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Efficient background subtraction method based on fast independent component analysis in video-surveillance

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ABSTRACT

Modern video surveillance has now become an active area of research with a large set of requirements and various applications. In order to detect moving objects in video surveillance scenes, background subtraction techniques are the most used. In this paper, we developed and tested an efficient background subtraction technique in video surveillance based on the fast-independent component analysis (fast-ICA) method. The proposed technique initiated, first, on the use of a developed fast-ICA algorithm in order to estimate the de-mixing matrix and the denoising matrix parameters. Second, the estimated foreground can simply model by multiplying the data matrix with the de-mixing matrix. After that, the data matrix is multiplied by the denoising matrix for removing the noise. In addition, we propose a pre-processing and post-processing operations to effectively segment the true foreground objects and improve our results. The proposed method is evaluated on the publicly available change detection datasets CDnet 2012 and CDnet 2014 using performance parameters such as recall, precision and $F_{measure}$. Experimental results show that our algorithm can detect effectively and accurately the moving objects in several background and foreground conditions compared to other methods in literature with real-time frame rate.

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1. INTRODUCTION

Background subtraction is a popular approach to segment moving objects under a stationary camera [1]–[6]. It detects moving objects in an image by evaluating the difference of pixel features of the current scene image against the reference background image [5], [7]–[9]. Furthermore, background subtraction techniques offer suitable solution [6], [10], [11] which provide a good compromise in terms of quality of detection and computation time. There are various problems that an effective background subtraction algorithm must resolve correctly [10], [12], [13], such as many levels of illumination at different times of the day, dynamic backgrounds,weather condition, shadows cast by moving objects, and objects being introduced or removed from the scene [9], [14], [15].

To take into account these difficulties, numerous background-modeling techniques have been developed in literature, where these methods can be classified into four main classes: basic techniques, statistical techniques, machine learning techniques, and other techniques [11], [16]. Although many relatively fast background-modeling methods have been proposed for real-time implementation, but the updating process still consumes an important amount of total computation time, and restricts the image frame to a small size. This causes a low image resolution, and the object of interest may seem as a small foreground region in the scene image [14], [17], [18]. Furthermore, it can incorrectly absorb a foreground object into the background if the object remains stationary for a long period. To manage with the problem of stationary foreground objects, a reference background image that has no moving objects may be required. Background subtraction based on a single reference image is very computationally fast. However, it is also very sensitive to illumination changes, which deters the use of such an approach in many surveillance applications [19]. The problem of identifying moving objects in complex environment is still an interesting domain of research [20], [21].

Recently, the independent component analysis (ICA) technique, which is known by its robustness in the signal-processing field, is getting much attention in the image-processing field [22]. ICA is a statistical technique, perhaps the most widely used, for solving the blind source separation (BSS) problem [23]. The purpose of ICA is to restore statistically independent source signals, given only a mixture of these signals without knowing the mixing matrix of the sources. ICA is used now in many diverse requests like sound separation, image processing , medical signal analysis, dimension reduction, coding and text analysis, and telecommunication [24]. Additionally, ICA has been introduced in video processing to cope with the issue of foreground estimation [25], [26].

In this paper, an efficient framework is presented for background subtraction by independent component analysis in video-surveillance. Wherever in an image the moving objects are considered to be independent from the background, thus we adapt and custom fast-ICA algorithm [27]–[29] to: first, estimate the best de-mixing matrix that can separate a scene image into foreground objects and motionless background and second, estimate the denoising de-mixing matrix that used for removing noise. The proposed ICA-based background subtraction technique consists of four steps: pre-processing, training step, detection step and post-processing. In the first step, we propose to convert all images to YCrCb color space, where the luma component Y (brightness of the color) is taken for all the treatments to improve the detection results. In the training phase, two selected images are carefully chosen to make the data matrix, one representing the reference background and the other containing an arbitrary foreground objects. Then, the fast-ICA algorithm is applied to estimate the de-mixing matrix parameters, which will be used in the detection step. Another, execute the fast-ICA algorithm on a data matrix obtained from two images, one representing the reference background and the other representing successive background images with different noise sort (various levels of illumination, waving trees, rain, and fog) for the denoising matrix estimation. In the detection phase, the data matrix is constructed from two images; one is an incoming image from the sequence and the other is the most modern offered background. The estimated foreground is then simply found by multiplying the data matrix one time with the de-mixing matrix and second time with the denoised de-mixing matrix for filtering noise. We suggest a post-processing operation to effectively segment the true foreground objects and improve our results. The proposed ICA-based background subtraction technique can successfully segment and filter the foreground objects under large environmental changes for indoor/outdoor surveillance applications.

