Foreground Segmentation and Change Detection Using Singular Value Decomposition

Priyanshi Sachan, Pooja Khanna
(CSE, Amity University Lucknow, India)
Corresponding Author: Priyanshi Sachan

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 datasets 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.

Key points: Background Subtraction, Singular Value Decomposition, Eigen Values, CDnet 2012.

II. SINGULAR VALUE DECOMPOSITION

Singular value decomposition is a method of decomposing a matrix into three other matrices:

\[ A = USV^T \]

Where:
- \( A \) is an \( m \times n \) matrix
- \( U \) is an \( m \times n \) orthogonal matrix which is made from Eigen vectors of \( AA^T \).
- \( S \) is an \( n \times n \) diagonal matrix with Eigen values of \( AA^T \) as diagonal elements in decreasing order.
- \( V \) is an \( n \times n \) orthogonal matrix which is made from Eigen vectors of \( A^TA \).

The diagonal entries of \( S \) are known as the singular values of \( A \). 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.
III. 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.

![Flow diagram](image1.png)

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

IV. 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 –
We have performed SVD for above images and following singular matrix was obtained

\[
\begin{array}{cccccccc}
72110.52 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 7588.27 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 881.73 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 482.38 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 403.50 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 384.49 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 372.48 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 369.31 \\
\end{array}
\]

Table 1
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 \( \mathbf{A} \) is our input matrix then

\[
\mathbf{A} = \mathbf{U} \mathbf{S} \mathbf{V}^T
\]

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

\[
\mathbf{A} \text{(back)} = \mathbf{U}(:,1:1) \ast \mathbf{S}(1,1) \ast \mathbf{V}(1:1,:)^T
\]

Similarly for foreground we have chosen remaining singular values,

\[
\mathbf{A} \text{(fore)} = \mathbf{U}(:,2:8) \ast \mathbf{S}(2:8,2:8) \ast \mathbf{V}(2:8,:)^T
\]

Now, \( \mathbf{A} \text{(back)} \) will provide back ground image of all frames and \( \mathbf{A} \text{(fore)} \) will provide foreground images of all the frames. Following is the segregated background and foreground for the 8th frame of input data-
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 were done for different data sets-

Following results are obtained for the above images after applying SVD-
**Table 2**

<p>| | | | | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>90699.09</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>0</td>
<td>6086.13</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>783.26</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td>621.99</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>541.48</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>485.40</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>448.49</td>
<td>0</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>408.70</td>
</tr>
</tbody>
</table>

**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.
V. 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.

BIBLIOGRAPHY-

[6]. Lili Guo, Dan Xu, ZhenpingQiang. School of Information and Engineering, Yunnan University. Background Subtraction using Local SVD Binary Pattern.
[12]. SaleheErfanianEbadi, Student Member, IEEE, Valia Guerra Ones, and EbroulIzquierdo, Senior Member, IEEE. Approximated Robust Principal Component Analysis for Improved General Scene Background Subtraction.