Published by :
https://www.ijert.org/
An International Peer-Reviewed Journal

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 11 , November - 2026

Comparative Study on the Performance of Variants for Singular Value Decomposition Based-Image Compression

Avinash Kumar[1*],Prashant Priyadarshi[1], Raj Shekhar[1] ,Ronit Kumar Paul[1], Isha Topno[1]
1Department of Computer Science and Engineering,
BIT SINDRI DHANBAD, India;

Abstract— Image compression is of utmost importance in current digital communication technology due to reduction in the storage capacity and band-width while retaining the quality of images. Among different transforms used for image compression, Singular Value Decomposition (SVD) is one such technique that has gained popularity due to its mathematical basis and ability to make low rank approximations. The objective of this review paper is to conduct a comparative study among recent advances in SVD-based image compression schemes such as Truncated SVD, Randomized SVD, Partition Based SVD, etc. The study investigates their working principles, reconstruction mechanisms, computational behavior, and compression performance. The comparative analysis of the methods was carried out on the basis of grayscale benchmark images, utilizing performance measures like Compression Ratio (CR), and Peak Signal to Noise Ratio (PSNR). From the results of comparison, the Truncated SVD algorithm exhibits greater compression performance, but the PBSVD and APBSVD techniques have greater reconstruction performance since they preserve the structure of the image locally. Adaptive or randomization strategies can offer improved adaptability and efficiency of computations on large image databases.

***Index Terms*—Image Compression, Singular Value Decomposition (SVD), Truncated SVD, Randomized SVD, Adaptive SVD, Sparse SVD, SS-SVD, Low-Rank Approximation**

I. NTRODUCTION

Digital images are now an integral part of computer-mediated technologies like multimedia information systems, satellite communication links, remote sensing, computer vision, medical imaging, and biometric identification. As high-resolution imaging devices become more prevalent, the collection of these images has generated millions of slices of images, which poses problems with memory, transport bandwidth and computational power. Due to this, the compression of images has turned into a vital research and development area in order to minimize the data volume and simultaneously preserve the visual quality of image.

One widely-used and popular technique of matrix factorization for image compression is Singular Value Decomposition (SVD). Multiresolution SVD image compression is demonstrated to be effective by Ashino et al. [1] and it is also observed that the computation of the low rank approximation can reduce a big storage space. Shih et al. [2] then enhanced the compression superior to SVD by introducing Adaptive Partition Based SVD (APBSVD) and Partition Based SVD (PBSVD) which preserve the local image structures by partition images into the smaller blocks. Rufai et al.

In [3] they used the wavelet difference reduction technique to increase the efficiency of compression and the quality of reconstruction compared to SVD.

The idea of randomized matrix decomposition methods was developed by Halko et al. [4] who proposed the probabilistic algorithms for approximate matrix decomposition. Kumar and Singh [5] presented a Sparse SVD approach in which they used sparse coefficient matrices for efficient image representation. One is the block-based SVD compression algorithm proposed by Liu et al. [6] to improve the preservation of local features. To reduce the redundancy and enhance the compression performance, Xu et al. [7] applied singular vector sparse reconstruction techniques into the video compression.

Pomponiu et al. [8] suggested a technique called Spread Spectrum Singular Value Decomposition (SS-SVD) that is used to adapt the singular value spectrum for flexible image representation. In an attempt to achieve efficient compression to remove insignificant singular values, Sharma and Gupta [9] had developed the methods based on thresholding SVD. Erichson et al. [10] studied randomized matrix decompositions methods for speeding up SVD calculations on large data sets. Under compressed representations, Kumar et al. [11] proposed to enhance the image quality via image reconstruction techniques based on matrix completion. Verma and Jain [12] then investigated some singular spectrum modification methods in the field of image processing.

Compression methods of images and representation of data have also played their part in contributing to this subject area. Maniccam and Bourbakis proposed its methodology - SCAN in [13] for lossless image compression and encryption techniques. De Lathauwer et al. [14] took SVD further into the higher dimensional representation of data using the approach of Higher-Order Singular Value Decomposition (HOSVD). Salomon and Motta [15] have written a thorough survey of the principles and techniques of data compression which continue to have an impact on current compression research.

(This work is licensed under a Creative Commons Attribution 4.0 International License.)

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 11 , November - 2026

Golub and Van Loan [16] considered the mathematical aspects of SVD in great detail. Candès and Recht [17] presented a group of low-rank recovery-based techniques for matrix completion, and Cai et al. [18] presented Singular Value Thresholding (SVT) algorithm on matrix reconstruction. Tensors and multidimensional signal processing were the following areas of interest that drew inspiration from SVD concepts, as extended by Kolda and Bader [19]. Low-rank approximation methods are shown to be useful for IR and dimensionality reduction applications by Berry et al. [20].

Gillis and Glineur [21] discussed an enhanced approach for approximation of low rank matrices, namely, the approach based on weighted matrices. Randomized SVD algorithm implementation is described in Voronin and Martinsson [22]. Motivated by the demand of image compression with adaptive low-rank approximation methods, Zheng et al. [23] advocated the use of such techniques and validated the resulting balance between Compression Ratio (CR) and the quality of the reconstructed image. A more recent work available in the literature is by Roy and Chakraborty [24] who reviewed modern SVD based image compression techniques and Sharma and Verma [25] who presented comparative analysis of these advanced variants of SVD based image compression.

