Robust hybrid technique for moving object detection and tracking using cartoon features and fast PCP

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Abstract

In various computer vision applications, the moving object detection is an essential step. Principal Component Analysis (PCA) techniques are often used for this purpose. However, the performance of this method is degraded by camera shake, hidden moving objects, dynamic background scenes, and / or fluctuating exposure. Robust Principal Component Analysis (RPCA) is a useful approach for reducing stationary background noise as it can recover low rank matrices. That is, moving object is formed by the low power models and the static background of RPCA. This paper proposes a simple alternative minimization algorithm to fix minor discrepancies in the original Principal Component Pursuit (PCP) or RPCA function. A novel hybrid method of cartoon texture features used as a data matrix for RPCA taking into account low-ranking and rare matrix is presented. A new non-convex function is proposed to better control the low-range properties of the video background. Simulation results demonstrate that the proposed algorithm is capable of giving consistent random estimates and can indeed improve the accuracy of object recognition in comparison with existing methods.

Keywords: principal component pursuit, robust principal component analysis, cartoon features, local binary patterns.

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Introduction

Motion detection is the primary step in computer vision, focusing at grouping moving objects into video images. It has originated many applications for human observation, image capture, motion behavior analysis and vision-based interaction of computer and humans. Several articles on motion detection have been published over the past 20 years. However, there are still significant difficulties in detecting fast moving objects, for example, against a complex background. For example, rapidly changing the frequency of bright objects in the background (such as branches and leaves), camera shake, side effects, stationary foreground, efficiency, etc. It is important to note that detecting static images and background is a trade-off as anyone expects to remove as many backgrounds as favorable while maintaining the forefront. Though, it is challenging to achieve the desired outcome because they have many similar functions. Existing methods rarely solve this problem [1]. Conventional motion detection techniques are established on noise reduction, which usually involves three phases. First, the background image is mathematically defined. Second, new observations of the background or foreground are ranked allowing to the resemblance between the background and observations. At final phase, updating the background model for new observations using an adaptive strategy.

Liu and Zhang [2] utilized the difference in histogram resemblance between the imaginary field and the real field of a moving object to complete the performance. However, this does not apply to the alignment of cover and moving objects.

Varcheie et al. [3] proposed a region based BGS method on color histograms and texture information with the GMM to model the background and detection motion. This method improved performance than classical BGS methods, but the intricacy was extremely high. Varadarajan et al. [4] developed a general structure of GMM by region that considered the pixel dependencies. The frame-level method models the entire image as a vector, rather than simulating changes in individual pixels or regions. The most popular types of approaches are electronic space decomposition and PCA [5 – 8]. In particular, a background model (matrix) is created on behalf of input frames with vector representations in an image frame, so that the correlation matrix is split into eigenvalues. Deep neural networks have become quite popular in recent years. CNN [9 – 12] examined the detailed structure of a large number of benchmark datasets, which significantly improved the performance of the project. However, real-time performance on embedded systems is not possible without a dedicated GPU or processor.

In the process of background subtraction, due to the internal time-domain coupling of the background image, the remodeled matrix has a low order. And the L-1 norm was used to characterize the scarcity in the foreground. But the model works for background subtraction tasks, assuming approximate dynamic and static components analogous to the foreground and background of the video, respectively. Therefore, it is necessary to take into account the best knowledge to solve emerging problems. Aiming on the restrictions of RPCA-based techniques, this paper presents rank-1 standardized RPCA and TV (Total variation) model that makes full use of the static and dynamic components in front of the information.

This article employs Robust Principal Component Analysis (RPCA) for background subtraction with various methods; Fast PCP, LADMAP for Low-Rank Representation, RPCA with stochastic optimization and RPCA using Inexact Augmented Lagrange Multiplier. Histogram equalization is used for pre-processing of input image. Feature extraction is done by using cartoon descriptors. Furthermore, median filter with active contour is used for post-processing.

The outline for remaining sections of the paper is structured as follows. The 2nd section offers the methodology for the above technique. Section 3 describes the simulation results for the implemented methodology and Section 4 contains the conclusive remarks with future scope.