The remainder of this paper is organized as follows. The proposed framework is presented in section 2. In section 3 shows the experiments results and demonstrates the detection performance of the proposed system. Finally, the conclusion is drawn in section 4.

2. METHOD

Assuming that the video scenes are acquired by a stationary camera, the moving objects are considered independent from the background image. Thus, to separate the motion objects, we apply a proposed background subtraction method based on the fast-ICA algorithm, which consists of four steps: pre-processing, training step, detection step and post-processing. Let's denote the reference background image by B of size $k = m \times n$, and any frame from the scene by F, the approximated foreground by F_g, the noise model by N, the data matrix by X, the de-mixing matrix by W, the denoising de-mixing matrix by W^d and the filtered foreground by ${F_g}^d$.

2.1. Pre-processing

Generally, the most common color space utilized in background subtraction is the red, green, blue (RGB) format [30], [31]. Many methods use the gray scale converted from RGB format to reduce the computational work for real time system. However, it is well known that R, G, and B color components are correlated and this results in the increased sensitivity to illumination changes. Other color spaces have been explored [32] with the best results being obtained with color spaces that separate luminance from chrominance, such as YCrCb or L, a, b. The advantages of using other color spaces than RGB are exactly to enhance robustness to noise and shadows in image processing applications [30]. Although YCrCb is considered as the best working mode in color images, the chance of misclassification of this color model increases when scenes contain dark pixels [33]. In our technique, we propose to convert all the input images from RGB format to YCrCb color space. Then, we take only the luminance component Y and reshape it from matrix to row vector by the following linear transformation:

$$V(1,\ [n \times (i-1)] + j) = Y(i,j) \tag{1}$$

where $i = 1,2,\dots,m$, $j = 1,2,\dots,n$, V is a row vector of size $(1 \times k)$. $B_V = [b_V^1\ b_V^2 \dots\ b_V^k]$, $F_V = [f_V^1\ f_V^2 \dots\ f_V^k]$ are respectively two row vectors obtained by (1) from the two images B and F. Indeed, this method is mainly used that has an effect on the foreground/background segmentation accuracy and it has proven its effectiveness in real time application, as we will see in what follows.

2.2. The training steps

In this step, two images are carefully selected to define first data matrix X_1, one represents the reference background and the other contains an arbitrary foreground object. To estimate the de-mixing matrix W, the fast-ICA algorithm is applied on the data matrix X_1 of size $(2 \times k)$, which is assembled from two row vectors B_V and F_V as (2):

$$X_1 = \begin{bmatrix} [B_V] \\ [F_V] \end{bmatrix} = \begin{bmatrix} b_V^1\ b_V^2 \dots\ b_V^k \\ f_V^1\ f_V^2 \dots f_V^k \end{bmatrix} \tag{2}$$

to get accurate estimation of W, the algorithm is implemented with a choice of the contrast functions cited in [27], [28] that offers more robustness and a convergence gone to order 10^{-30}. After few iterations, we obtain the resulting de-mixing matrix $W = \begin{bmatrix} [w_{11} & w_{12}] \\ [w_{21} & w_{22}] \end{bmatrix}$, where the first row of W is associated to isolate the background and the second row is related to separate the foreground object without details of the reference background.

