DATA DRIVEN ANALYSIS OF FLUID FLOW

Fluid Mechanics | MEL2040

By Group-14

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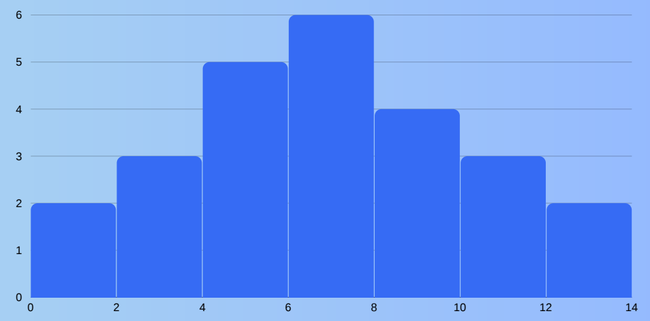
INTRODUCTION

In our project for **Data Driven Analysis of Fluid Flows** in the course of Fluid Mechanics, we explored the intersection of two domains **Machine Learning & Fluid Mechanics**, I which we first studied about the **advances of machine learning** in the domain of fluid mechanics & how ML can be applied in the domain of fluid mechanics. Then we explored the use of **Proper Orthogonal Decomposition(POD)** in video analysis of a flow over three cylinders present in staggered configuration, we observed the behavior of POD modes & its response to different type of noises.

Review of Machine Learning in Fluids



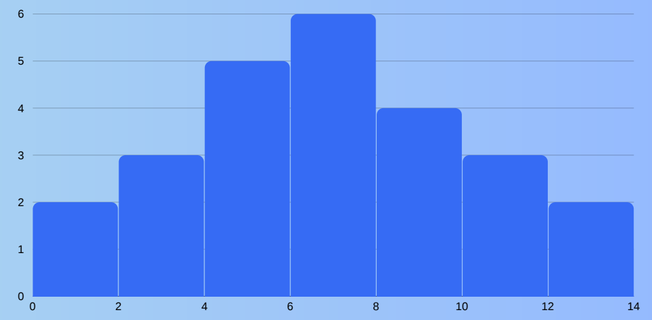
In fluid mechanics we deal with the **abundance of data** and the use of data to study the properties of fluids.

This creates an **ideal environment** for the application of machine learning.

In machine learning we study about construction of models for the **optimization of data.**

Machine learning techniques that are developed to address **non-linear and high-dimensional data** are good enough to solve the problems of fluid mechanics.

Advances of Machine Learning in Fluid Domain



Reinforcement Learning for flow controls in Experiments and Simulations

Reinforcement Learning is utilized for the purpose of conducting **idealized computer flow simulation studies**.

RL agents are used to used to **identify the control strategies** for fluids.

We can **verify the the results** obtained in an experiment of fluid mechanics through these simulations.

This pave the way for the **efficient exploration** of active flow control strategies in complex fluid mechanics application.

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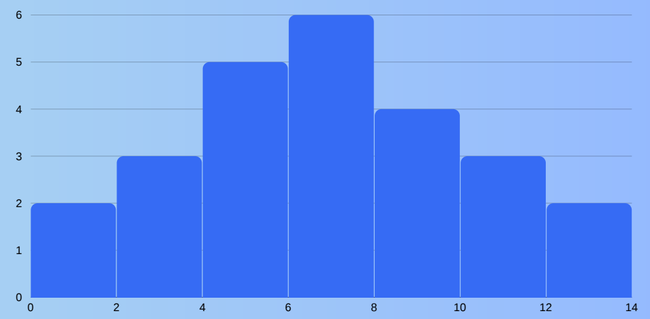
Advances of Machine Learning in Fluid Domain



Accelerated Computational Fluid Dynamics: Data Driven Modelling

In the modelling of a wide variety of physical processes, including metrology, climate, aerodynamics, plasma physics, etc. **numerical simulation** of fluids is extremely important component.

All these involves **solving complex equations**, that was very challenging.

By the use of Data driven modelling we can use **end-to-end deep learning** in order to improve approximations developed inside computational fluid dynamics.