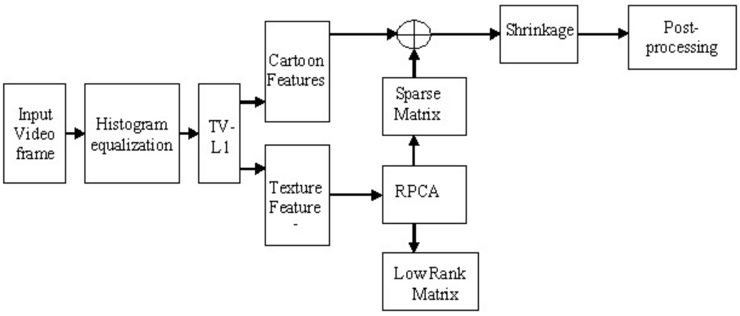

Fig. 1. Block diagram for proposed hybrid method

Proposed methodology

The proposed hybrid method computes background models with different conditions and videos to observe the performance of different RPCA approaches and the effect of preprocessing on results. In this article, we present a fast and computationally efficient algorithm for solving PCP problems with a focus on foreground / background video detection modeling, where the D column resembles for each video frame. Fig. 1 shows the video frame histogram equalization as an initial process.

After that histogram equalization is used to enhance the frame image and TV-L1 decomposition [16] is performed. This process gives two features cartoon features and texture features. This calculated texture features is sampled for RPCA where the low rank and sparse matrices are computed. The low-ranked matrix (background image) was then resolved using the "lansvd" procedure from the PROPACK optimized library [13]. The sparse matrix was calculated from element-wise compression (soft edge) [14]. Further Sparse matrix is combined with cartoon features and morphological post processing is happened to get moving object from foreground images.

The foreground is achieved by applying post-processing to the sparse matrix. Fig. 2 shows the post-processing used. This measurement includes a hard threshold, a morphological filter, and an active border with a negative compression offset [15]. Rest of methodology is explained in following subheadings.

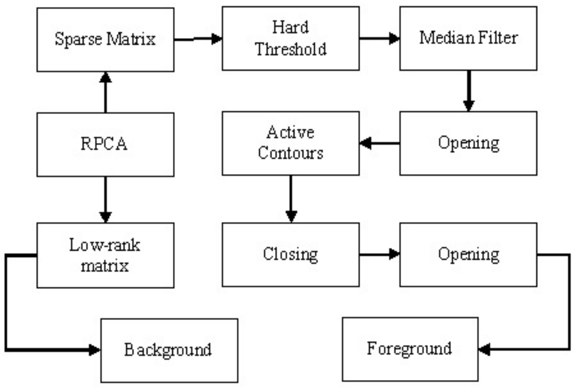

Fig. 2. Block diagram for post-processing [15]

1. Feature extraction using cartoon descriptors

The cartoon feature in images is classically obtained by using a pair of high pass and low-pass filters to the image *I* by the following minimization [16]:

$$\min_u \left\{ \sigma^4 \int | Du |^2 + \| I - u \|^2_{H^{-1}} \right\}. \tag{1}$$

Where u represents the cartoon part of the image I, D represents the first derivative of u, σ^2 is variance of image I [16].

The texture and cartoon image parts are achieved by the following equations (referred from Buades et al., [17]):

$$u(x) = \omega(\lambda_\sigma(x))(L_\sigma * I(\mathrm{x})) + (1 - \omega(\lambda_\sigma(x)))I(x), \tag{2}$$

$$v(x)=I-u(x). \tag{3}$$

Where ω(.) symbolizes the weight function, L_σ is a low pass filter and $\lambda_\sigma$is high pass filter [17].

Equation (4) defines the data matrix M obtained by RPCA, $f_t(x,y)$ is the function for cartoon texture descriptor extracted from each image. L and S matrices are derived from matrix M by RPCA [18].

$$M(x,y)=\beta f_t(x,y). \tag{4}$$

2. Fast principal component pursuit

The classification performance can be improved with the utilization of the fast principal component pursuit method focusing on the incremental PCP algorithm [14] [19, 20].

Various approaches based on histogram [21], subspace training [22] and neural networks [23] are used to implement the background video modeling. The latter model is based, in particular, on PCP [5] [24].

The PCP algorithm is defined by the equation (5) [24]:

$$\arg\ \min_{L,S} rank(\mathrm{L})+\lambda\,\|S\|_0 \ \ \text{s.t D=L+S}. \tag{5}$$

Where $D\in\mathbb{R}^{mxn}$ is the observation video of n images, each with size $m=N_r*N_c*N_d$ (row, column and depth or channel), $L\in\mathbb{R}^{mxn}$ is a lower-order matrix demonstrating the background of the plane, and $S\in\mathbb{R}^{mxn}$ is a sparse matrix signifying the foreground (moving object).

