Original Article

Foreground Detection in Dynamic Scenes using Robust Principal Component Analysis in comparison with Gaussian Mixture Model to measure F-score

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Abstract

Aim: This paper describes the poor performance of accuracy and F-Score in the detection of moving objects using a novel Robust Principal Component Analysis (RPCA). **Materials and Methods:** ClinCalc is a tool to compute sizes and display the results of sample analyses. Cdnet 2014 dataset demonstrates our foreground detection using Robust Principal Component Analysis algorithm. In this study, the Robust Principal Component Analysis is compared with the Gaussian Mixture model. **Results:** Poor detection of moving objects is improved by using Robust Principal Component Analysis algorithm with mean F-score rate of 83% and accuracy of 87%. **Conclusion:** Robust Principal Component Analysis subtracts the background and detects the moving objects by measuring the f-score and accuracy of the dataset.

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INTRODUCTION

The importance of this study is to dynamically construct color categories for each pixel in the photos and to create background categories that can adjust the color disruption of the background (Chiu, Chiu, and Xu 2018). It also identifies background pixels from foreground pixels from statistical models such as the MOG and MOGG to deliver the distributions to background image pixels (Yong et al. 2018). Then lighting changes, dynamic backgrounds, bootstrapping, camouflage, and so on are improved (Xin et al. 2015). To adjust to the color disruption of the background, the algorithm employs the notion of a joint category (Chiu, Chiu, and Xu 2018). To obtain the best low rank approximation of a given matrix, difference between the actual matrix and the low rank approximation to be measured (Anderson et al. 2011). Robust Principal Component Analysis provides a powerful foundation for a wide range of applications, including image processing, video processing, and 3D computer vision (Bouwmans et al. 2018).

A lot of research has been done for foreground detection using the robust principal component analysis (RPCA). Total number of citations published was 17,699 from Google Scholar and 413 from Sciencedirect. Robust Principal Component Analysis was utilized to create the background by lowering the data's dimension, and it can be used for video surveillance (Bouwmans et al. 2014). In RPCA, the strong low-rank property of background layer (temporal correlation of static component) and 3-D variation is described by the rank-1 constraint and L1 norm is used to describe the smoothness of foreground layer.All these properties of framework are combined to form TR1-RPCA (Xue et al. 2018). The Online RPCA (OR-PCA) is an extended version of RPCA. OR-PCA includes spatiotemporal constraints and provides accurate segmentation with the utilization of both color and depth features(Javed, Bouwmans, and Jung 2015). A novel tensor-based robust PCA (TenRPCA) is proposed to subtract the background of video stream or image sequence from the compressed measurements by decomposing video frames into backgrounds with spatial-temporal correlations and foregrounds with spatio-temporal continuity in a tensor framework (Cao et al. 2016). A modified robust PCA algorithm that can handle moving cameras and exploits the block sparse structure of the pixels corresponding to moving objects.For the case of rank-1 background, a novel SVD-free algorithm is proposed that performs the current state of methods (Bouwmans, Aybat, and Zahzah 2016). A method for real-time background subtraction based on tensor decomposition and tensor analysis. To avoid the iterative approach while keeping the L1 norm of the RPCA rank function, a closed form TUCKER2 decomposition solution is adopted (Kim and Choe 2018). A novel online subspace learning algorithm that aims to make background subtraction in practical films as fast and accurate as possible (Yong et al. 2018). To process backdrops with shifting textures, masked RPCA is proposed. A mask that roughly classifies moving objects and backgrounds is generated using a first-order Marcov random field. The rank minimization procedure is then used to estimate the background, with the mask multiplied (Ahn and Kang 2021). A new robust principal component analysis is found for the separation of foreground and background on a freely moving video with possible dense and sparse corruptions. This technique creates a panoramic background component and also eliminates the noise of video streams (Moore, Gao, and Nadakuditi 2019). An online compressive robust principal component analysis with optical flow that divides a sequence of video frames into foreground (sparse) and background (low-rank) components iteratively. In contrast to batch-based RPCA, which analyzes the entire data, this separation method works with a small number of measurements taken every frame (Prativadibhayankaram et al. 2018).