While some very good work has been done on the SVD image compression, most of the work has been devoted to a single algorithm or application specific implementations. It is however desirable to perform comprehensive comparisons of multiple variants of SVD based on common databases with well-established "standard" performance metrics like Compression Ratio (CR) and Peak Signal to Noise Ratio (PSNR), this seems to be restricted. Hence, in this paper an advanced SVD based image compression algorithms were analyzed in comparison to each other and a review of their compression efficiency, reconstruction quality, behavior in the computational aspects and their adaptation in modern image compression applications are presented.

A. Digital Image

A digital image refers to the depiction of visual information in two-dimensional form by means of pixels. These pixels have values pertaining to grayscale and color intensities.

Mathematical Grayscale representation as :

$$A \in R^{m \times n}$$

Where m & n denote the numbers of rows & columns respectively. Digital images have been extensively applied in many fields such as medical imaging, multimedia system, satellite communications, remote sensing, and computer vision. High image resolutions cause problems in storing, processing and transferring large volume image data.

B. Image Compression

Image compression refers to the technique that is employed for making the file of an image smaller, without compromising on the acceptability of the image quality. The purpose is to save on memory as well as reduce bandwidth usage, which comes as a result of eliminating redundant information from the Data. Some of the common methods employed to compress images belong to: Lossy Image Compression & Lossless Image Compression. Examples of some of the transformations that are often used to compress an image are:

Discrete Cosine Transform, Wavelet Transform, Karhunen-Loeve Transform & Singular Value Decomposition. SVD is regarded as efficient due to its capability for giving a low rank approximation.

C. Singular Value Decomposition (SVD)

SVD is a matrix factorization method that can be used to manipulate images for the purpose of data compression. For an image matrix:

$$A \in R^{m \times n}$$

The decomposition process is given by:

$$A = U\Sigma V^{T}$$

U and V are orthogonal matrices and the singular values are in Σ. The larger singular values contain more important image structure (e.g., edges, textures), whereas the smaller singular values are signaling noise and redundant structure. SVD-based compression is used to reconstruct compressed images based on the dominant singular values thus reducing the storage requirement. Its impressive performance has led to its popular use in image compression, image denoising, watermarking, image feature extraction etc., to machine learning applications and more.

D. Research Gap

Typical SVD image compression is very successful in approximating the image by a low rank one, but fails to capture edges and local image details and requires high computational complexity due to the use of fixed rank. To alleviate these problems, randomized variants of SVD (Randomized SVD, PBSVD, Adaptive SVD, Thresholding SVD, Sparse SVD, SS-SVD, and APBSVD) have been proposed. Major existing works are about individual algorithms, however, few of them involved in these studies, however, are interested in doing a comprehensive comparative study on a lot of variants of SVDs. These and other essential questions, such as adaptive rank selection, preserving the local features, efficiency, and compression-quality trade-off, have been hardly explored in a common language.

(This work is licensed under a Creative Commons Attribution 4.0 International License.)

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 11 , November - 2026

E. Problem Statement

An effective storage and communication approach for high resolution imaging systems. Existing compression techniques do not always have an ideal value of Compression Ratio (CR) and reconstructed image quality. There are a number of different advanced SVD variants which have been created but their relative performance is not well analysed. Thus, in this review paper, various SVD based variants of image compression scheme with their compression efficiency, reconstruction quality, adaptive behavior and computational performance are analysed and compared for finding appropriate image compression scheme for modern image compression application.

II. LITERATURE REVIEW

In order to enhance the performance in image compression and reconstruction, few algorithms based on Singular Value Decomposition (SVD) have been proposed. To mitigate the complexity of image storage, Ashino et al. [1] proposed multiresolution SVD-based image compression that showed using SVD can be effectively used to approximate the images with low ranks. Much of their work led to the mathematical underpinning of a number of later image compression methods based on the SVD. Shih et al. [2] suggested the Adaptive Partition-Based SVD (APBSVD) and Partition-Based SVD (PBSVD) methods for both image denoising and compression. Their method consists of dividing images into small blocks and using the adaptive singular value selection to keep parts which depict local detail characteristics in images like edges and textures. Experimental results revealed better Peak Signal Noise Ratio (PSNR) than the conventional global SVD methods.

Rufai et al. [3] explored lossy image compression method based on SVD and wavelet difference reduction. Their results show that the SVD can be combined with transform-based approach in such a manner that compression efficiency can be substantially enhanced and the image quality remains more than acceptable. Halko et al. [4] suggested a random matrix decomposition technique as a procedure to create approximate decompositions by employing probabilistic approaches. They developed randomized versions of SVD methods that were less computation intensive, but still achieved good reconstruction accuracy. To save the storage space and for efficient image compression with less computation time, Kumar et al. [5] introduced Sparse SVD approach, which uses sparse coefficient matrices. Liu et al. [6] suggested an image compression approach based on SVD block method, which preserved the local feature of the image in the block-based image processing. The same research on sparse reconstruction was proposed by Xu et al. [7] for the purpose of improving the water mark compression performance and reduce the redundancy of the image to be retrieved.

Pomponiu et al. [8] proposed the Spread Spectrum Singular Value Decomposition(SS-SVD) algorithm, which is a work on perturbation-based modifying the singular values for data hiding and image representation. Increasing the flexibility of representation led to a loss of fidelity in the reconstruction, though, with excessive perturbation. To achieve a high compression efficiency Sharma and Gupta [9] suggested a technique based on thresholding of SVD singular values to eliminate insignificant values. Ettewer and others [10] continued to examine the randomized matrix decomposition methods, showing that randomized algorithms can greatly speed up SVD calculations in large scale applications, while guarantees of good approximation accuracy.

