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Foreground Segmentation and Change Detection Using Singular Value Decomposition

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Abstract :*Separating background from a video image is an important step for change detection. Most of the change detection methods depend on intensity and texture variations. These algorithms may not give very satisfactory results because of the illumination variation and presence of noise. In this paper we have attempted to segregate moving foreground from video data set and change detection in time series data sets using singular value decomposition (SVD) which is a generalization of the Eigen decomposition which can be used to analyze rectangular matrices. 'CDnet 2012', an open source dataset is used as input image dataset. We have taken SVD for all input images and singular values of all these images were used for detecting any change present in images. A comparison was made for obtained results with the results of 'CDnet 2012'. It is found that the obtained results are very effective and clearly segregate foreground.*
Keywords *: Background Subtraction, Singular Value Decomposition, Eigen Values, CDnet 2012.*

I. Introduction

Segmentation of foreground object is a big problem in computer vision tasks such as image processing, medical image analysis and traffic data surveillance etc. A large number

of algorithms and techniques to achieve this task have been already developed. In this paper we have presented a method to segment foreground non-static object from static background in a time series data set. We have used Singular value decomposition (SVD) technique for our work. We have also used SVD for change detection. SVD is basically a factorization of a matrix and is a widely used algorithm in image processing and signal processing for different applications such as dimensionality reduction and image compression .The main aim of our work is to find out the static background of image. Once we know the background then the non-static objects can be easily segregated by simply subtracting the background from image. SVD provides the singular values for our dataset. Graphical analysis of these singular values will help in setting a threshold for background and foreground. This is explained in methodology part in detail.

This paper is organized as follows. In section 4 we present the SVD algorithm and its application for our work. In section 5 we have presented our methodology and approach. Section 6 presents the results and section 5 is the conclusion of this paper.

II. Foreground Segmentation

Foreground segmentation is any technique which allows image foreground to be extracted from the image for further application (object recognition etc.). Foreground is not static in nature ,it represents changes which occur in an image while background is static scene in an image.

Detecting foreground in an image is considered as one of the most important task in field of image processing and computer vision .Task of image segmentation is to find changes which has occurred in an image because only region of interest in an image are objects (text ,human ,car etc) in the foreground .Every detection technique are usually based on modeling background of an image (settle the background and then figure out the changes which occur in an image)

In many of the applications we need not to know each and everything related to evolution of movement of a particular video the only thing we require is information related to changes which has occurred in an image.

Background + moving objects (people) **Foreground**

III. Image Subtraction

Image subtraction which is also known as pixel subtraction is the process by which digital numeric no. of the whole image or one pixel is subtracted from any other image .The pixel subtraction method can be used like sub step in any complex image processing or it can also be used as an operator for its own right Image .Image subtraction is mainly used for leveling sections of images which are uneven or for highlighting changes which has occurred in an image .If the picture element value of a given image is vector in place of a scalar(colored images) then each and every single component(green, blue, red) are subtracted individually for extracting output values.

Subtracting image can sometime result in the negative output for certain pixels in some cases an image format supports negative values but in case if the image format is such that it does not support negative values then the image value is set to zero (black image). Image subtraction is used to produce a single different image as an output from different input images.

Image subtraction is expressed as follows

$$Y = \frac{1}{K}(a_i x_i - a_j x_j)$$

a_i and a_j are weights which are important to make sure that differencing is performed in a balanced way. If suppose brightness of x_i are more than that of x_j then the difference between $x_i - x_j$ will be dominated by x_i because of which exact difference between both the image will not be revealed exactly.

Image subtraction is one of the effective and simplest technique used for change detection and foreground extraction.

IV. Singular Value Decomposition

Singular value decomposition has a surprising and log history, svd origin belongs to social sciences (intelligence testing).Researchers who are involved in the early phases of intelligence testing noted that the test which they are performing on distinct situation of intelligence like spatial and verbal are closely correlated to each other this is the reason they assumed that general measure of intelligence is customary for the general intelligence which is known as I.Q .During early days SVD is known by many different names like “factor analysis” or “empirical orthogonal function”. Today svd is very useful in different branches of science specially svd is extremely useful in machine learning in both predictive statistics as well as in descriptive statistics. Singular value decomposition is a method of decomposing a matrix into three other matrices:

$$\boxed{A = USV^T}$$

Where:

- **A** is an m × n matrix
- **U** is an m × n orthogonal matrix which is made from Eigen vectors of $\mathbf{AA^T}$.
- **S** is an n × n diagonal matrix with Eigen values of $\mathbf{AA^T}$ as diagonal elements in decreasing order.
- **V** is an n × n orthogonal matrix which is made from Eigen vectors of $\mathbf{A^TA}$.