In addition, we propose to introduce an estimated denoising matrix W^d, where the noise $N\ (\mu, \sigma)$ is modelled by its mean μ and standard deviation σ. Thus, a second data matrix X_2 is composed from reference background and consecutive background images with different noises, such as various levels of illumination and waving trees. Estimation of W^d is similar to that of W except that the data matrix is now collected from the reference background B_V and consecutive background images B_V^*;

$$X_2 = \begin{bmatrix} [B_V] \\ [B_V^*] \end{bmatrix} = \begin{bmatrix} b_V^1\ b_V^2 \dots\ b_V^k \\ b_V^{*1}\ b_V^{*2} \dots\ b_V^{*k} \end{bmatrix} \tag{3}$$

the resulting denoising matrix is $W^d = \begin{bmatrix} [w_{11}^d & w_{12}^d] \\ [w_{21}^d & w_{22}^d] \end{bmatrix}$, where the second row associated with noise model N. Now, B, W, W^d and N are fixed to be used in the detection phase to separate foreground objects and noise removal from each frame of the sequence (the training step is completed just one time).

2.3. The detection steps

In this step, for every incoming frame at time t, a new data matrix X_t is constructed from the current frame and the reference background image (after the passage with the linear transformation given by (1):

$$X_t = \begin{bmatrix} [B_V] \\ [F_V]_t \end{bmatrix} \tag{4}$$

the estimated foreground is found simply by multiplying the data matrix X_t with W as (5):

$$(F_g)_t = W \times X_t \tag{5}$$

then, another data matrix $X^n{}_t$ is assembled from the estimated foreground $(F_g)_t$ and the noise model N:

$$X^n{}_t = \begin{bmatrix} [N_V] \\ \left[F_{g_V}\right]_t \end{bmatrix} \tag{6}$$

the estimated foreground is filtered by multiplying $X^n{}_t$ with W^d:

$$(F_g{}^d)_t = W^d \times X^n{}_t \tag{7}$$

the final result $(F_g{}^d)_t$ is reshaped to obtain a matrix $(m \times n)$ by inversing the linear transformation in (1).

2.4. Post-processing

Since the classification decision is independently made for each pixel, the foreground segmentation result can be profited from regularization step, which combines information from neighbouring pixels and allocates homogeneous labels on uniform regions [34]. We suggest a post-processing operation to effectively segment the true foreground objects and improve our results. First, if necessary, we apply a second simple filtering using a gaussian filter $G(\mu, \sigma)$ with the parameters mean μ and standard deviation σ obtained from the training step (the noise model $N\ (\mu, \sigma)$), to perform our results:

$$(F_g{}^d)_t = (F_g{}^d)_t \times G(\mu, \sigma) \tag{8}$$

second, a morphological transformation is used to perform the open and close operation, respectively.

$$(F_g{}^d)_t = Open\ ((F_g{}^d)_t) \tag{9}$$

$$(F_g{}^d)_t = Close((F_g{}^d)_t) \tag{10}$$

The block diagram is shown in Figure 1.