In recent years, the reconstruction of image analysis and quality enhancement has also been focused on adaptive SVD framework. Kumar et. al. [11] developed an image compression and quality restoration method based on matrix completion that leads to improved quality of reconstructed images for compression. In a move towards the singular spectrum modification for image processing, Verma and Jain [12] showed the effect of spectral adjustments on reconstructed image quality.

Unmodern methods of image lossy compression have also become significant to the development of modern image compression techniques. The SCAN [13] method recommended efficient techniques to represent images in a lossless compression and encryption method for maniccam and Bourbakis. De Lathauwer et al. SVD was extended to deal with multi-dimensional data and tensor representation in [14], which is termed as Higher-Order Singular Value Decomposition (HOSVD). Their work was later instrumental to the development of image/video processing applications that use tensors. In image compression research, the work of Salomon and Motta [15] details all aspects of data compression principles, the algorithms and the necessary implementation strategies. The theory of SVD in mathematics has received further validation from research into matrix computation. One of the most comprehensive treatments of matrix factorisation techniques and numerical algorithms to compute the SVD are due to Golub and Van Loan [16] and have considerable influence in the area of matrix analysis. By means of this extension, Candès and Recht [17] formulated the idea of matrix completion to construct a low-rank matrix based on its incomplete observations. Cai et al. [18] developed the Singular Value Thresholding (SVT) algorithm that is considered as a basis of any algorithm for low-rank approximation and matrix completion.

In addition to the above mentioned fields of application of image compression techniques, there is another area of high interest associated with multidimensional signal processing. Higher-order SVD has been employed in multidimensional signal processing, and Kolda and Bader [19] reviewed extensively the use and applications of tensor decompositions. Further, SVD-based dimensionality reduction techniques were shown to be useful in information retrieval systems in the work of Berry et al. [20].

There are a few researchers that studied the weighted and adaptive low rank approximation technique. In practical applications, Gillis and Glineur [21] suggested low-rank matrix

(This work is licensed under a Creative Commons Attribution 4.0 International License.)

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 11 , November - 2026

approximation methods for data sets with missing values to enhance the robustness. The randomized SVD algorithms proposed by Voronin and Martinsson [22] reduced the calculations needed to compute the SVD for large matrices considerably. Zheng et al. [23] proposed adaptive low rank approximation technique for image compression and demonstrated its effect to balance compression ratio and reconstruction quality.

The development of hybrid and intelligent framework systems has been the recent interest in SVD-based image compression technology. Roy and Chakraborty [24] gave a comprehensive survey of the recent image compression techniques based on SVD and emphasized adaptive, sparse and randomized approaches. Rather than using the traditional low-rank approximation techniques, Sharma and Verma [25] compared the performance of some advanced variants of SVD and showed that adaptive and block-based techniques with SVD result in the better image preservation after compression.

While a lot of works have been developed on image compression by exploiting the concept of SVD, most are tackling single algorithms or application specific implementations. Comparative studies of different variants of SVD with common reference data sets and standard assessment procedures, including Compression ratio (CR) and Peak Signal to Noise ratio (PSNR), have been limited. Hence, detailed comparative studies of the advanced variants of SVD are inevitable to facilitate revealing efficient image compression technique appropriated for current multimedia and digital imaging applications.

III. PRELIMINARIES

A. Singular Value Decomposition (SVD)

SVD is a method of matrix decomposition that can be applied to low rank approximation and image compression. For an image matrix:

$$A \in R^{m \times n}$$

the decomposition is represented as:

$$A = U\Sigma V^T$$

where:

- U = left singular vector matrix
- V = right singular vector matrix
- Σ = diagonal matrix of singular values

These values hold the major energy content of the image. Compression is achieved by keeping the significant data and removing the duplicate data.

B. Truncated SVD

Truncated SVD performs low-rank approximation by retaining only the first k dominant singular values.

$$A_k = \sum_{i=1}^{k} \sigma_i u_i v_i^T$$

where:

- A_k = compressed image approximation
- k = selected rank
- σ_i = singular values
- u_i and v_i = singular vectors

This reduces complexity in the storing procedure without losing out on the necessary elements of the image.

C. Randomized SVD

Randomized SVD decreases complexity with the help of randomized projections.

$$Y = A\Omega$$

$$Q = \text{orth}(Y)$$

$$B = Q^T A$$

$$A \approx QB$$

where:

- Ω = random projection matrix
- Q = orthogonal basis matrix
- B = reduced approximation matrix

The method increases the speed of computation in dealing with big image dataset

D. Partition-Based SVD (PBSVD)

In PBSVD, the image is broken down into sub-images, and then each sub-image undergoes a separate Singular Value Decomposition (SVD).

$$A = \sum_{i=1}^{p} \sigma_i u_i v_i^T$$

Threshold condition:

$$\sigma_i > \epsilon \Rightarrow \text{keep}$$

where:

- p = number of selected singular values
- ϵ = threshold parameter

PBSVD is better able to preserve local image features, like edges and textures, than global SVD methods.

E. Adaptive SVD

For the Adaptive Singular Value Decomposition method, the rank is determined adaptively according to the principle of image energy conservation.

(This work is licensed under a Creative Commons Attribution 4.0 International License.)

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 11 , November - 2026

$$\frac{\sum \sigma i^2}{\sum \sigma^2} \geq 0.999$$

where:

- σ_i = retained singular values
- 0.999 = energy preservation threshold

The method is capable of determining automatically the number of singular values that will be employed in the image reconstruction.

