004	**72.66**	**90.56**	**80.63**	**95.91**	**92.60**	**94.23**
Lab_005	**88.79**	**49.31**	**63.41**	**94.42**	**82.36**	**87.98**
Lab_006	**44.36**	**74.81**	**55.70**	**75.47**	**72.48**	**73.95**

CONCLUSION

This paper has presented a high-quality moving object detection strategy for lightweight applications. The background is modeled by using the combination of chromaticity and gradients; it reduces the influence of shadows and reflected light. The foreground model combines this information and spatial information. Thus, we reduced several orders of magnitude, the computational cost of other nonparametric-based modeling strategies, using spatial information in both background and foreground.

Additionally, we proposed a particle filter-based tracking strategy that enhanced the foreground modeling, also to increase the number of correct detections, decrease the amount of misdetections, and achieve an additional reduction of the computational and memory requirements.

The results of our approach were analyzed both quantitatively and qualitatively in a wide range of natural video sequences.

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