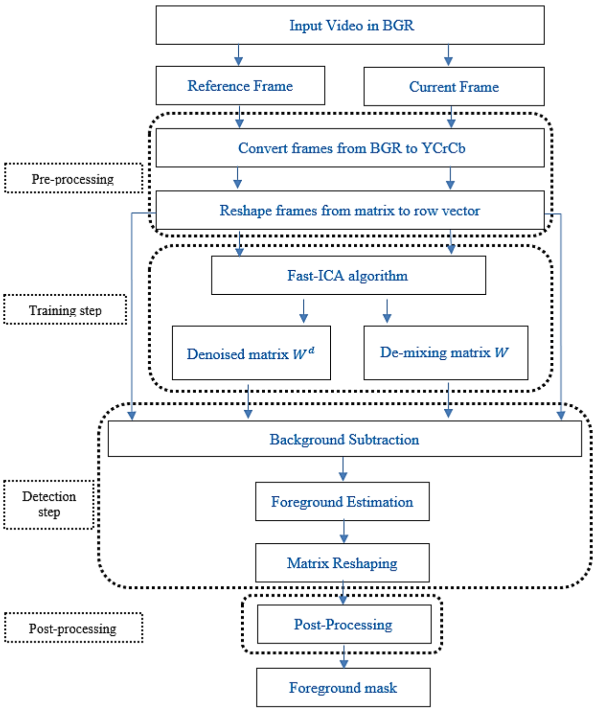


Figure 1. Design of the proposed system

3. RESULTS AND DISCUSSION

3.1. Evaluation datasets

In order to evaluate the efficiency of the proposed algorithm [35], we use a publicly available change detection dataset 2012 (CDnet 2012) [36] and 2014 dataset (CDnet 2014) [37]. As one of the most challenging detection benchmark dataset, the CDnet 2014 dataset is a second version of the CDnet 2012 dataset. In this framework, we have used four categories from CDnet 2012 and three categories from CDnet 2014 in several areas with different challenges. Pedestrians from the "baseline" category, overpass from the "dynamic background" category, traffic from the "camera jitter" category, winter driveway from the "intermittent object motion" category, turnpike_0_5fps (frames per second) from the "low frame-rate" category, StreetCornerAtNight from the "night videos" category, and turbulence0 from the "turbulence" category.

3.2. Evaluation metrics

To measure how well our process matches the ground-truth, we use three performance measures [37]: $Recall$, $Precision$, and $F_{measure}$, which they are defined as (11), (12) and (13):

$$Recall = \frac{TP}{TP+FN} \tag{11}$$

$$Precision = \frac{TP}{TP+FP} \tag{12}$$

$$F_{measure} = \frac{2\times Recall\times Precision}{Recall+Precision} \tag{13}$$

where TP is the number of true positives, TN is the number of true negatives, FN is the number of false negatives, and FP is the number of false positives.

$Recall$ is a ratio of true detection to the ground truth that measures the capability of an algorithm to detect the true foreground pixels, it can be seen from (11) that $(TP + FN)$ represent the number of the true foreground pixels obtained by the ground truth. $Precision$ is a ratio between the number of true detections and the number of all detections, it gives a hint to the exactness of the detection. From (12), $(TP + FP)$ represent the foreground pixels classified by a given algorithm. $F_{measure}$ is the harmonic mean between $Recall$ and $Precision$ (a large value of $F_{measure}$ is better).

When applied to the entire sequence, $Recall$ and $Precision$ reported are averages over all the measured frames. Typically, there is a trade-off between $Recall$ and $Precision$, $Recall$ usually increases with the number of foreground pixels detected, which in turn may lead to a decrease in $Precision$. A good algorithm should attain as high a $Recall$ value as possible without sacrificing $Precision$.

3.3. Quantitative results

These experimental sequences are chosen to test the effectiveness of the proposed algorithm in many areas and to demonstrate how it can recover a suitable performance. Table 1 presents the quantitative measures of each sequence using $Recall$, $Precision$ and $F_{measure}$. We can see that our method achieves an overall $F_{measure}$ of 0.8887 on the datasets. On CDnet 2012 dataset (the first two categories), the $F_{measure}$ scores between 0.87 and 0.96 for the four sequences. For the latter three new add categories from CDnet 2014 although these categories are much harder to deal with, the results show that the $F_{measure}$ marks between 0.85 and 0.87. Since the CDnet 2014 comprise more problematic noises model than CDnet 2012, also it contains many out of scope regions in the ground truth labels at pixel level (05 labels) [37]. These results show the competence of our method.