Our institution is passionate about high quality evidence based research and has excelled in various fields (Parakh et al. 2020; Pham et al. 2021; Perumal, Antony, and Muthuramalingam 2021; Sathiyamoorthi et al. 2021; Devarajan et al. 2021; Dhanraj and Rajeshkumar 2021; Uganya, Radhika, and Vijayaraj 2021; Tesfaye Jule et al. 2021; Nandhini, Ezhilarasan, and Rajeshkumar 2020; Kamath et al. 2020). The major drawback of the existing algorithm is less storage size and cost-efficient. Gaussian mixture model (GMM) cannot adjust internal sensitivity because of its low pixels. In GMM, the efficiency of the sequence will be reduced. GMM cannot capture the video that could have sudden motion, parametric transformation, quality, motion blur, or deformation of dynamic scenes. GMM method has no access to adapt background rotations, scalings and distortions. As the background rank increases, the weight of the rank constraint term decreases and is not suitable for computer vision tasks like object tracking and activity detection. To upgrade the texture of images in the proposed framework, programmatic coding experiences are done to check the presentation of the proposed approach. The main aim is to achieve an improvement in accuracy and F score and compare the novel robust principal component analysis with GMM.

Materials And Methods

This entire work is done in the Department of Electronics and Communication Engineering at Saveetha School of Engineering, SIMATS, Tamil Nadu, India. MATLAB software was used for the simulation of foreground detection in dynamic scenes. ClinCalc is a tool to compute compute sizes and display the results of sample analyses (Charan et al. 2021). Each dataset consists of 10 samples which in total gives 20 samples. Cdnet 2014 dataset demonstrates the foreground detection in dynamic scenes using Robust Principal component analysis (RPCA) in comparison with the Gaussian Mixture Model (GMM) (Wang et al. 2014). Pretest power is determined to be 80% with an error rate of 0.05.

For Group-1, the sample preparation for novel Robust Principal Component Analysis has been taken from a kaggle dataset extracted from Cdnet 2014. Robust principal component analysis is a statistical procedure of principal component analysis which works well with the grossly corrupted observations. It allows summarizing the information content in large data tables by a smaller set of “summary indices” which can be more easily visualized and analyzed. The eigendecomposition of the data covariance matrix or singular value decomposition of the data matrix can be used to analyze the principal components in a novel Robust principal component analysis. It is a type of multivariate analysis that is based on eigenvectors and is closely related to factor analysis. It focuses primarily on Eigendecomposition.

$$\mathrm{cov}(X,Y) = \frac{1}{n-1} \Sigma^{n}{}_{i=1}(X_i - \underline{x})\,(Y - \underline{y}) \quad (1)$$

For Group-2, the sample preparation for the Gaussian mixture model has been taken from a kaggle dataset extracted from Cdnet2014. GMM detects objects from video images; the remaining pixels are then connected into groups to represent the foreground object. Every pixel in RGS color space is divided by its intensity in GMM. Each pixel's probability is computed. Every pixel is computed for its probability. Every pixel is computed for its probability. Gaussian Mixture is a function that has the same number of Gaussians as the entire number of clusters. Each Gaussian in the mixture has a set of parameters, which are as follows: The center is defined by a mean, the width is defined by the covariance and the probability.

$$p(X) = \Sigma K_{k=1} \Pi_k G(X|\mu_k,\Sigma_k) \quad (2)$$

For the system setting, Windows-10 HP, Intel Core i5, 10th generation was used to do the simulation of novel Robust principal component analysis in comparison with GMM. The statistical software used was Matlab and SPSS analysis. MATLAB includes computation, algorithm development and simulation. SPSS is used to compare the proposed and existing algorithm.

Statistical Analysis

SPSS version 21 was used for statistical analysis of collected data for parameters by gain in dB and frequency in GHz (Gogoi* et al. 2020). The dependent variables of the background subtraction in detecting the foreground are precision, accuracy, F-score and recall.The independent variables of the foreground detection are TrueNegatives(TN), TruePositives(TP), FalseNegatives(FN), FalsePositives(FP). F-score and accuracy are calculated for comparing the two groups.

Precision = TruePositives / (TruePositives + FalsePositives)
Recall = TruePositives / (TruePositives + FalseNegatives)
F-Measure = (2 * Precision * Recall) / (Precision + Recall)
Accuracy = (TN+TP) / (TN+FP+TP+FN)