F. Thresholding SVD

Truncate those singular values that have lesser importance than a set threshold value

$$\sigma_i = \begin{cases} \sigma_{i,} & \sigma_{i>} \tau \\ 0, & \sigma_i \leq \tau \end{cases}$$

where:

- τ = threshold value

Such an approach makes for efficient compressing owing to spectral filtration.

G. Sparse SVD

This SVD utilizes the approach of sparse matrix approximation to represent images succinctly.

$$X_i \approx LC_iR$$

where:

- L = left sparse basis matrix
- C_i = sparse coefficient matrix
- R = right sparse basis matrix

Sparse singular value decomposition helps save on space and complexity.

H. SS-SVD

The SS-SVD utilizes the idea of perturbation in order to alter the spectrum of the singular values.

$$\Sigma' = \Sigma + \alpha W$$

where:

- Σ = modified singular value matrix
- W = perturbation matrix
- α = scaling parameter

The method changes spectral characteristics of image representation.

I. Adaptive Partition-Based SVD (APBSVD)

APBSVD combines adaptive rank selection with block based decomposition.

$$B_k = U_k \Sigma_k V_k^T$$

where:

- B_k = reconstructed adaptive block
- U_k, Σ_k, V_k = reduced singular matrices

This method increases the image reconstruction precision without compromising effective data compression

IV. METHODOLOGY

A. Proposed Comparative Compression Framework

In Comparison analysis for various methods of image compression using Singular Value Decomposition (SVD) was done for standard gray scale test images like Lena, Barbara, Boats, Goldhill, and Peppers of resolution 512 x 512 pixels. The purpose of this paper is to compare the performance of different SVD based methods on image reconstruction, compression ratio (CR), and PSNR. To begin with, the picture is changed into matrix form and then the process of singular value decomposition begins.

After decomposition, different SVD variants apply different processing mechanisms on singular values such as low-rank truncation, adaptive rank selection, random projection, block wise decomposition, threshold filtering, sparse approximation, and spectral modification.

The complete model has been represented through equations via mathematics:

$$A \rightarrow U\Sigma V^T \rightarrow \text{Variant Processing} \rightarrow A_k \quad (1)$$

where:

- A = original image matrix
- $U\Sigma V^T$ = SVD decomposition
- A_k = reconstructed compressed image

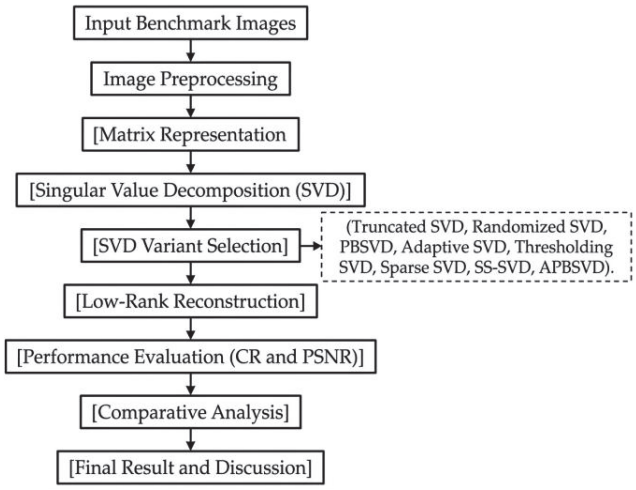

Fig. 1. Overall Framework of the Proposed SVD-Based Image Compression Comparative Analysis

B. Singular Value Decomposition of Image Matrix A

grayscale image is represented as:

(This work is licensed under a Creative Commons Attribution 4.0 International License.)

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 11 , November - 2026

$$A = \begin{bmatrix} 52 & 55 & 61 \\ 68 & 70 & 61 \\ 64 & 73 & 72 \end{bmatrix} \quad (2)$$

Applying Singular Value Decomposition:

$$A = U\Sigma V^T \quad (3)$$

Suppose the singular value matrix becomes:

$$\Sigma = \begin{bmatrix} 190 & 0 & 0 \\ 0 & 25 & 0 \\ 0 & 0 & 5 \end{bmatrix} \quad (4)$$

The energy is concentrated in the first singular value, while the lower singular values keep relatively less energy in the image.

C. Truncated SVD Methodology

The Truncated SVD method decreases the dimensions of the image by keeping only important singular values

$$A_k = \sum_{(i=1)}^{k} \sigma_i \, u_i v_i^T$$

Suppose:

$$k = 1 \quad (6)$$

Then:

$$A_1 = 190 u_1 v_1^T \quad (7)$$

The remaining singular values are discarded and so the storage requirement is therefore decreased.