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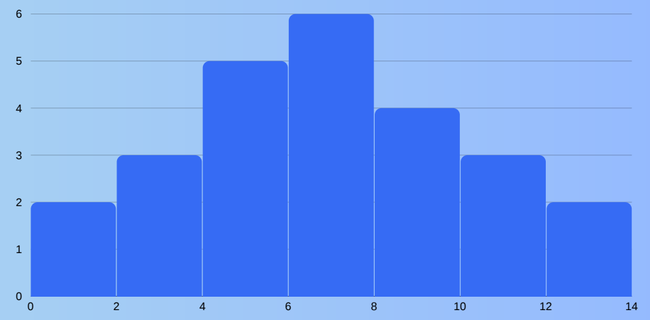
Advances of Machine Learning in Fluid Domain



Computational Fluid Dynamics

Computational Fluid Dynamics(CFD) is a branch of fluid mechanics that uses **numerical analysis** and **data structures** to **analyze and solve problems** that involve fluid flows.

Computers are used to perform the calculations required to **simulate the free-stream flow** of the fluids, and interaction of the fluid with surfaces defined by boundary conditions.

LINK

New Ideas

Self Learing Process Modelling Method to Optimize up-stream operations

Upstream production optimization is concerned with optimizing the entire **hydrocarbon value chain** from reservoir to sales.

Light weight models should be made for **fast computation** which is required for optimization and process control including **IoT edge devices**.

LINK

New Ideas

Hybrid Modelling in Computational Fluid Dynamics

Data-Driven Modelling: Obtain the input-output relationship without involving any physical mechanics.

Physical Model: to optimize the existing model by AI algorithms.

LINK

New Ideas

Artificial Intelligence Optimized Flow Based Manufacturing Processes

Flow based manufacturing processes optimized by artificial intelligence signify a fundamental change in the **management** and **optimization** of manufacturing operations.
Manufacturers can achieve enhanced levels of **efficiency**, **productivity**, and **innovation** in their production processes through the utilization of AI.

This can result in **sustainable development** and a competitive edge in the ever changing marketplace of the twenty-first century.

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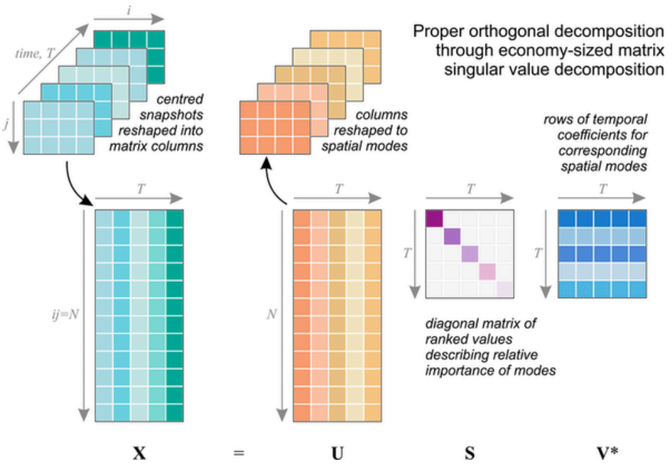
Understanding POD

Step-1: Snapshot Generation

Divide the collected data into discrete snapshots. These snapshots capture the state of the system at different time instances.

Step-2: Data Matrix Formation

Arrange the snapshot data into a matrix, where each column corresponds to a snapshot and each row corresponds to a spatial location or sensor measurement.



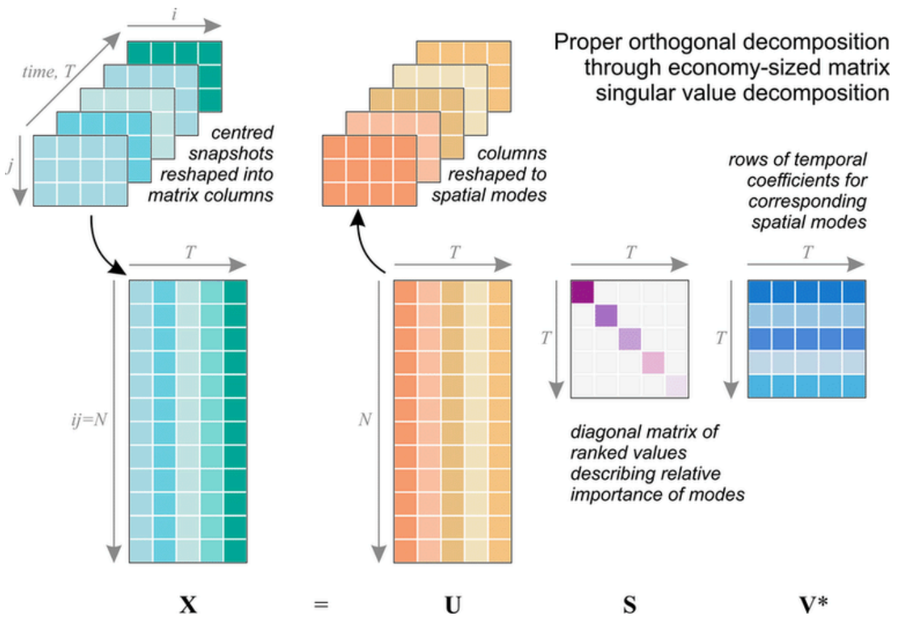
Understanding POD

Step-3: Singular Value Decomposition

Compute the Singular Value Decomposition of the snapshot matrix X:

