

Comparative Discussion: Algorithmic Trade-offs and Implementation Choice

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Table 1: Comparison of SVD-based Image Compression Methods

Algorithm	Advantages	Disadvantages
Golub–Kahan SVD (Householder + Givens)	<ul style="list-style-type: none">• Most numerically stable and accurate full SVD method.• Well-conditioned for both symmetric and non-symmetric matrices.• Produces exact orthogonal U, Σ, and V^T.	<ul style="list-style-type: none">• Computationally expensive ($O(n^3)$) — impractical for large images.• Requires full reduction even when only top-k singular values are needed.• Memory-heavy due to dense transformations.
Lanczos Bidiagonalization + Implicit QR (My Implementation)	<ul style="list-style-type: none">• Efficient truncated SVD: $O(kn^2 + k^3)$ with minimal accuracy loss.• Uses only matrix–vector products — memory-light and scalable.• Implicit QR with Wilkinson shift ensures fast, stable convergence.• Ideal for image compression where small approximation is acceptable.	<ul style="list-style-type: none">• Sensitive to orthogonality loss if re-orthogonalization is skipped.• Slower convergence for tightly clustered singular values.• Slight numerical drift compared to full SVD, but visually negligible.• Yields only leading singular vectors, not a full decomposition.
Jacobi Algorithm	<ul style="list-style-type: none">• Extremely accurate and numerically stable.• Produces well-orthogonalized singular vectors naturally.• Useful for small matrices or benchmark-level precision.	<ul style="list-style-type: none">• Very slow convergence ($O(n^3)$).• Inefficient for high-resolution image matrices.

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Algorithm	Advantages	Disadvantages
Power / Subspace Iteration	<ul style="list-style-type: none"> • Simple to implement conceptually. • Works well for computing dominant singular values. • Requires minimal memory. 	<ul style="list-style-type: none"> • Converges slowly for clustered or similar singular values. • Needs multiple passes over data. • Yields only leading singular vectors, not a full decomposition.
Randomized SVD (rSVD)	<ul style="list-style-type: none"> • Extremely fast for very large or sparse datasets. • Reduces computation via random projection and oversampling. 	<ul style="list-style-type: none"> • Complicated to implement from scratch; requires knowledge beyond classical numerical linear algebra. • Accuracy depends on data distribution and random seed — non-deterministic output.