Although most PCP algorithms directly rely on convex relaxation shown in equation (6):

$$\arg\ \min_{L,S} \|\mathrm{L}\|_* +\lambda\,\|S\|_1 \ \ \text{s.t D=L+S}. \tag{6}$$

As presented in [25], equation (7) is also a suitable convex relaxation of the equation (1).

$$\arg\ \min_{L,S} \frac{1}{2}\|\mathrm{L+S-D}\|_F^2 \ \ \text{s.t} \|S\|_1\le\tau,\text{rank(L)}\le r. \tag{7}$$

What can be done repeatedly using alternative optimizations:

$$L_K^{(j+1)}=\arg\ \min_L \frac{1}{2}\|\mathrm{L}_k+\mathrm{S}_k^{(j)}-\mathrm{D}_k\|_F^2 \ \ \text{s.t rank}(\mathrm{L}_k)\le r, \tag{8}$$

$$S_K^{(j+1)}=\arg\ \min_S \frac{1}{2}\|\mathrm{L}_k^{(j+1)}+\mathrm{S}_k-\mathrm{D}_k\|_F^2 \ \ \text{s.t} \|\mathrm{S}_k\|_1\le\tau. \tag{9}$$

Where $L_k=[L_{k-1}\, l_k]$, $S_k=[S_{k-1}\, s_k]$ and $D_k=[D_{k-1}\, d_k]$. The minimization of equation (6) can be calculated using the incremental thin SVD method [23],while the equation (7) is the prediction (d_k-l_k) against the sphere l_1.

The PCP algorithm [14] [18] [19], utilized in this research work, uses a special structure of solutions suggested in [20] to convert them into incremental solutions: solutions (and packages) of computationally intensive problems with partial equations (8) can be computed efficiently by changing the 1st classification for thin SVD [26], which is computed with the availability of a new video (image).It provides a fully incremental algorithm which is independent of background variations.

Algorithm to Solve Fast PCP Method [26]:

1. *Input video D, initialize parameter: $S_1=0$, rank =1 (the initial rank)*
2. *While not converge do*
3. *Solve L_{k+1} with rank =t and preserve singular values to v*
4. *Calculate* $\left(v_{rank} / \sum_{k=1}^{rank} v_k\right)$
5. *If* $\left(v_{rank} / \sum_{k=1}^{rank} v_k\right)>\tau$, *then ++rank*
6. *Solve S_{k+1}*
7. *end while*
8. *Output: L, S.*

Since the video background modeling application L is low rank matrix and upper bound of τ is controlled to get new singular values Lk+1 from equation 5. If observed contribution are small enough then increment in τ is stopped. The proposed simulation τ is increased up to 3.

3. Online robust PCA via stochastic optimization

We now present robust PCA using stochastic optimization [27]. The main objective of this approach is to present a cost function minimization method utilizing a stochastic optimization [27]:

$$f_n(L)\triangleq\frac{1}{n}\sum_{i=1}^{n} l(\mathrm{z}_i,\mathrm{L})+\frac{\lambda}{2n}\|L\|_F^2. \tag{10}$$

Factor *r*, noise e and *L* base are optimized as alternatives. At the time t, a base estimate for L_t is used by minimizing the accumulated loss with respect to preliminary predictable coefficients Factor r, noise e and L base are optimized as alternatives. At the time t, a base estimate for L_t is used by minimizing the accumulated loss with respect to preliminary predictable coefficients $\{r_i\}_{r=1}^t$ and spurious noise $\{e_i\}_{r=1}^t$. The L_t database is updated by utilizing the following objective function and spurious noise. The L_t database is updated by utilizing the following objective function [27]:

$$g_t(L)\triangleq\frac{1}{t}\sum_{i=1}^{t}\left(\frac{1}{2}\|\mathrm{z}_i-Lr_i-e_i\|_2^2+\frac{\lambda_1}{2}\|r_i\|_2^2+\lambda_2\|e_i\|_i\right)+ +\frac{\lambda_1}{2t}\|L\|_F^2. \tag{11}$$

It is a substitution function for the empirical cost function $f_t(\mathrm{L})$ demarcated in equation (5). This gives an upper bound for $f_t(\mathrm{L})$:$g_t(\mathrm{L})\ge f_t(\mathrm{L})$.