$$X = U\Sigma V^T,$$

U is a matrix whose columns are the left singular vectors,
V is a matrix whose columns are the right singular vectors, and
Σ is a diagonal matrix containing the singular values in descending order.

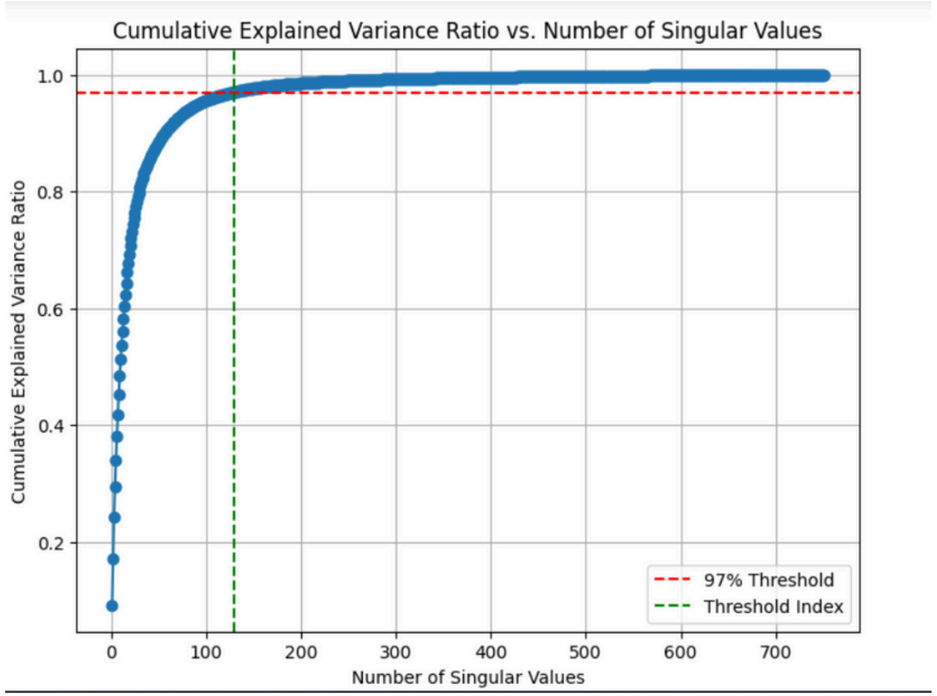