The diagonal entries of **S** are known as the singular values of **A**. Singular values are also known as s-numbers. Singular values are obtained by square roots of the eigenhvalues of a non negative operator .Concept of singular values was suggested by Erchard Schmidt in the year 1907 .In general singular values are arranged in descending order. In this case, the diagonal matrix, **S**, is uniquely determined by **A.** The columns of **U** are called left singular vectors, while those of **V** are called right singular vectors.

The matrix A which is a linear transformation matrix which is further decomposed into three different sub transformation that is rotation, re-scaling and rotation thus USV^T are known as composition of geometrical transformation . Rotation matrix in linear algebra is a matrix in which rotation is performed in Euclidean space for any matrix of n-dimension matrix rotation A acting on A^N

$$A^T = A^{-1}$$

Scaling is defined as a linear transformation that is used to shrink or enlarge object by scale factor which is similar in every direction.

V. Methodology

We have taken 'CDnet 2012' open source data as our input images. This data set contains a lot of images of different categories. For our experiment we have chosen 'shadow' and 'baseline' datasets. The input data set is selected in such a way that few images will have no moving or changing objects and few image frames will have non-static objects.

As explained in previous section, SVD factorizes a matrix and provides its singular values. The input image matrices are converted into an array and all of these arrays are arranged in a matrix in such a way that all image vectors will be in row. Now singular value decomposition algorithm is applied on this matrix of images and all singular values are arranged in decreasing order. A plot has been made for these singular values and based on the plot we will decide the threshold for segregating foreground from image. These steps are explained in below flow diagram.

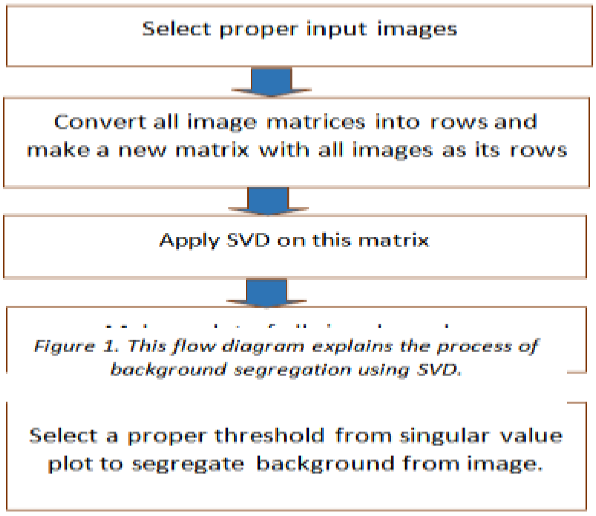

Figure 1. This flow diagram explains the process of background segregation using SVD.

VI. Results

We have used CDnet 2012 data for our experiment. We have taken 10 images for our experiment from video frames in such a way that in few frames there is no moving object and in other few frames some changes are present. As explained in previous section that SVD provides the Eigen decomposition of input matrix. Following are the input images we have chosen for our experiment –

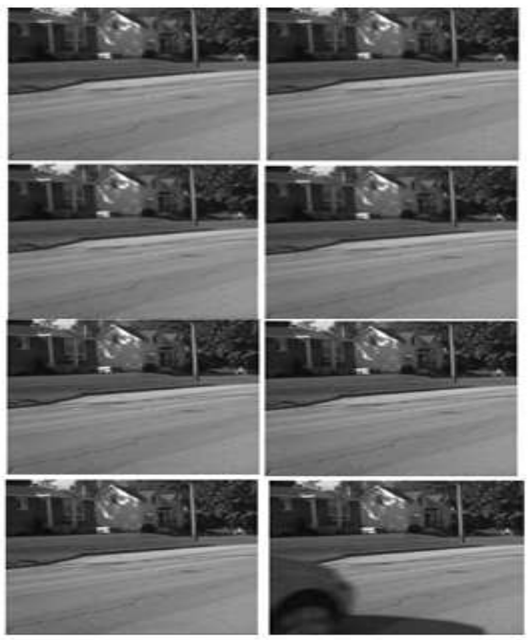

Figure 1 In this figure first 7 frames are having static background but in last frame there is a car.