4. RPCA using inexact augmented lagrange multiplier

In this section we contemplate the nonlinear scalar problem with constraints in the form of:

$$\begin{aligned} &Minimize\ f(x), \\ &Subject\ to\ x \in \Omega. \end{aligned} \tag{12}$$

Where $f = \mathbb{R}^n \to \mathbb{R}$ is continuously differentiable in$\mathbb{R}^n$.Given $x^* \in \Omega$, $A(x^*) = \{j \in \{1,..,p\} : g_i(x^*) = 0\}$ denote to the set of dynamic discrimination constraints on x^*.

To solve equation (12), the classical Augmented Lagrangian method is easily solved by a succession of sub-problems. In each sub-problem, given the fixed penalty parameter $\rho > 0$ and estimates of the Lagrange multipliers $\lambda \in \mathbb{R}^m$, $\mu \in \mathbb{R}^p$, $\mu \geq 0$. Although there are several penalty functions [28], the external penalty function used in this work is the quadratic function. Due to its simplicity, the quadratic penalty function is the most used in practice, although from time to time the use of other penalty functions may have advantages, see for example [28] [29] and its references.

Given $x \in \mathbb{R}^n$, $\rho > 0$, $\lambda \in \mathbb{R}^m$, $\mu \in \mathbb{R}^p$, $\mu \geq 0$ the generalized formula of the Augmented Lagrangian function associated with the scalar problem (12) considering the quadratic penalty function is:

$$\begin{aligned} &L(x,\lambda,\mu,\rho) = f(x) + \\ &+\frac{\rho}{2}\left[\sum_{i=1}^{m}\left(h_i(x)+\frac{\lambda_i}{\rho}\right)^2 + \sum_{j=1}^{p}\left(\max\left\{0, g_j(x)+\frac{\mu_j}{\rho}\right\}\right)^2\right]. \end{aligned} \tag{13}$$

Simulation results

In this paper, we compare four background subtraction techniques such as RPCA STOC, LRR-LADMAP, RPCA-IALM and RPCA Fast PCP using the CD Net dataset [30]. The database contains 1700 frames with a resolution of 320×240, the first 100 frames are used for background initialization, and the rest of the images are used for background updates for object detection. Each frame has a separate ground truth. Four techniques of background subtraction are compared. Precision, sensitivity, false positive rate, specificity and accuracy are the parameters used for evaluation of the proposed techniques.

The 2014 DATASET offers a variety of realistic camera images (no CGI) and various videos [31]. They have been selected to address a wide range of detection and presentation challenges for typical internal and external visual data captured in today's video databases, intelligent environments, and surveillance scenarios. The dataset is accompanied by precise ground-truth segmentation and displacement / motion zone annotations for each video frame. Similarity measurements were performed using Euclidean distance.

Fig. 3, 4 and 5 demonstrate the RPCA operation on Escalator and Highway video respectively. The video sequence is decomposed into sparse and low-rank matrices. Further low rank matrices are processed with morphological operation to get the filtered outcome as a moving object detection.

In the background subtraction process, the difference between previous frame and current frame is computed by a parameter which is known as running average. In other way it is the absolute difference between two frames where previous background model and current background model with new object introduced in the background.

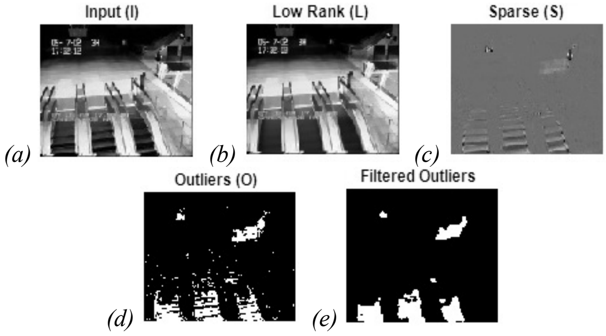

Fig. 3. Simulation performed on escalator image
a) Input, b) Low rank, c) Sparse, d) Outliers, e) Filtered Outliers