Table 1. Quantitative evaluation of the proposed framework

Dataset	Category	Sequence	Recall	Precision	F_measure
CDnet 2012	Baseline	Pedestrians	0.9968	0.8142	0.8963
	Dynamic background	Overpass	0.9801	0.8135	0.8890
	Camera jitter	Traffic	0.9888	0.9422	0.9649
	Intermittent object motion	Winter driveway	0.9942	0.7823	0.8756
CDnet 2014	Low frame-rate	Turnpike_0_5_fps	0.9926	0.7771	0.8717
	Night videos	StreetCornerAtNight	0.9901	0.7496	0.8532
	Turbulence	Turbulence0	0.7809	0.9822	0.8701
Overall			**0.9605**	**0.8373**	**0.8887**

The obtained performance is compared with different frequently-cited techniques, which are the Gaussian mixture model (GMM) by Stauffer and Grimson [38], kernel density estimation (KDE)-based estimation by Elgammal *et al.* [39], k-nearest neighbor (KNN) method in [40] as a recursive GMM method with an improved update of the gaussian parameters, self-balanced sensitivity segmenter (SuBSENSE) in [41] and boosted of Gaussians modeling (BMOG) in [32]. Among the more recent methods, we have chosen deep background subtraction (DeepBS) by Babaee *et al.* [42]. This use a deep convolutional neural network for video sequence background subtraction. multiscale fully convolutional network (MFCN) by Zeng and Zhu [34]. This method draws on the recent success of transfer learning and fully convolutional network for semantic segmentation. Fast detection (Fast-D) by Hossain *et al.* [43]. The results of this comparison are recapitulated in Table 2. These results are from [44] or from their original papers.

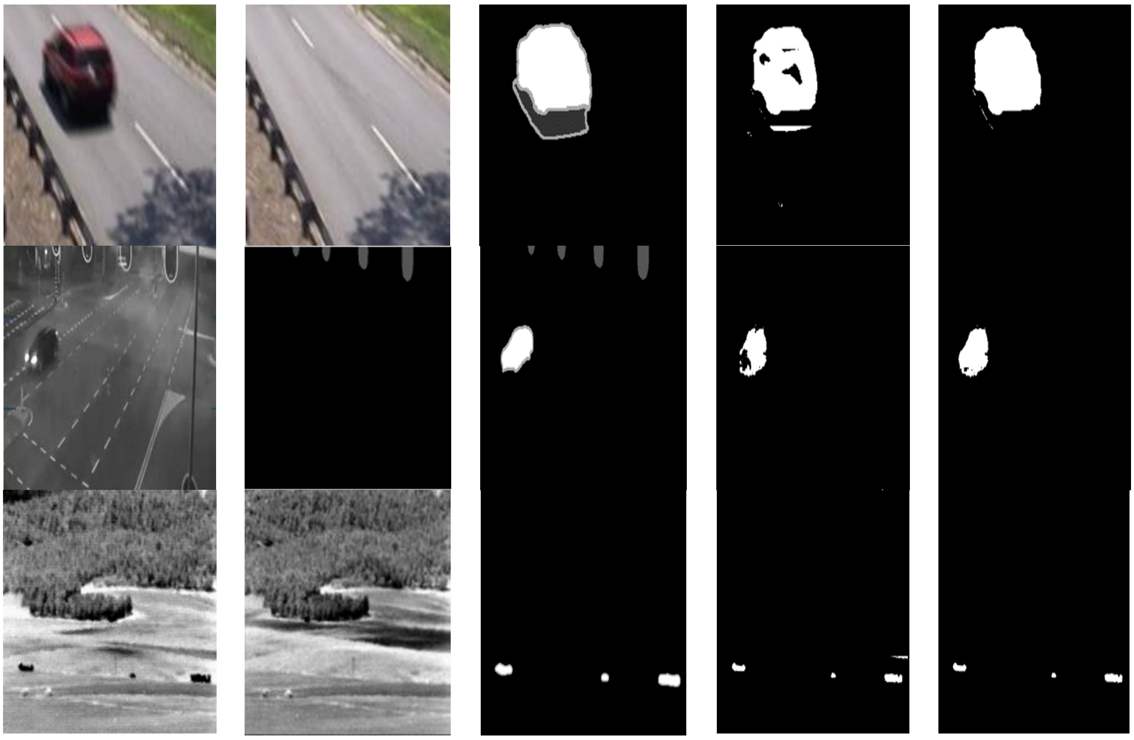
Table 2. Comparison of overall performance scores on the CDnet 2012 and CDnet 2014 datasets by different methods