Proper Orthogonal Decomposition

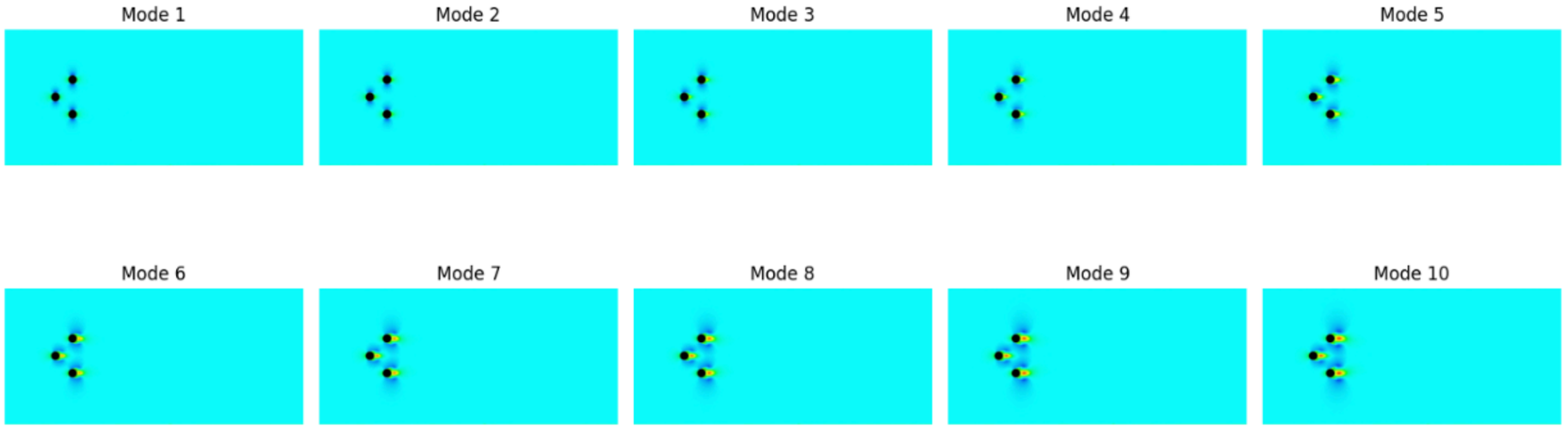
3.1. Image Generation

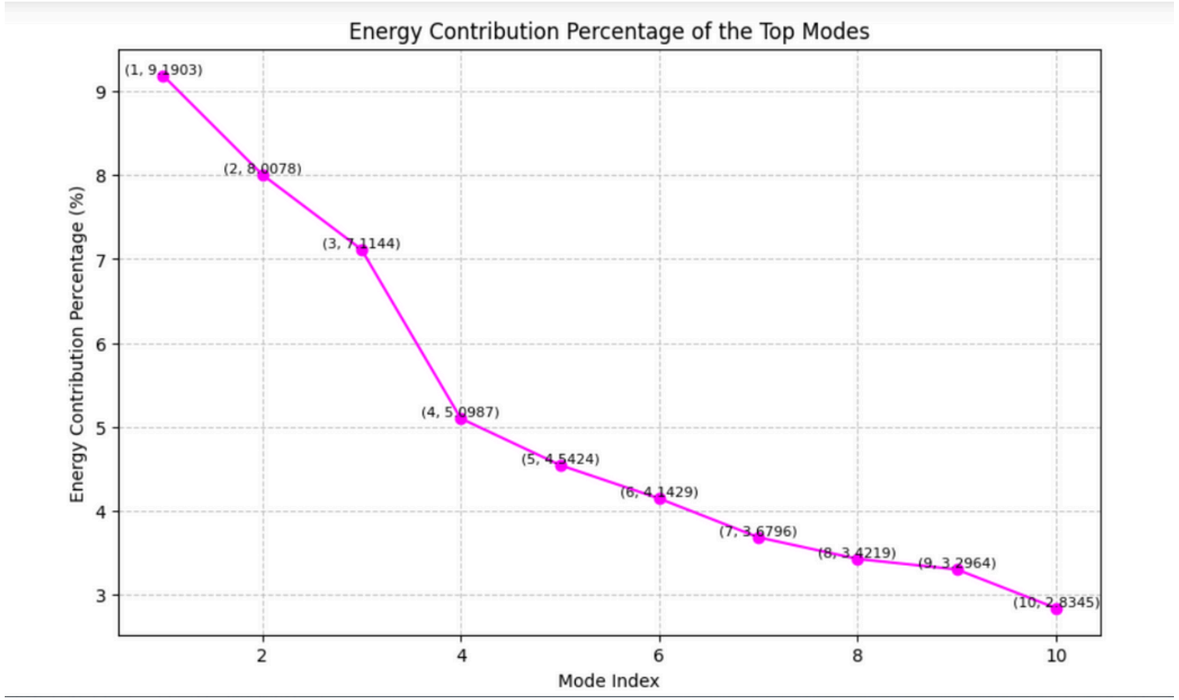
extracted 751 images from video

3.2. Execute POD



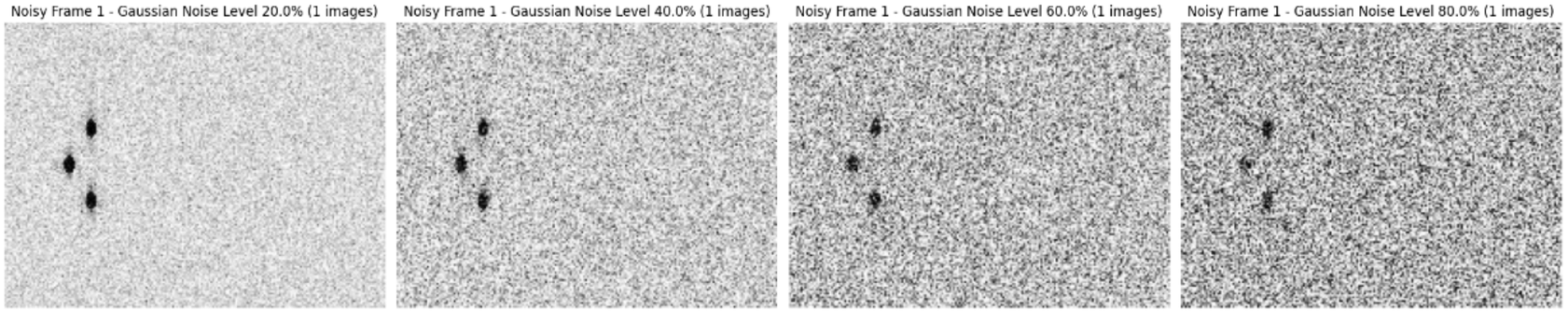
3.3. Analyses POD Modes



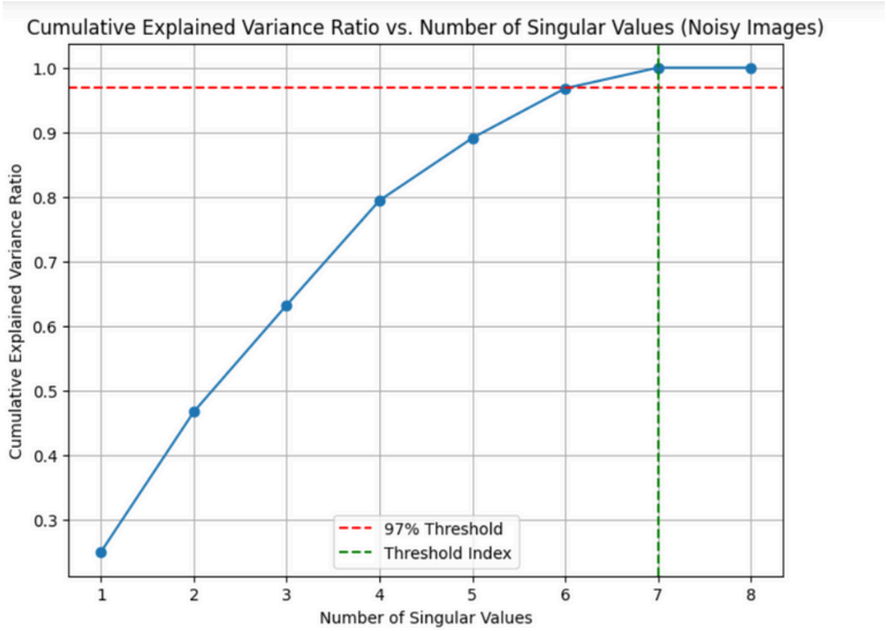


