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Separating Moving Objects from Stationary Background using Dynamic Mode Decomposition

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Abstract— Real-time background/foreground separation of a video is necessary for detecting an object, identifying, tracking vehicle, as well as recognizing objects**.** Several algorithms were already found for background initialization and foreground detection. Recent examinations have presented a robust method, Dynamic Mode Decomposition (DMD) for separating video frames into a background (low-rank) model and foreground (sparse) segments. The full video stream first converted to frames and applied DMD on each frame for the separation of background/foreground objects. Since the method uses full video frames it had more computational complexity and difficult to analyze. For a better solution, this paper shows that the large continuous video stream first converted to frames and each frame breaks into segments and then DMD applied on the segment where the moving object or foreground is obtained. The issue using DMD is the burden of working with large information and now it can be easy work using the segmented video frames. The strength of DMD is demonstrated using a publicly available Scene Background Initialisation (SBI) dataset. The objective of this work is to obtain a background/foreground model from a video sequence where the background is filled with a number of foreground objects with less complexity. Finally compared the accuracy parameters between different background/foreground separation methods with DMD and shows the performance of DMD_Segmented is much better.

Keywords— Background/Foreground Separation, SBI Dataset, Dynamic Mode Decomposition (DMD), Segmentation.

I. INTRODUCTION

There is a developing interest in accurate and real-time video surveillance techniques [1]. In particular, the algorithms that can remove background variations in a video stream, are highly related between frames, to feature foreground objects. Background/foreground separation is necessary for detecting an object, identifying, tracking vehicle, as well as recognizing objects in video sequences. Foreground/Background separation [2] is a developing interest in video surveillance procedures.

A variety of iterative procedures and techniques have been already proposed to perform background/foreground separation. The methods that used for attaining a background model from a given video frames are Spatially Coherent Self-Organizing Foundation Subtraction (SCSOBS) [3], WS2006 [4], RSL2011 [5], Photomontage [6], SR-RPCA [7], R-SpaRCS [8], DG-PCA [9], MAMR [10]. In Spatially Coherent Self-Organizing Background Subtraction (SC-SOBS) algorithm, the background model is estimated by detecting foreground objects using a self-organizing neural background model without any previous knowledge, and this model can handle the positions that containing moving backgrounds, illumination changes as well as camouflage. WS2006 developed for background initialization and the primary quality is in that its high robustness against casual occurrences of foreground objects, as well as against noise in data. RSL2011 is a background estimation algorithm in an MRF (Markov Random Field) structure that can precisely estimate the static background from jumbled observation recordings containing picture noise and foreground objects that may not generally be in movement or may occlude the background for many of the time. A structure that enables a client to effortlessly and rapidly make an advanced photomontage and showed a framework that consolidates graph cut enhancement and a gradient domain image-fusion algorithm with an instinctive user interface for characterizing nearby and worldwide destinations. SR-RPCA (Switched Randomized Robust Principal Component Analysis) joins an arbitrary projection method with a singular value estimation procedure to show the static background and moving foreground while exchanging among various irregular projection matrices to pick the best one in the sense of having a lower mistake. R-SpaRCS algorithm is a regularized version of SpaRCS is a greedy algorithm for background/foreground separation which exploits the way that the foreground component in characteristic recordings shows connectedness. In DG-PCA (Depth-weighted Group-wise Principal Component Analysis) a novel PCA structure was proposed that uses depth based group sparsity for an effective division of foreground and background in video streams and additionally used the depth data in a depth-enhanced homography demonstrate for worldwide movement compensation. MAMR (Motion-Assisted Matrix Restoration) was proposed to encourage efficient foreground/background separation, a thick motion field is assessed for each frame, and mapped into a weighting matrix to allocate the probability of pixels which is belonging to the background. These various methods have some drawbacks like less robustness, the image with grey scale sequences and shadowing effects [3], invariant to moderate brightening change [5], as well as the subsequent composite image is captured with the goal that the last image may show a consistent photography [6]. For more robustness and largescale readings recently a new method Dynamic Mode Decomposition (DMD) were developed against the aforementioned list of methods.

Dynamic Mode Decomposition (DMD) [11] is a modal decomposition technique for separating video frames into a background (low-rank) model and foreground (sparse) segments. This technique is a novel use of a procedure for describing a nonlinear dynamical system in an equation-free way by decomposing the condition of the system into low-rank terms. DMD terms with Fourier frequencies near the origin (zero-modes) are translated as background (low-rank) segments of the given video frames, and the terms with Fourier frequencies limited far from the origin are their foreground (sparse) counterparts. An estimated low-rank/sparse separation is accomplished at the computational cost of only one singular value decomposition and one linear equation solve.