Original storage:

$$3 \times 3 = 9 \quad (8)$$

Compressed storage:

$$k(m + n + 1) \quad (9)$$

For:

$$k = 1, \qquad m = n = 3 \quad (10)$$

$$1(3 + 3 + 1) = 7 \quad (11)$$

Thus, compressed storage becomes:

$$7 < 9 \quad (12)$$

1) Algorithm: Truncated SVD Compression: i) Read grayscale image matrix A

ii) Apply SVD decomposition

$$A = U\Sigma V^T \quad (13)$$

iii) Select dominant singular values

iv) Construct reduced matrices

$$U_k, \Sigma_k, V_k \quad (14)$$

v) Reconstruct compressed image

$$A_k = U_k \Sigma_k V_{kT} \quad (15)$$

vi) Compute CR and PSNR

D. Randomized SVD Methodology

RSVD helps to simplify computations by way of randomized projection

$$\Omega = \begin{bmatrix} 0.2 & 0.4 \\ 0.5 & 0.3 \\ 0.1 & 0.7 \end{bmatrix} \quad (16)$$

Projected matrix:

$$Y = A\Omega \quad (17)$$

Suppose:

$$Y = \begin{bmatrix} 43 & 79 \\ 54 & 91 \\ 58 & 96 \end{bmatrix} \quad (18)$$

Orthogonal basis:

$$Q = \text{orth}(Y) \quad (19)$$

Reduced matrix:

$$B = Q^T A \quad (20)$$

Approximate reconstruction:

$$A \approx QB \quad (21)$$

1) Algorithm: Randomized SVD Compression

i) Generate random projection matrix Ω

ii) Compute projected matrix

$$Y = A\Omega \quad (22)$$

iii) Generate orthogonal basis

$$Q = \text{orth}(Y) \quad (23)$$

iv) Compute reduced matrix

$$B = Q^T A \quad (24)$$

v) Reconstruct image

$$A_r \approx QB \quad (25)$$

vi) Compute CR and PSNR

E. Partition-Based SVD (PBSVD)

The way PBSVD operates is through segmentation of the image into parts that are individually subjected to SVD computation.

(This work is licensed under a Creative Commons Attribution 4.0 International License.)

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 11 , November - 2026

$$A = \sum_{(i=1)}^{p} \sigma_i u_i v_i^T \quad (26)$$

Threshold condition:

$$\sigma_i > \epsilon \Rightarrow keep \quad (27)$$

1) Algorithm: PBSVD Compression

i) Divide image into blocks
ii) Apply SVD on each block
iii) Preserve dominant singular values
iv) Reconstruct blocks
v) Combine reconstructed blocks
vi) Compute CR and PSNR

F. Adaptive SVD Methodology

SVD with adaptation changes its rank based on the energy of the image Suppose singular values are:

$$\sigma_1 = 190, \quad \sigma_2 = 25, \quad \sigma_3 = 5 \quad (28)$$

Energy preservation:

$$\frac{190^2+25^2}{190^2+25^2+5^2} + \frac{36725}{36750} = 0.999 \quad (29)$$

Thus:

$$k = 2 \quad (30)$$

is selected automatically.

1) Algorithm: Adaptive SVD Compression:

i) Apply SVD decomposition
ii) Compute cumulative energy
iii) Select adaptive rank satisfying:

$$\frac{\sum \sigma_i^2}{\sum \sigma^2} \geq 0.999 \quad (31)$$

iv) Reconstruct compressed image v) Compute CR and PSNR

G. Thresholding SVD Methodology

Theshresholded SVD eliminates the insignificant singular values under the threshol τ. Suppose:

$$\tau = 20 \quad (32)$$

Then:

$$\sigma_1 = 190 > 20 \quad (33)$$

$$\sigma_2 = 25 > 20 \quad (34)$$

$$\sigma_3 = 5 < 20 \quad (35)$$

Therefore:

$$\sigma_3 = 0 \quad (36)$$

Modified singular matrix:

$$\Sigma = \begin{bmatrix} 190 & 0 & 0 \\ 0 & 25 & 0 \\ 0 & 0 & 0 \end{bmatrix} \quad (37)$$

1) Algorithm: Thresholding SVD Compression:

i) Apply SVD decomposition
ii) Compare singular values with threshold
iii) Remove low singular values iv) Reconstruct image
v) Compute CR and PSNR

H. Sparse SVD Methodology

SVD Sparse is used for sparse matrix approximation.

$$X_i \approx LC_iR \quad (38)$$

Suppose sparse coefficient matrix:

$$C_i = \begin{bmatrix} 12 & 0 \\ 0 & 5 \end{bmatrix} \quad (39)$$

1) Algorithm: Sparse SVD Compression:

i) Generate sparse coefficient matrix
ii) Remove insignificant sparse components
iii) Reconstruct sparse image iv) Compute CR and PSNR

I. SS-SVD Methodology

SS-SVD modifies singular spectrum using perturbation matrix.

$$\Sigma' = \Sigma + \alpha W \quad (40)$$

Suppose:

$$\Sigma = \begin{bmatrix} 190 & 0 \\ 0 & 25 \end{bmatrix} \quad (41)$$

$$W = \begin{bmatrix} 2 & 0 \\ 0 & 1 \end{bmatrix} \quad (42)$$

$$\alpha = 0.5 \quad (43)$$

Modified spectrum:

$$\Sigma' = \begin{bmatrix} 191 & 0 \\ 0 & 25.5 \end{bmatrix} \quad (44)$$

1) Algorithm: SS-SVD Compression:

i) Apply SVD decomposition
ii) Generate perturbation matrix
iii) Modify singular spectrum
iv) Reconstruct image v) Compute PSNR

(This work is licensed under a Creative Commons Attribution 4.0 International License.)