4. Noise!

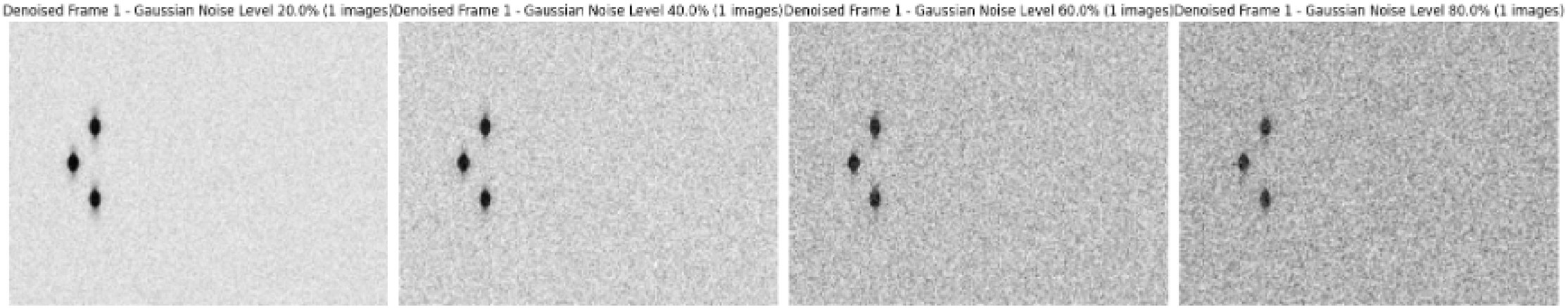
4.1. Adding Gaussian Noise



4.2. Effect of Gaussian Noise on POD Modes



5. Super-Resolving for Gaussian Noise

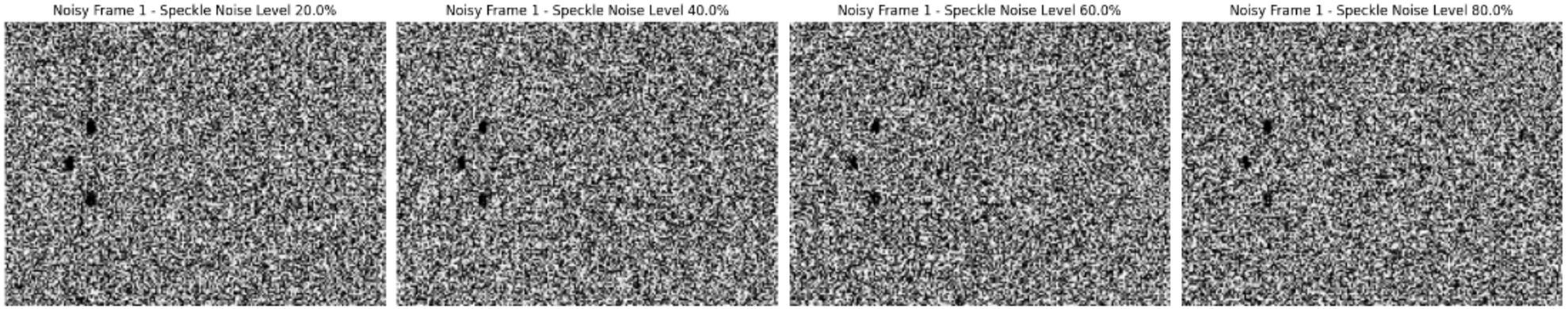


Gaussian blur filter

Gaussian Noise