The issue using DMD is the burden of working with a large scale data, with high-resolution pictures as well as numerous frames per video stream. It can be difficult due to lessened computational speeds and large memory sizes. For taking care of this issue, break the continuous video stream into segments large enough to guarantee that there is sufficient data to finish a satisfactory background/foreground separation for ongoing applications. Furthermore, moving objects that turn, stop, and additionally, quicken is handled by the DMD method, than in one huge video segment. Thus, it is anticipated that would make the entire system less complex and keep away from the burden of working with too large data.

The objective of this work is to obtain a background/foreground model from a video sequence where the background is filled with a number of foreground objects. It has a number of applications, including video surveillance, video segmentation etc. Finally, this paper compares the difference between some background/foreground separation methods with DMD that using full video frames and segmented video frames.

This paper is organized as follows: in section II, we provide a brief explanation of DMD, a robust method developed for background/foreground separation. Materials used and methodology of the work are given in section III. Section IV presents the experiment and results. The comparison of different background/foreground separation methods with DMD are given in section V and finally conclude the work in section VI.

II. DMD

Dynamic mode decomposition (DMD) initially presented in 2008 [12], is a method used to analyze the time development of fluid flows. DMD has risen as an effective tool for analyzing the dynamics of nonlinear frameworks. Be that as it may, existing DMD theory deals fundamentally with successive time arrangement for which the estimation measurement is considerably bigger than the number of estimations taken. DMD defined as the eigendecomposition of an approximating linear operator. This sums up DMD to a bigger class of datasets, including Non-sequential time arrangement. Here exhibit the utility of this approach by introducing novel sampling systems that expansion computational efficiency and relieve the effects of noise, respectively.

A. DMD FORMULATION

Consider estimations taken from 'n' observable areas at times $k \Delta t$, and organize estimations at snapshot 'k' to make a column vector x_k [13]. For instance, these estimations may be voltages from 'n' channels of an electrode array sampled each $k \Delta t$.

Gathering estimations from 'm' focuses in time, develop two nx (m-1) raw data matrixes:

$X = [x_1 \; x_2 \; \ldots\ldots \; x_{m-1}]$,

$X^1 = [x_2 \; x_3 \; \ldots\ldots \; x_m]$ ……………………………….. (1)

Here the X and X^1 contain a great overlapping data, contrasting in that columns of X^1 are moved one Δt from those in X.

Assume that there is an unknown linear operator *A* such that that [14], [15],

$X^1 = AX$.. (2)

The dynamic mode decomposition of the information matrix pair X and X^1 is given by the Eigen decomposition of *A*. *A* is describing a high-dimensional linear regression of the nonlinear flow which relates X to X^1.

To get an estimation of *A*, one approach is to use the Singular Value Decomposition (SVD) of the data matrix,
$X = U \Sigma V^*$

B. DMD ALGORITHM

1. Compute the SVD of our first information matrix,
   $X = U \Sigma V^*$

   Now make the substitution into Equation (2) and compose,
   $X^1 = AU \Sigma V^*$

2. Define $\tilde{A} = UAU = U X^1 V \Sigma^{-1}$

3. Compute the Eigen decomposition of $\tilde{A}$
   $\tilde{A} W = W \Lambda$ Where, W is the matrix of Eigenvectors, and,

   Λ is the diagonal matrix of eigenvalues.

   Each eigenvalue λ_i is a DMD eigenvalue.

4. Compute the DMD modes,

   $\phi = X^1 V \Sigma^{-1} W$ ………………………….. (3)

   Each column of ϕ is a DMD mode ϕ_i identifying with eigenvalue λ_i.

A DMD mode ϕ_i is a vector that has an undefined estimation from x; its magnitude represents to spatial relationships between the 'n' detectable regions. The eigenvalue λ_i relates to the temporal dynamics of the spatial mode ϕ_i. In particular, its rate of growth/decay and frequency of oscillation are reflected in the magnitude and phase parts of λ_i, individually.