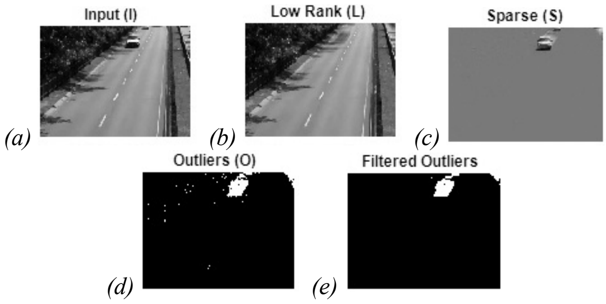

Fig. 4. Simulation performed on Highway image-1
a) Input, b) Low rank, c) Sparse, d) Outliers, e) Filtered Outliers

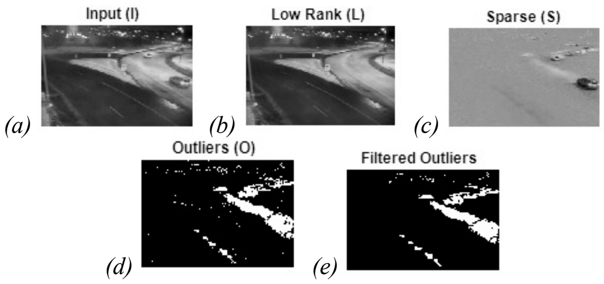

Fig. 5. Simulation performed on Highway image-2
a) Input, b) Low rank, c) Sparse, d) Outliers, e) Filtered Outliers

The running average is calculated using the following equation [35]:

$$\mu_t = \alpha x_t + (1-\alpha)\mu_{t-1}. \tag{14}$$

Where μ_t is the mean computed up to frame t, α is the learning rate of the model, and x_t is the pixel value in frame t.

It can be seen in fig. 6 running average is high at initial video index, as data index points increase the RPCA-PCP performs with lower average error values. Subsequently it can be seen in fig. 7. RPCA-PCP yields very lower residual error.

Tab. 1 represents the comparative analysis of various proposed methods on meet video, with cartoon features.it can be seen Proposed Hybrid Fast PCP methods gives higher accuracy 97.5 % as compare to RPCA+STOC (95 %), RPCA+IALM (94.2 %) and LLR+LADMAP

(96 %). F-Score, MCC and kappa statistics are 97.6 %, 95.1 % and 95.1 % respectively from method RPCA+FASTPCP, which is higher than other proposed methods. Higher MCC, Kappa Statistics and F-Score indicate better classification. Hence Fast PCP along with cartoon feature performs better than other algorithm used in paper.

Tab. 2 represents the comparative analysis of various proposed methods on meet video, with LBP features.it can be seen Proposed Hybrid Fast PCP methods gives higher accuracy 95.01 % as compare to RPCA+STOC (92.5 %), RPCA+IALM (87.5 %) and LLR+LADMAP (94 %).F-Score, MCC and Kappa statistics are 95.2 %, 90.5 % and 90 % respectively from method RPCA+FAST PCP, which is higher than other proposed methods.

From fig. 8, it can be seen clearly that all algorithm incorporated with cartoon feature gives better accuracy than LBP features.

The above tab. 3 represents the comparative analysis of background subtraction in meet video [32] has used wavelet transform based background segmentation which increase the more complex structure and volatile to change detection. This method claim sensitivity to 83.91 %. Authors of [33] used the deep learning methods for background subtraction which may not be applicationspecific because of trained network. In general deep learning methods can work in generalized way and may have accuracy compromise, whereas proposed hybrid method with cartoon features yields 98.9 % of sensitivity.

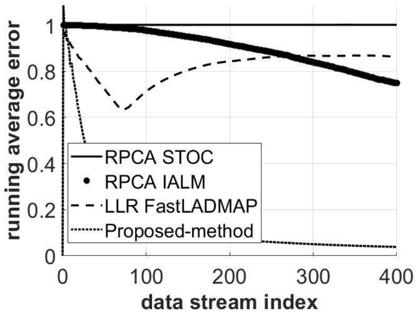

Fig. 6. Running average error graph

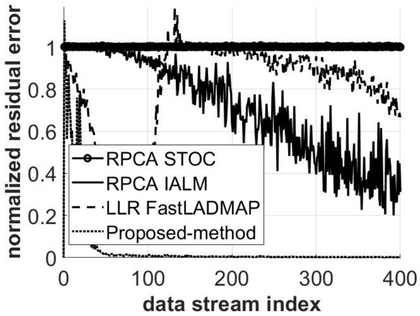

Fig. 7. Normalized residual error graph

Tab. 1. Proposed hybrid method evaluation for Dataset14 (Meet) with cartoon features