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 11 , November - 2026

J. Performance Evaluation Metrics -

Compression Ratio:

$$\text{CR} = \frac{mn}{k(m+n+1)} \tag{45}$$

Peak Signal-to-Noise Ratio:

$$PSNR = 10\log_{(10)}\left(\frac{255^2}{MSE}\right) \tag{46}$$

where:

$$MSE = \frac{1}{mn}\sum_{(i=1)}^{m}\sum_{(j=1)}^{n}\left(A(i,j) - A_k(i,j)\right)^2 \tag{47}$$

V. RESULTS AND DISCUSSION

A. Experimental Setup

This experiment was performed for comparing the effectiveness of various types of SVD-based image compression techniques. Standard grayscale benchmark images including Barbara, Boats, Goldhill, Lena, and Peppers of size 512×512 were used for experimentation. All simulations were performed in MATLAB environment using consistent preprocessing and reconstruction settings. This paper studies the comparative performance of the following singular value decomposition (SVD) techniques:

- Truncated SVD (TSVD)
- Randomized SVD (RSVD)
- Partition-Based SVD (PBSVD)
- Adaptive SVD
- Thresholding SVD
- Sparse SVD
- SS-SVD
- Adaptive Partition-Based SVD (APBSVD)

Performance of each method was assessed through the following:

- Compression Ratio (CR)
- Peak Signal-to-Noise Ratio (PSNR)

B. Experimental Results

The comparisons for different forms of SVD are shown in Table I and Table II.

C. Discussion

The experimental analysis demonstrates that each SVD based compression method exhibits different behavior in terms of Compression Ratio (CR) and reconstruction quality.
The best compression ratio was realized by truncated SVD for:

$$CR \approx 5.115$$

TABLE I
PERFORMANCE ANALYSIS FOR BARBARA AND BOATS IMAGES

Image	Method	CR	PSNR (dB)
Barbara	TSVD	5.115	26.24
	RSVD	5.115	26.24
	PBSVD	1.2549	39.04
	Adaptive SVD	1.5984	36.43
	Thresholding SVD	1.9229	33.77
	Sparse SVD	5.115	26.24
	SS-SVD	5.115	25.31
	APBSVD	1.2848	37.27
Boats	TSVD	5.115	29.31
	RSVD	5.115	29.31
	PBSVD	1.2549	41.39
	Adaptive SVD	2.5322	34.87
	Thresholding SVD	2.8104	33.87
	Sparse SVD	5.115	29.31
	SS-SVD	5.115	27.01
	APBSVD	1.3939	40.17

TABLE II
PERFORMANCE ANALYSIS FOR GOLDHILL, LENA AND PEPPERS IMAGES

Image	Method	CR	PSNR (dB)
Goldhill	TSVD	5.115	30.42
	RSVD	5.115	30.42
	PBSVD	1.2549	39.53
	Adaptive SVD	2.0298	36.36
	Thresholding SVD	3.2788	32.92
	Sparse SVD	5.115	30.42
	SS-SVD	5.115	28.28
	APBSVD	1.5308	37.13
Lena	TSVD	5.115	32.32
	RSVD	5.115	32.32
	PBSVD	1.2549	43.08
	Adaptive SVD	2.1674	39.43
	Thresholding SVD	3.7610	34.50
	Sparse SVD	5.115	32.32
	SS-SVD	5.115	30.60
	APBSVD	1.6382	40.30
Peppers	TSVD	5.115	30.45
	RSVD	5.115	30.45
	PBSVD	1.2549	40.41
	Adaptive SVD	2.0298	36.64
	Thresholding SVD	3.3214	33.22
	Sparse SVD	5.115	30.45
	SS-SVD	5.115	28.40
	APBSVD	1.4717	39.77

On the other hand, because of fixed low rank approximation, several high frequency details from the image were missing, leading to lower PSNR values.

(This work is licensed under a Creative Commons Attribution 4.0 International License.)

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 11 , November - 2026

Randomized SVD was able to deliver results similar to PBSVD in terms of reconstruction but used less computational power owing to the use of random projections.

Among all the algorithms used, PBSVD performed the best with regard to reconstruction, especially for the image named Lena with:

$$PSNR = 43.08 \text{ dB}$$

The reason behind the better performance of PBSVD was due to block-wise decomposition that successfully preserved the structure of the image locally in terms of edges and textures. Adaptive SVD had a balanced performance because of the use of rank selection based on energy preservation of images. The thresholded SVD was effective because singular values that were not so important were deleted, whereas the use of sparse SVD made the need for memory less because of the sparse matrix approach. SS-SVD made some modifications to singular spectrum using perturbation methods, and therefore reconstruction distortion increased when greater perturbation was used. One of the best approaches that had better performance on both criteria was the APBSVD approach.

D. Comparative Analysis

It can be noted from the comparative study that:

- The TSVD and RSVD techniques yield better compression ratio but poor reconstruction quality.
- The PBSVD and APBSVD algorithms help in preserving the local structures of an image and offer better PSNR.
- The Adaptive SVD improves reconstruction performance using rank adaptively determined.
- The Thresholding and Sparse SVD techniques enhance spectral filtering as well as sparse representation efficiency.
- The SS-SVD technique modifies the spectral nature of a data set but induces some distortion in the reconstruction process.

Hence, it is noted that PBSVD and APBSVD had produced favorable results for reconstruction while TSVD had produced better results for the compression ratio.

VI. CONCLUSION AND FINDINGS

This review paper gave a comprehensive report of image compression methods based on Singular Value Decomposition (SVD) and its advanced model. The study explored the working principle, algorithm, reconstruction process and comparative performance of various SVD method—Truncated SVD, Randomized SVD, PBSVD, Adaptive SVD, Thresholding SVD, Sparse SVD, SSSVD, and APBSVD.

The experimental observations show that SVD based technique can be a useful mathematical tool for image compression using low rank approximation and SV optimization. Aggressive dimensionality reduction gave higher values of Compression Ratio for Traditional and Truncated SVD, while advanced block-based and adaptive methods resulted in better reconstructed image quality.