Results

The accuracy and F-Score of the proposed Robust principal component analysis (RPCA) is compared with the existing algorithm Gaussian mixture model (GMM). The problems faced in detecting the objects in foreground are rectified by using novel Robust principal component analysis. Figure 1 shows the images extracted from Cdnet2014 dataset which are represented as inputs for this study. Figure 2 represents the output images of the proposed algorithm RPCA obtained by using MATLAB. Figure 3 represents the output images of the existing algorithm GMM extracted by using MATLAB. Table 1 compares the F-score obtained for sample 10 images of Robust principal component analysis and Gaussian Mixture model where the mean F-score rate of RPCA is 83% and GMM is 78%. Table 2 represents accuracy obtained for sample 10 images of novel Robust principal component analysis and Gaussian Mixture model where the mean accuracy rate of RPCA is 87% and GMM is 84%. In table-3 and table-4, the descriptive and group statistics of RPCA and GMM are analyzed using SPSS where the mean (0.8187000), standard deviation (0.0094169) and standard mean error rate (0.0029779) of RPCA and the mean (0.8187000), standard deviation (0.0094169) and standard mean error rate (0.0029779) of GMM. Table 5 represents the statistical analysis of independent sample tests for both the sample groups with significance p < .001, 95% confidence interval difference, the mean difference (.0213400, .0213400, .0274300, .0274300) and standard error difference (.0044806, .0044806, .0011929, .0011929) is obtained. Figure 4 represents the F-score graph between RPCA and GMM using MATLAB. Figure 5 represents the accuracy graph between RPCA and GMM. Figure 6 and Figure 7 represent the SPSS comparison graph between RPCA and GMM.

Discussion

Poor detection of moving objects is improved by using the novel Robust Principal Component Analysis (RPCA). RPCA reduces the complexity in images and removes the noise. Robust principal component analysis has better accuracy with 87% and F-score of 83% compared with the Gaussian Mixture model (GMM).

Robust Principal Component Analysis was utilized by lowering the data's dimension, and it can be used for higher applications than in GMM (Bouwmans et al. 2014). RPCA includes spatiotemporal constraints and provides accurate segmentation with the utilization of both color and depth features than the existing algorithm (Javed, Bouwmans, and Jung 2015). A novel tensor-based robust PCA subtract the background of a video stream or image sequence from the compressed measurements by decomposing video frames into backgrounds which results in better output compared with the existing algorithm (Cao et al. 2016). A modified novel robust PCA algorithm that can handle moving cameras and exploits the block sparse structure of the pixels corresponding to moving objects which gives exact color information than the existing algorithm (Yong et al. 2018; Ebadi, Ones, and Izquierdo 2015). A novel online RPCA algorithm makes background subtraction in practical films as fast and accurate as possible compared with the existing algorithm (Yong et al. 2018). A masked RPCA was used for the better shifting textures which improves the pixels of the image in the proposed algorithm compared with the existing algorithm (Ahn and Kang 2021). RPCA separates foreground and background on a freely moving video with possible dense and sparse corruptions than GMM (Moore, Gao, and Nadakuditi 2019). The proposed algorithm (RPCA) gives small measurements for every frame compared with the existing algorithm (Prativadibhayankaram et al. 2018).

In RPCA, because of usage of lower data dimensions in the background, the foreground area becomes smaller. Usage of RPCA gives noise and is less robust and rigorous compared to our proposed algorithm. The RPCA model needs more encoding capability and it can’t be used in a complex background with the change in illumination. The project's goal is to detect real-time objects in images or videos in real time. Around the detected objects, bounding boxes are drawn. Future improvements can be concentrated by putting the project on a system with a GPU for faster results and more accuracy.

Conclusion

In this project, a Robust Principal Component Analysis (RPCA) is proposed for foreground detection in dynamic scenes. Here RPCA is compared with the Gaussian Mixture Model (GMM) by measuring F-score and accuracy. The mean F-score rate obtained for sample 10 images is 83% for novel Robust Principal Component Analysis and 78% for GMM. This shows that the proposed algorithm has a better mean F-score compared to the existing algorithm. The mean accuracy rate obtained for sample 10 images is 87% for Robust Principal Component Analysis and 84% for GMM. This shows that the proposed algorithm has a better mean accuracy compared to the existing algorithm.

DECLARATION

Conflict of Interest

No conflict of interest in this manuscript.

Author Contribution

Author GS was involved in writing the code for the Robust Principal Component Analysis for the foreground detection and manuscript writing. Author PJ was involved in Guiding to analyze the performance, data validation, and the review of the manuscript.

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4. Saveetha School of engineering.

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TABLES AND FIGURES

Table 1. F-score obtained for sample 10 images where the mean Fscore rate is 83% for Robust Principal Component Analysis (RPCA) and 78% for Gaussian Mixture model (GMM).