III. MATERIALS AND METHODS

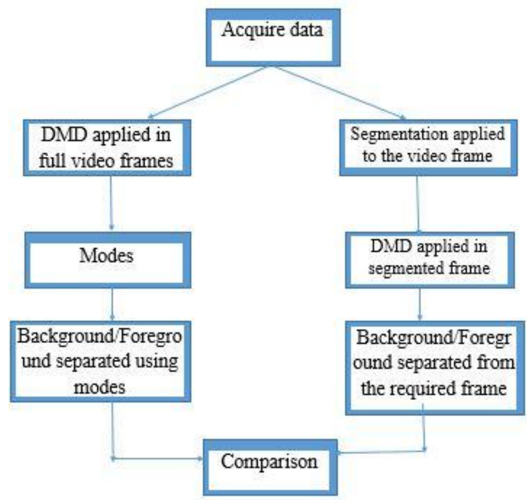

Figure 1. Flow Chart

The flowchart shows a brief idea of the work. First, acquire the input data from publicly available Scene Background Initialisation (SBI) dataset. The input data is the "viptraffic.avi" video stream of size 1x120 and 6939008 bytes. The video will be converted into 150 frames of size 120x160 with framerate of 15 and bits per pixel 24. Then DMD will be applied to the full video frames for background/foreground separation.

Due to the high computational complexity to work with large continuous video streams, segmentation will be done. As usual, the same video "viptraffic.avi" converted into frames. Each frame will be broken into segments. Segmentation is the partitioning of a digital image into multiple segments. Segmentation process converts each frame into 4 blocks of size 60x240 and considers the only block which contains foreground or moving object. Finally, applied DMD on the specified block for separation.

IV. EXPERIMENT AND RESULT

Experiment presents and compared the results using the method DMD with full video frames and segmented video frames. The total number of frames includes 150. 2 of 150 frames shown in the Fig. 2 (a) and (b). All experiments were conducted on a personal computer with Intel i5 Processor and 32GB RAM running MATLAB R2017a (64 bits). The number of measurements is with respect to the total number of pixels in the video stream.

(a)

(b)

Figure 2 (a) and (b). Video Frames

DMD modes ϕ_i are obtained from equation (3) that is shown in Fig.3. DMD computes a set of modes each with fixed oscillation frequency and decay/growth rate. The mode which is in the origin represents the low rank and the modes away from the origin represents the sparse components. The low-rank components show the stationary background which has low frequency and the sparse components shows the dynamic foreground objects having high frequencies. The background and foreground are separated according to the modes obtained. Since the background is stationary the low-rank components are less and lot of sparse components that represents foreground objects are packed in a common area. Fig. 4 shows the separate 150 modes which represent foreground sequence specifically.

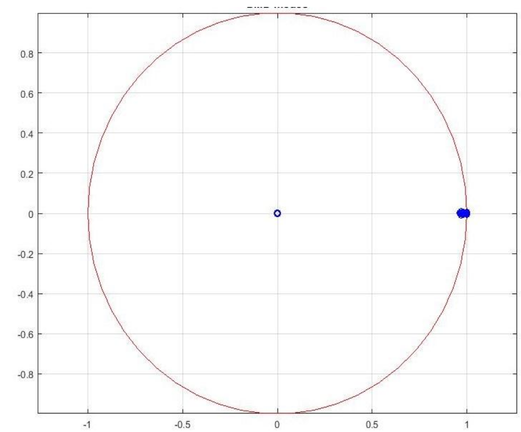

Figure 3. : DMD Modes.

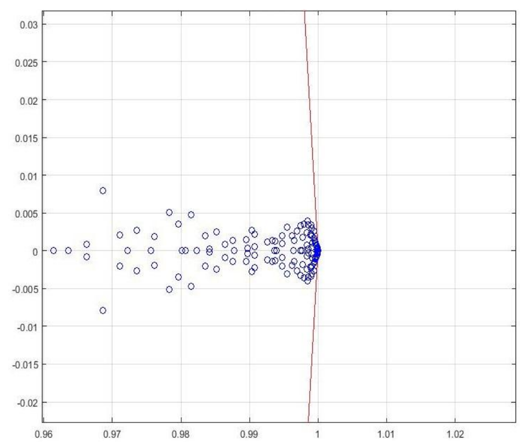

Figure 4. DMD Modes (Foreground). The modes which represent the foreground objects include all the 150 frames.

DMD essentially implements Fourier decomposition of video frames in time from the modes. Basically non-linear systems are difficult to analyze and DMD is a linear model for modeling dynamical systems. It uses a couple of spatial-temporal modes. DMD defined as an Eigen decomposition of an approximating linear operator. It is the dimensionality reduction algorithm. This distinguishes the stationary background from the dynamic foreground. By differentiating the near-zero modes and remaining modes away from the origin DMD accurately separate video frames into Background and Foreground components, in real-time shown in Fig. 5 and Fig. 6.