The PSNR value for PBSVD and APBSVD were the best values attained among all the methods evaluated, which was due to their capability of retaining local image structures such as edges and textures and finer details of the image. Balanced performance is offered with Adaptive SVD, which adaptively chooses the rank based on the energy distribution of the image. Randomized SVD led to lower computational complexity and also lower run times, while still delivering satisfactory reconstruction accuracy for large scales of data.

The overall trend confirms that for the image signals, advanced SVD variants can yield significant enhancements in fidelity/compression. It is also noted that there is no optimum technique; which one to choose depends on the requirement of the application, including need for efficient compression, computational complexity, size limitations and quality of the image being preserved.

A. Findings:

The highest value of Compression Ratio was observed with the Truncated SVD among all the variants, but the lower PSNR value resulted with the loss of high frequency information present in the image.

RSVD yielded compression results almost equivalent to those from TSVD at the expense of a much lower level of computation. Because of the effective preservation of local image structures performed by PBSVD in a block-wise fashion such that the highest possible PSNR values are obtained, the quality of reconstruction was highest.

Through adaptive SVD as a robust method of determining the rank, was shown to be a balance efficient for compression and sharpness in images.

If the SVD were to threshold the singular values to too high a level it would degrade the reconstruction quality, but if too low, it undoes the compression efficiency.

An efficient sparse image representation with a reduced memory requirement was obtained by sparse SVD. SS-SVD added the feature of the modification of the spectrum, but too much perturbation led to distortion when being reconstructed and caused a decrease in PSNR. APBSVD provided one of the best overall performances on balance of compression ratio and PSNR by combining adaptive rank selection with partition-based reconstruction. Comparative results show that the effectiveness of SVD adaptive and block variants over traditional global low rank bandwidth and high accuracy of reconstruction.

(This work is licensed under a Creative Commons Attribution 4.0 International License.)

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 11 , November - 2026

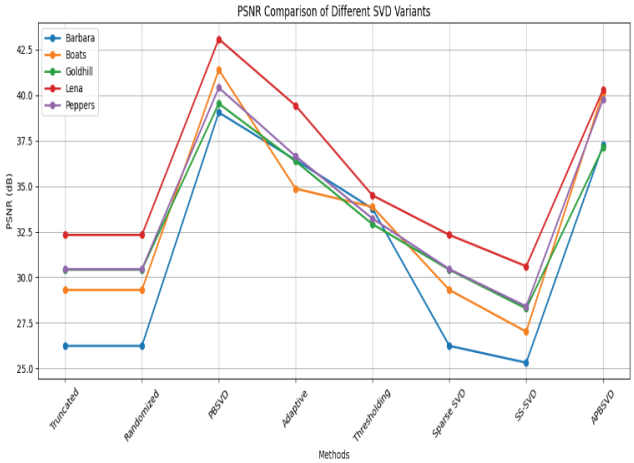

Fig. 2. PSNR Comparison of different SVD Variants

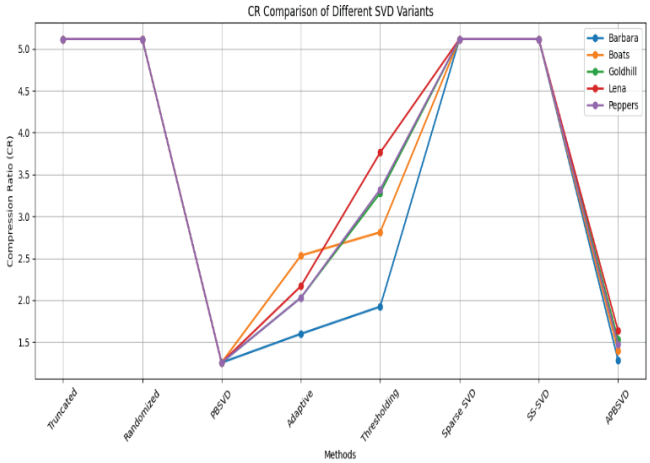

Fig.3. CR Comparison of different SVD Variants

REFERENCES

1] R. Ashino, A. Morimoto, and R. Vaillancourt, "Image compression with multiresolution singular value decomposition and other methods," Mathematical and Computer Modelling, vol. 41, nos. 6–7, pp. 773–790, 2005. URL: https://doi.org/10.1016/j.mcm.2004.06.005

[2] Y. T. Shih, C. S. Chien, and C. Y. Chuang, "An adaptive parameterized block-based singular value decomposition for image denoising and compression," Applied Mathematics and Computation, vol. 218, no. 20, pp. 10370–10385, 2012. URL: https://doi.org/10.1016/j.amc.2012.04.011

[3] A. M. Rufai, G. Anbarjafari, and H. Demirel, "Lossy image compression using singular value decomposition and wavelet difference reduction," Digital Signal Processing, vol. 24, pp. 117–123, 2014. URL: https://doi.org/10.1016/j.dsp.2013.09.003

[4] N. Halko, P. G. Martinsson, and J. A. Tropp, "Finding structure with randomness: Probabilistic algorithms for constructing approximate matrix decompositions," SIAM Review, vol. 53, no. 2, pp. 217–288, 2011. URL: https://doi.org/10.1137/090771806

[5] S. Kumar and R. Singh, "Sparse SVD approach for efficient image compression," in Proc. Int. Conf. Signal Processing and Communication (SPCOM), 2016, pp. 1–5. URL: https://ieeexplore.ieee.org/