Robust Principal Component Analysis (RPCA- Group 1)	**Gaussian Mixture Model (GMM- Group 2)**
0.8090	0.7840
0.8100	0.7880
0.8120	0.7924
0.8140	0.7930
0.8150	0.7940
0.8160	0.7942
0.8180	0.7950
0.8250	0.8030
0.8300	0.8120
0.8380	0.8180

Table 2. Accuracy obtained for sample 10 images where the mean accuracy rate is 87% for Robust Principal Component Analysis (RPCA) and 84% for Gaussian Mixture model (GMM).

Robust Principal Component Analysis (RPCA- Group 1)	**Gaussian Mixture Model (GMM- Group 2)**
0.8650	0.8430
0.8670	0.8432
0.8690	0.8440
0.8710	0.8448

0.8728	0.8450
0.8730	0.8451
0.8740	0.8452
0.8747	0.8453
0.8750	0.8436
0.8760	0.8440

Table 3. Represents descriptive statistics for both sample groups.

	N	**Minimum**	**Maximum**	**Mean**	**Std.Deviation**
Fscore	20	0.7840	0.8380	0.808030	0.0146607
Accuracy	20	0.8430	0.8760	0.858035	0.0143088

Table 4. Represents group statistics for both sample groups.

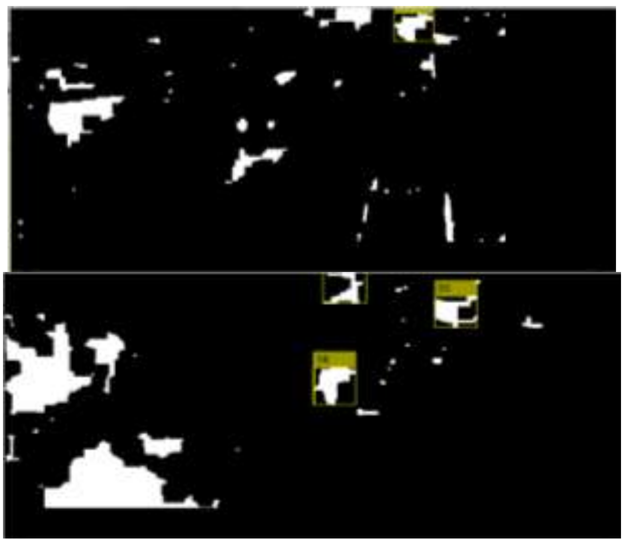
	Groups	**N**	**Mean**	**Std.Deviation**	**Std.Error Mean**
F Score	RPCA	10	0.818700	0.0094169	0.0029779
	GMM	10	0.797360	0.0105867	0.0033478
Accuracy	RPCA	10	0.871750	0.0036713	0.0011610
	GMM	10	0.844320	0.0008664	0.0002740

Table 5. Represents the statistical analysis of independent sample tests for both sample groups.

						Significance		**T-test for equality of means**		**95% confidence interval of the difference**	
		F	**Sig.**	**t**	**df**	**One - sided p**	**Two sided p**	**Mean Difference**	**Std.Error Difference**	**Lower**	**Upper**
Fscore	Equal variances assumed	.098	.758	4.763	18	<.001	<.001	.0213400	.0044806	.0119267	.0307533
	Equal variances not assumed			4.763	17.759	<.001	<.001	.0213400	.0044806	.0119267	.0307625

Accuracy	Equal variances assumed	13.987	.001	22.995	18	<.001	<.001	.0274300	.0011929	.0249239	.0299361
	Equal variances not assumed			22.995	9.999	<.001	<.001	.0274300	.0011929	.0247721	.0300879

Fig. 1. Represents a set of input images of CdNet2014 dataset.