Method	Year	Recall	Precision	F_measure
Our method	-	0.9605	0.8373	0.8887
GMM [38]	2000	0.68	0.60	0.57
KDE [39]	2002	0.74	0.58	0.57
KNN [40]	2006	0.67	0.68	0.59
SubSENSE [41]	2014	0.81	0.75	0.73
BMOG [32]	2018	0.7265	0.6981	0.6543
DeepBS [42]	2018	-	-	0.7922
MFCN [37]	2018	0.9828	0.9841	0.9830
Fast-D [43]	2020	0.8225	0.7915	0.7690

As it can be seen from Table 2, our method achieves higher $F_{measure}$ compared to all methods, except the MFCN methods. This is due to: first, the architecture of MFCN takes advantage of different layer features for background subtraction. Second, it can simplify complex background modeling and updating processes into a simple network classification process [34], but the complexity computing is very high. Thus, our method remains suitable for practical application and proves its efficiency and robustness in challenging environments.

3.4. Qualitative results

In this section, a better visual evaluation using a variety of different challenges scenarios is carried out by applying only the proposed method. Sample results are presented to illustrate the efficiency and robustness of our approach. We select the following sequences: traffic (1210th) from the "camera jitter" category, streetcornerat-Night (1360th) from "night videos" category and turbulence0 (2259th) from the "turbulence" category. Figure 2 represented the qualitative performance for the different sequences cited previously. Figure 2(a) displays the input frames, Figure 2(b) shows the background images, Figure 2(c) demonstrates the corresponding ground truth, and Figures 2(d) and 2(e) illustrate the segmented results without post-processing and with post-processing, respectively.



(a) (b) (c) (d) (e)

Figure 2. Qualitative performance for the sequences traffic (1210th), streetcornerat-night (1360th) and turbulence0 (2259th), respectively (a) input frame, (b) background image, (c) ground truth, (d) detection without post-processing, and (e) detection with post-processing

As can be seen in Figure 2, the moving objects are detected with an accurate precision with post-processing, which shows good arrangement with the quantitative evaluation results. Visually, we can observe that the major undesirable pixels are removed and the void in the detected objects is filled after the proposed post-processing. In fact, our method gives a perfect foreground mask except a few false positive, which is due to the various challenges in the different scenes.

3.5. Processing speed

The processing time of the algorithm was analyzed on the sequences previously mentioned from datasets CDnet 2012 and CDnet 2014, which resolutions varied from 320×240 to 720×480. We have one sequence of 720×480, one sequence of 595×245, one sequence of 360×240 and four sequences of 320×240. It is worth mentioning that the run-time of each algorithm will increase if the size of the analyzed images increases, otherwise, the run-time will decrease. Table 3 shows a processing frame speed of our method. We calculated the average of the run-times of the sequences of (320×240) and the sequences of (720×480).

Table 3. Processing speed

Sequences resolution	Processing speed (fps)
320×240	58
720×480	26

As it can be seen from Table 3, the average frame rate of our method is all about 58 fps for the sequences of (320×240) and nearly 26 fps for the sequences of (720×480). Thus, our proposed method can exactly detect moving objects and run frames faster than real-time frame speed.

4. CONCLUSION

In this paper, we have presented and tested an efficient background subtraction method using fast independent component analysis for moving objects detection in real time. In our proposed method, the fast-ICA algorithm is reformed to estimate the de-mixing matrix and the denoising matrix in the training step. In the detection step, the background subtraction procedure is easily solved by multiplying the data matrix with the two matrixes from the first step. An adaptive post-processing is useful in order to increase the detection accuracy at a low computational calculation. Experimental results show that our method achieves the higher overall values of 0.9605, 0.8373, and 0.8887 for $Recall$, $Precision$, and $F_{measure}$, respectively, except MFCN method. Further, the processing speed is nearly 59 fps faster than real-time frame rate. In the future work, we will try to apply this method in stereo vision system for 3D localization, autonomous vehicles, security robots, and so on, which requires limited computing and low memory devices.

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