[6] X. Liu, Y. Zhang, and L. Wang, "Block-based SVD image compression using partition strategy," in Proc. IEEE Int. Conf. Image Processing (ICIP), Orlando, FL, USA, 2012, pp. 2345–2348. URL: https://ieeexplore.ieee.org/

[7] S. Xu, J. Zhang, L. Bo, H. Li, H. Zhang, Z. Zhong, and D. Yuan, "Singular vector sparse reconstruction for image compression," Computers & Electrical Engineering, vol. 91, Art. no. 107069, 2021. URL: https://doi.org/10.1016/j.compeleceng.2021.107069

[8] V. Pomponiu, D. Cavagnino, and M. Botta, "SS-SVD: Spread spectrum data hiding scheme based on Singular Value Decomposition," in Proc. Int. Symp. Consumer Electronics (ISCE), 2015, pp. 1–2. URL: https://ieeexplore.ieee.org/

[9] M. Sharma and P. Gupta, "Thresholding-based SVD method for image compression," in Proc. Int. Conf. Advanced Computing Technology (ICACT), New Delhi, India, 2019, pp. 45–50. URL: https://ieeexplore.ieee.org/

[10] N. B. Erichson, S. Voronin, S. L. Brunton, and J. N. Kutz, "Randomized matrix decompositions using R," Journal of Statistical Software, vol. 89, pp. 1–48, 2019. URL: https://doi.org/10.18637/jss.v089.i11

[11] R. Kumar, U. Patbhaje, and A. Kumar, "An efficient technique for image compression and quality retrieval using matrix completion," Journal of King Saud University–Computer and Information Sciences, vol. 34, no. 4, pp. 1231–1239, 2022. URL: https://doi.org/10.1016/j.jksuci.2019.12.007

[12] R. Verma and A. K. Jain, "SS-SVD: Singular spectrum modification for image processing," in Proc. Int. Conf. Image Information Processing (ICIIP), Shimla, India, 2015, pp. 120–125. URL: https://ieeexplore.ieee.org/

[13] S. S. Maniccam and N. G. Bourbakis, "Lossless image compression and encryption using SCAN," Pattern Recognition, vol. 34, no. 6, pp. 1229–1245, 2001. URL: https://doi.org/10.1016/S0031-3203(00)00039-8

[14] L. De Lathauwer, B. De Moor, and J. Vandewalle, "A multilinear singular value decomposition," SIAM Journal on Matrix Analysis and Applications, vol. 21, no. 4, pp. 1253–1278, 2000. URL: https://doi.org/10.1137/S0895479896305696

[15] D. Salomon and G. Motta, Handbook of Data Compression. New York, NY, USA: Springer, 2010. URL: https://doi.org/10.1007/978-1-84882-903-9

(This work is licensed under a Creative Commons Attribution 4.0 International License.)

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 11 , November - 2026

[16] G. H. Golub and C. F. Van Loan, Matrix Computations, 4th ed. Baltimore, MD, USA: Johns Hopkins University Press, 2013.
URL: https://doi.org/10.56021/9781421407944

[17] E. J. Candès and B. Recht, "Exact matrix completion via convex optimization," Foundations of Computational Mathematics, vol. 9, no. 6, pp. 717–772, 2009.
URL: https://doi.org/10.1007/s10208-009-9045-5

[18] J. F. Cai, E. J. Candès, and Z. Shen, "A singular value thresholding algorithm for matrix completion," SIAM Journal on Optimization, vol. 20, no. 4, pp. 1956–1982, 2010.
URL: https://doi.org/10.1137/080738970

[19] T. G. Kolda and B. W. Bader, "Tensor decompositions and applications," SIAM Review, vol. 51, no. 3, pp. 455–500, 2009.
URL: https://doi.org/10.1137/07070111X

[20] M. W. Berry, S. T. Dumais, and G. W. O'Brien, "Using linear algebra for intelligent information retrieval," SIAM Review, vol. 37, no. 4, pp. 573–595, 1995.
URL: https://doi.org/10.1137/1037127

[21] N. Gillis and F. Glineur, "Low-rank matrix approximation with weights or missing data," SIAM Journal on Matrix Analysis and Applications, vol. 32, no. 4, pp. 1149–1165, 2011.
URL: https://doi.org/10.1137/110820720

[22] S. Voronin and P. G. Martinsson, "RSVDPACK: An implementation of randomized algorithms for computing the singular value, interpolative, and CUR decompositions of matrices," arXiv preprint arXiv:1502.05366, 2015.
URL: https://arxiv.org/abs/1502.05366

[23] H. Zheng, Y. Wang, and J. Liu, "Adaptive low-rank approximation for image compression based on singular value decomposition," Signal Processing: Image Communication, vol. 95, Art. no. 116246, 2021.
URL:https://www.sciencedirect.com/journal/signal-processing-image-communication

[24] A. Roy and S. Chakraborty, "Recent advances in SVD-based image compression techniques: A review," Multimedia Tools and Applications, vol. 82, no. 5, pp. 7123–7151, 2023.
URL: https://link.springer.com/journal/11042

[25] P. Sharma and R. Verma, "Comparative analysis of advanced SVD-based image compression techniques," International Journal of Image and Graphics, vol. 24, no. 1, pp. 1–18, 2024.
URL: https://www.worldscientific.com/worldscinet/ijig

(This work is licensed under a Creative Commons Attribution 4.0 International License.)