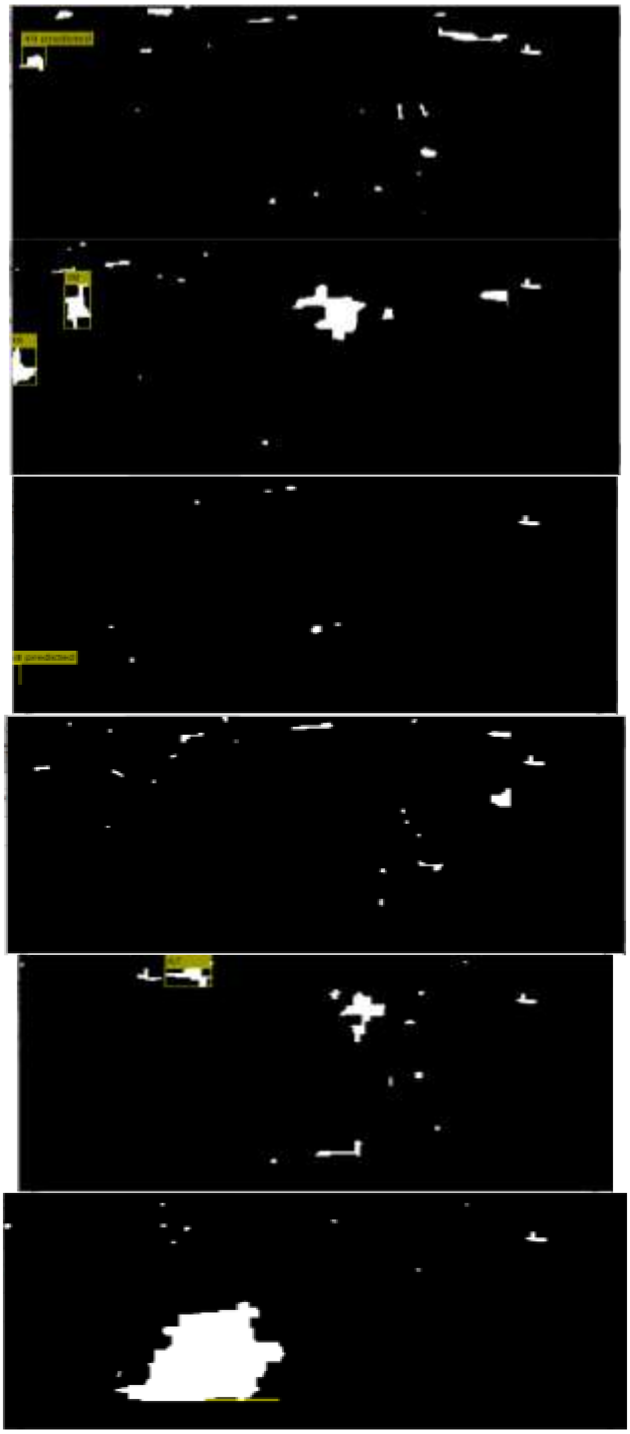
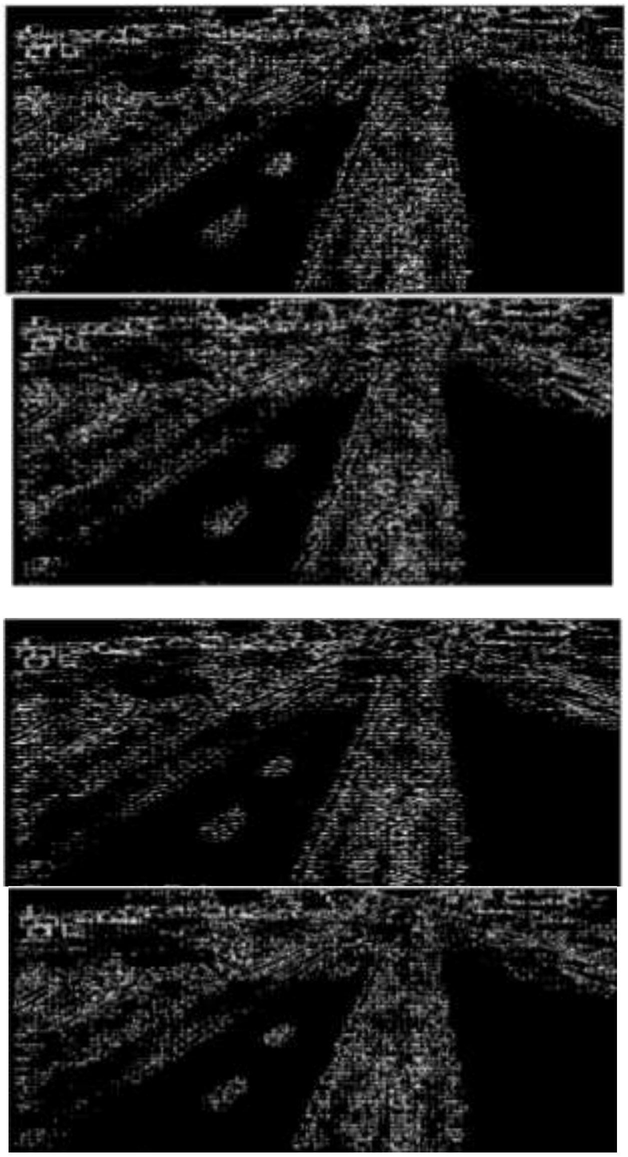


Fig. 2. The following figures represent a set of output images of RPCA.