	RPCA+STOC+Cartoon	RPCA+IALM+Cartoon	LLR+Fast-LADMAP+Cartoon	Proposed Hybrid RPCA+FAST PCP+Cartoon
Accuracy	9.50e – 01	9.42e – 01	0.96	9.75e – 01
Error Rate	5.00e – 01	5.83e – 02	0.22	2.50e – 02
Sensitivity	1.00e + 00	1.00e + 00	1	1.00e + 00
Specificity	0.9	0.8833	0.92	9.50e – 01
Precision	0.909	0.8955	0.926371	9.52e – 01
FPR	0.0999	0.1167	0.07996	5.00e – 02
F-Score	9.52e – 01	9.45e – 01	0.96164	9.76e – 01
MCC	9.05e – 01	8.89e – 01	0.923183	9.51e – 01
Kappa Statistics	9.00e – 01	8.83e – 01	0.91998	9.50e – 01

Tab. 2. Proposed method evaluation for Dataset14 (Meet) with LBP features

	RPCA STOC+LBP	RPCA IALM+LBP	LLR+Fast LADMAP+LBP	Proposed Hybrid RPCA FAST PCP+LBP
Accuracy	9.25e – 01	8.75e – 01	0.94	9.50e – 01
Error Rate	7.50e – 02	1.25e – 01	0.06	5.00e – 01
Sensitivity	1.00e + 00	1.00e + 00	1	1.00e + 00
Specificity	8.50e – 01	7.50e – 01	0.88	0.9
Precision	8.70e – 01	8.00e – 01	0.8967	0.909
FPR	1.50e – 01	2.50e – 01	0.12	0.0999
F-Score	9.30e – 01	8.89e – 01	0.94454	9.52e – 01
MCC	8.60e – 01	7.75e – 01	0.88824	9.05e – 01
Kappa Statistics	8.50e – 01	7.50e – 01	0.88	9.00e – 01

Tab. 3. Comparison with previous research works for Meet input video

Methods	Sensitivity	Precision	FPR	Specificity
Khare et al. [32]	83.19 %	79.15 %	17.33 %	82.67 %
Dou et al. [33]	93.58 %	93.15 %	3.11 %	96.89 %
Sengar and Mukhopadhyay [34]	91.99 %	95.98 %	07.49 %	92.51 %
Proposed Hybrid Method	98.9 %	95.2 %	5 %	95 %

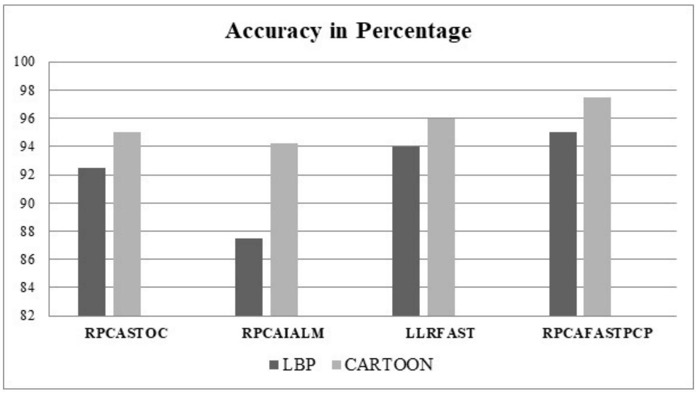

Fig.8. Comparative analysis of average accuracy using LBP and Cartoon features

Conclusion

Multi-Layer RPCA has been proposed for video background subtraction, using texture descriptors. The proposed algorithm consists of preprocessing, RPCA and post-processing. The preprocessing utilizes Gaussian filtering, histogram equalization, or a combination of both. Cartoon features are used for the texture information, and the background subtraction is accomplished by the low-rank and sparse matrix computation achieved by RPCA algorithm. Post-processing calculates active contours and morphological filters with negative shrinkage offset. The proposed hybrid Multi-Layer RPCA FAST PCP+ Cartoon algorithm produce better results than other cited method in a database. Numerical comparisons suggest that RPCA+ Fast PCP+ Cartoon algorithm has superior performances on synthetic as well as real-world datasets with a maximum accuracy of 97.5 %. It was found that the proposed work attains highest sensitivity (100 %) as compared to the other works. The proposed hybrid algorithm overwhelms the effect of dynamic background and also, it is less complex for real-time processing. In future, the role of deep learning can be explored for background modeling.

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