Figure 5. Foreground Separation

Figure 6. Background Separation

Now segmentation is applied to each frame. Segmentation in the sense that a digital image or a frame is partitioning into multiple blocks. Segmentation of one frame will be like Fig.7. In the segmented frame (Fig.7) only one block is needed to be separated or only one block contains foreground objects that shown in Fig.8. Then DMD applied on the block containing moving objects. From each frame after segmentation selects the blocks with moving objects and finally applied DMD. This reduces the difficulty of work with a larger class of datasets. Advantages of using segmentation are computational efficiency, robustness, better quality of image compared to other methods as well as no limited memory sizes.

Figure 7. Segmented Frame

After applying DMD separate the dynamic foreground object from the stationary background which is shown in the Fig. 9 from the modes extract.

Figure 8. Block with moving object

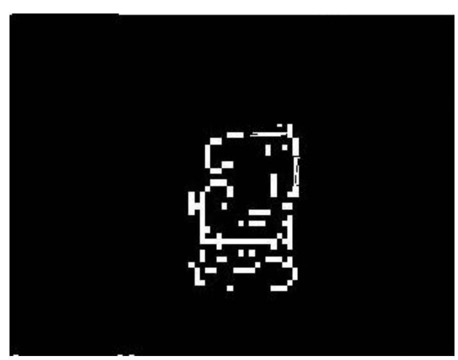

Figure 9. Foreground Separation

V. COMPARISON

Table I shows the comparison of Multi-scale Structural Similarity Index (MS-SSIM) and Peak Signal to Noise Ratio (PSNR) of the different background/foreground separation methods. SSIM really measures the perceptual difference between two comparative images. SSIM can provide a better approximation of image quality. It includes Single-scale SSIM and Multi-scale SSIM for measuring the image quality. Multi-scale SSIM gives more flexibility than Single-scale approach incorporating the changes of image resolution and seeing conditions. MS-SSIM can be measured using,

Let $x = \{x_i \mid i = 1,2,\ldots..N\}$, $y = \{y_i \mid i = 1,2,\ldots..N\}$ be 2 discrete non-negative signals that aligned with each other, and let μ_x, σ_x^2 and σ_{xy} be the mean of x, the variance of x, and the covariance of x and y, respectively.

Structure comparison measures were given as follows,

$l(x, y) = 2\,\mu_x\,\mu_y + C_1 / \mu_x^2 + \mu_y^2 + C_1$,

$c(x, y) = 2\,\sigma_x\,\sigma_y + C_2 / \sigma_x^2 + \sigma_y^2 + C_2$,

$s(x, y) = \sigma_{xy} + C_3 / \sigma_x\,\sigma_y + C_3$

where C1, C2, and C3 are small constants given by $C_1 = (K_1 L)^2$, $C_2 = (K_2 L)^2$ and $C_3 = C_2/2$,

The general form of the Structural Similarity (SSIM) index between signal x and y is defined as:

$SSIM(x, y) = [l(x, y)]^{\alpha} \cdot [c(x, y)]^{\beta} \cdot [s(x, y)]^{\gamma}$,

where α, β and γ are parameters that define the relative importance of the three components. Specifically, we set α = β = γ = 1, and the resulting SSIM index is given by,

$$SSIM(x, y)=[l_M (x, y)]^{\alpha_M}.\prod_{j=1}^{M} [c_j (x, y)]^{\beta_j} [s_{j}(x, y)]^{\gamma_j}$$

Peak Signal to Noise Ratio (PSNR), is the ratio between the peak possible power of a signal and the power of a noise. Since numerous signals have a wide unique range, PSNR is generally expressed in logarithmic decibel scale. It is defined as,

$PSNR = 10 \log_{10} ((L-1)^2/MSE)$,

where L is the maximum number of grey levels and MSE is the Mean Squared Error between Ground Truth and Colored Background images. Higher the PSNR value, better the background estimate.

From this comparison table, it is clearly mentioned that MS-SSIM and PSNR of DMD is found to be the better method and its performance is further improved in DMD_Segmented.

TABLE I. Comparison

METHODS	MS-SSIM	PSNR
RSL2011	0.9172	29.9272
Photomontage	0.9334	31.8573
WS2006	0.9349	28.8791
DMD	0.9992	43.1920
DMD_SEGMENTED	0.9995	45.5154

VI. CONCLUSION

This paper has been demonstrated that the method of dynamic mode decomposition, typically used for evaluating the dynamics of complex systems, can be used for background/foreground separation in videos with visually appealing results and excellent computational efficiency. The issue using DMD is a load of working with an excess of information and it can be easy work using the segmented video frames. This work obtained a background/foreground model from a video sequence where the background is filled with a number of foreground objects with less complexity and compared the results of DMD with other methods.

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