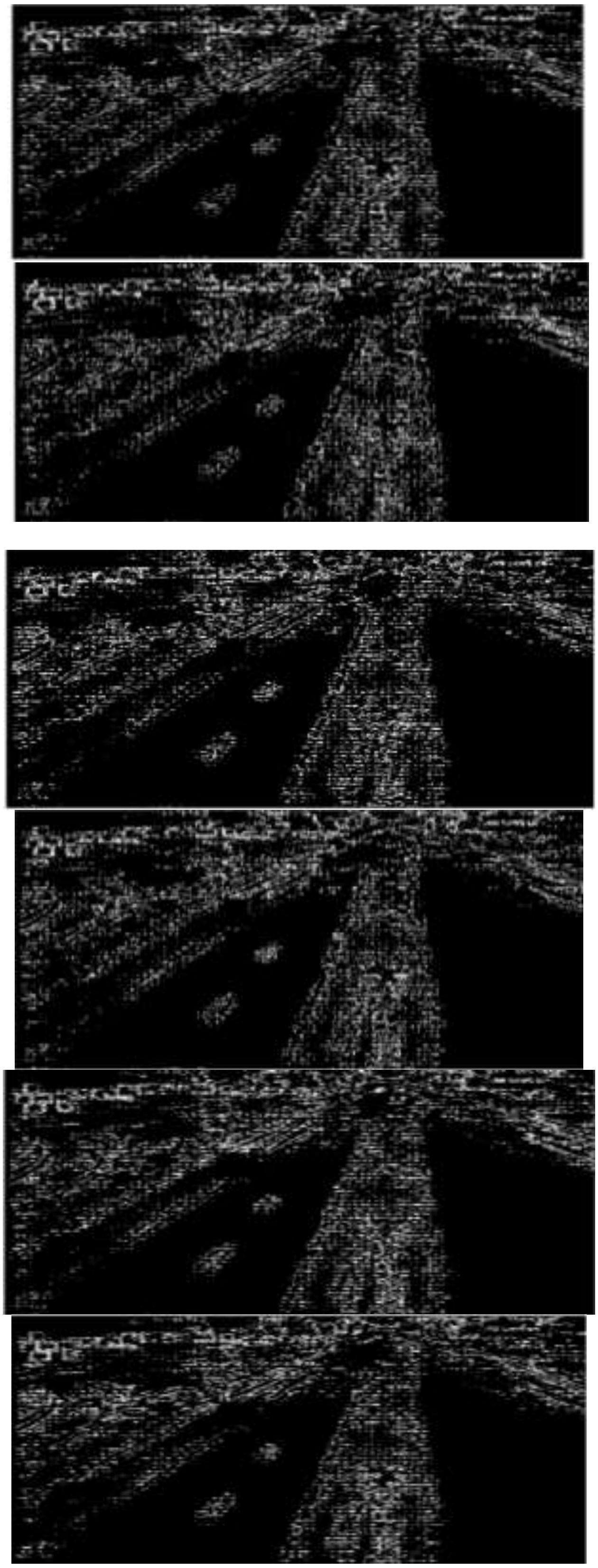


Fig. 3. Represents the set of output images of GMM

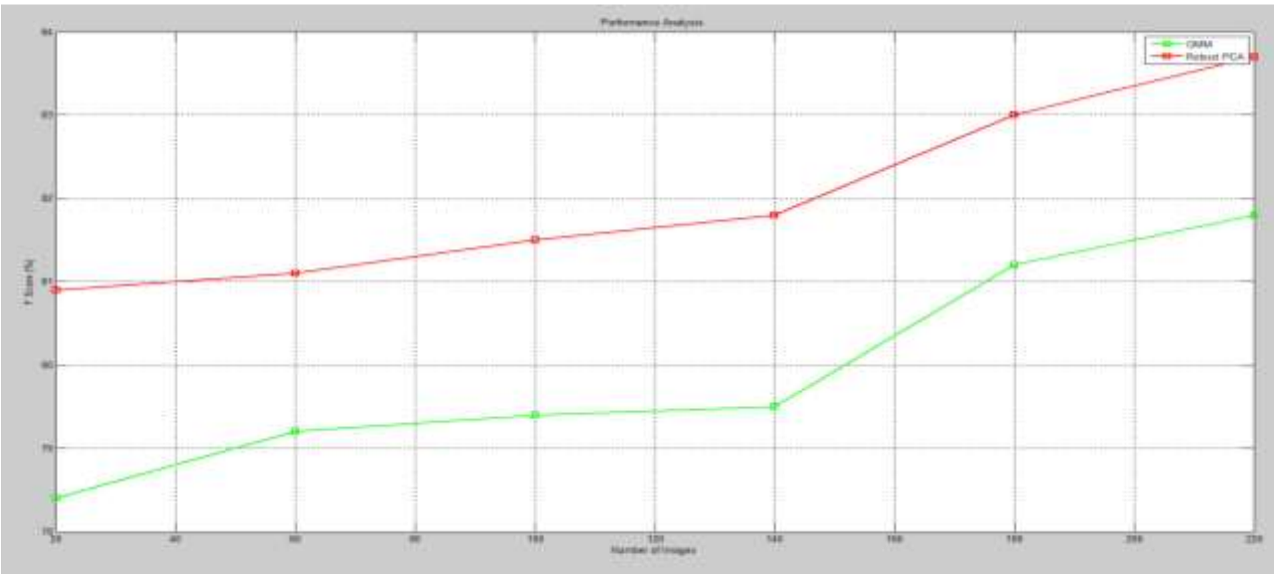


Fig. 4. The following figure shows the