We have performed SVD for above images and following singular matrix was obtained:

Table 1

72110.52	0	0	0	0	0	0	0
0	7508.27	0	0	0	0	0	0
0	0	881.73	0	0	0	0	0
0	0	0	482.38	0	0	0	0
0	0	0	0	403.50	0	0	0
0	0	0	0	0	384.49	0	0
0	0	0	0	0	0	372.48	0
0	0	0	0	0	0	0	369.31

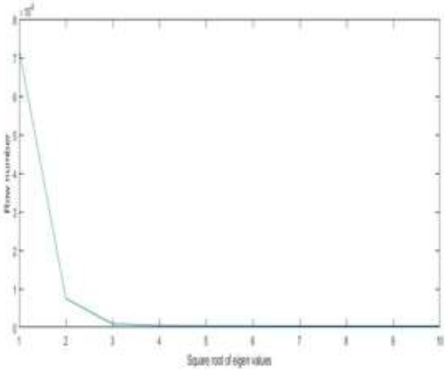

Figure 2 Plot representing diagonal elements of singular values matrix.

From above plot we can select first singular value as our background and remaining singular values as our foreground. The processors is explained below-
If **A** is our input matrix then

$$\boxed{A = USV^T}$$

As explained earlier also **U** is an m × n orthogonal matrix which is made from Eigen vectors of $\mathbf{AA^T}$, **S** is an n × n diagonal matrix with Eigen values of $\mathbf{AA^T}$as diagonal elements in decreasing order and **V** is an n × n orthogonal matrix which is made from Eigen vectors of $\mathbf{A^TA}$. Now, from the above plot, for selecting background, we have taken only first singular value. The following equation is used in MATLAB code-

$$\mathrm{A(back)} = \mathrm{U}(:,1:1) * \mathrm{S}(1,1) * \mathrm{V}(1:1,:)'$$

Similarly for foreground we have chosen remaining singular values,

$$\mathrm{A(fore)} = \mathrm{U}(:,2:8) * \mathrm{S}(2:8,2:8) * \mathrm{V}(2:8,:)'$$

Now, **A(back)** will provide back ground image of all frames and **A(fore)** will provide foreground images of all the frames. Following is the segregated background and foreground for the 8thframe of input data-

(a) (b) (c)

The image on the left (a) is the original image and the center image (b) is the background image and image on the right (c) is foreground image.
Similar experiments was done for different data sets-

Following results are obtained for the above images after applying SVD

Table 2

90699.09	0	0	0	0	0	0	0
0	6086.13	0	0	0	0	0	0
0	0	783.26	0	0	0	0	0
0	0	0	621.99		0	0	0
0	0	0	0	541.48	0	0	0
0	0	0	0	0	485.40	0	0
0	0	0	0	0	0	448.49	0
0	0	0	0	0	0	0	408.70

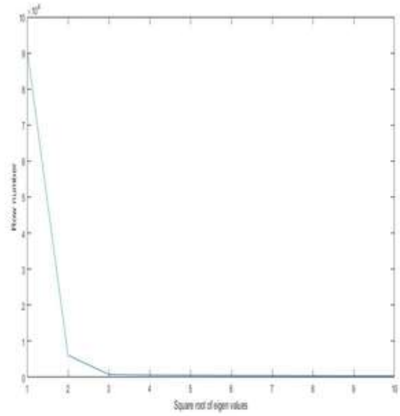

Figure 2 Plot representing diagonal elements of singular values matrix.

The image on the left is the original image and the center image is the background image and image on the right is foreground image.

VII. Conclusion And Future Scope

Many techniques for background segregation and change detection from images are already established. We have attempted to exploit the utility of singular value decomposition to detect the change in any time series image. In our experiment we have implemented SVD using MATLAB software. It can be seen that the results obtained are very good and can be compared with any established change detection and background segregation algorithm. Our technique worked well with almost all the datasets we have chosen. It generates singular vectors for equivalent to number of input images. It has been observed from the plots of singular vectors that only first singular value provides the background information in all cases.

This technique is very fast when compared to other established techniques for background segregation from time series data sets.

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