F-score graph between Robust Principal Component analysis (RPCA) and Gaussian Mixture Model (GMM).

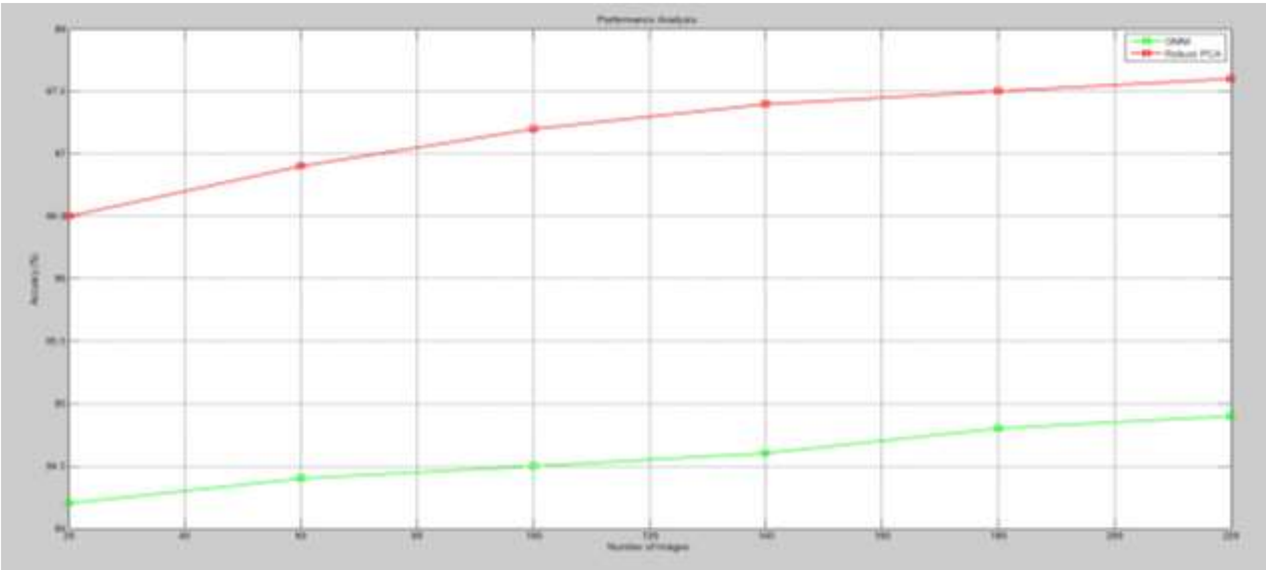
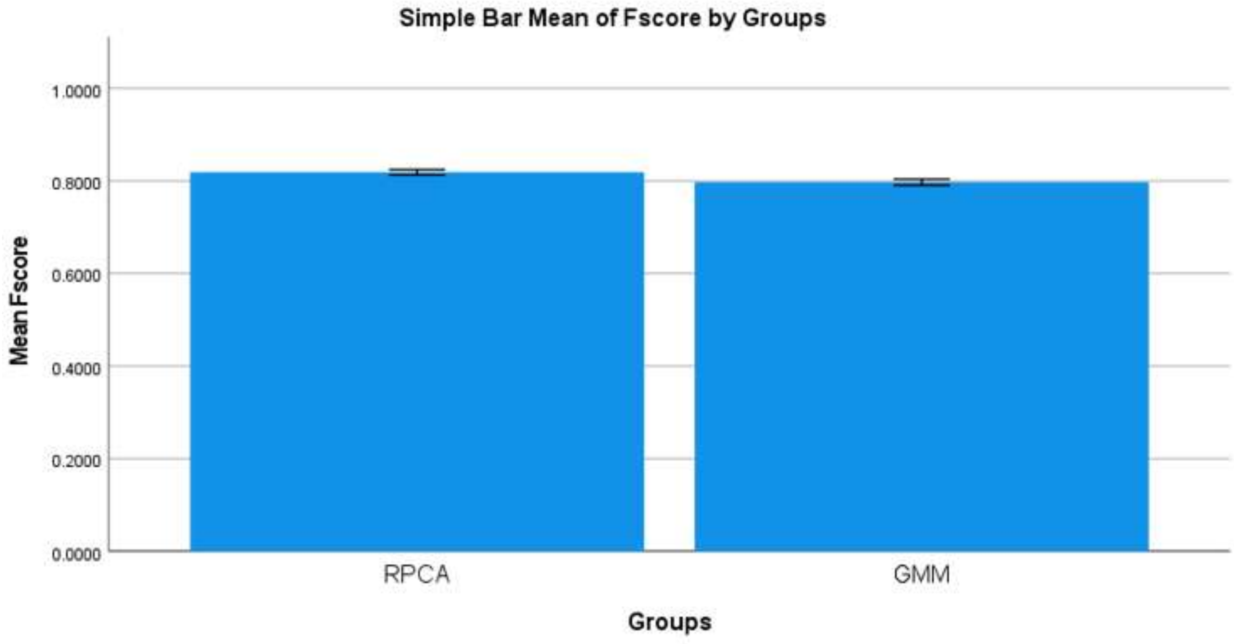


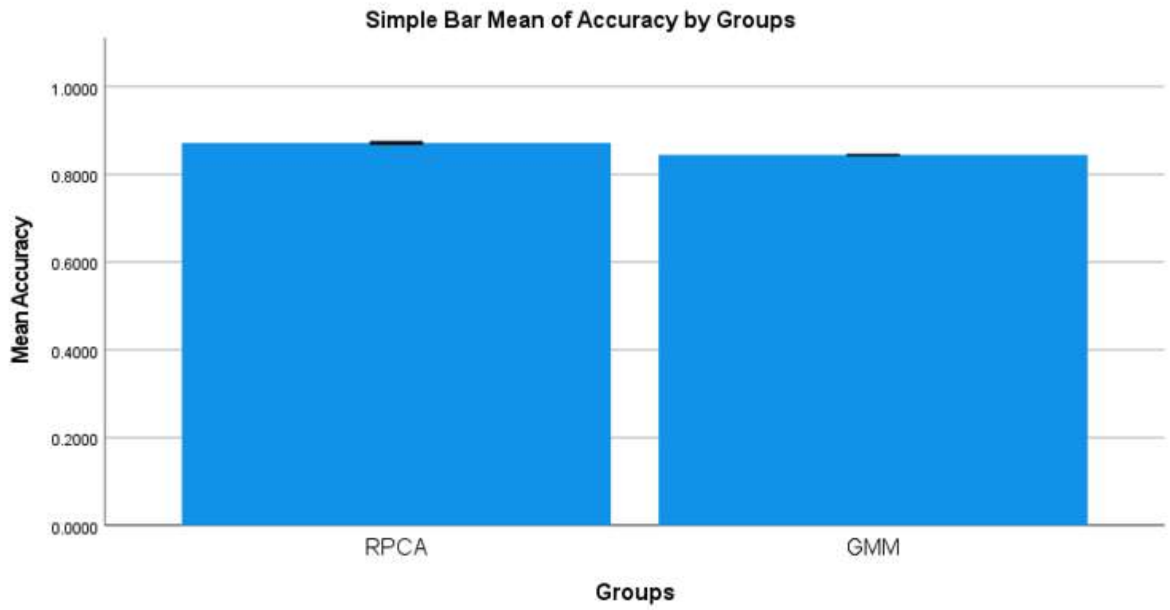
Fig. 5. The following figure shows the accuracy graph between Robust Principal Component analysis (RPCA) and Gaussian Mixture Model (GMM).



Error Bars: 95% CI

Error Bars: +/- 1 SD

Fig.6. Comparison graph for RPCA (82%) and GMM (80%). This shows that the proposed algorithm has a better mean F-score compared to the existing algorithm.



Error Bars: 95% CI

Error Bars: +/- 1 SD

Fig.7. Comparison graph for RPCA (84%) and GMM (82%). This shows that the proposed algorithm has a better mean accuracy compared to the existing algorithm