Gaussian noise is random variation that follows a bell-shaped distribution with zero mean and constant power across all frequencies.

4.1. Adding Speckle Noise



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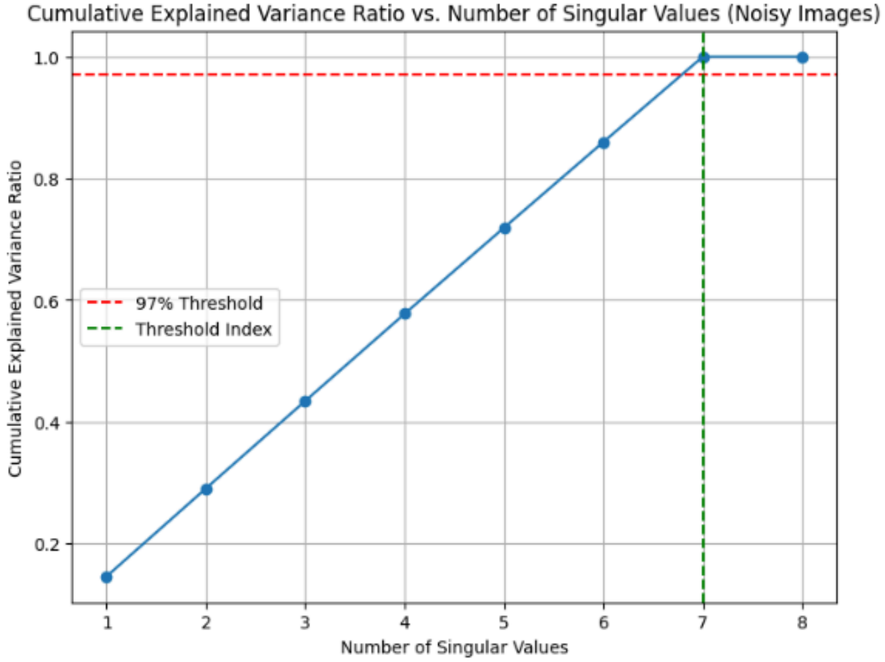
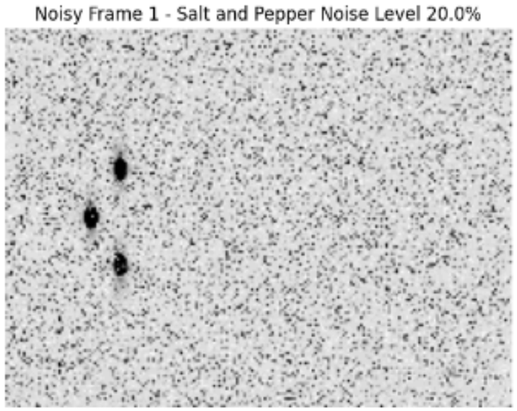
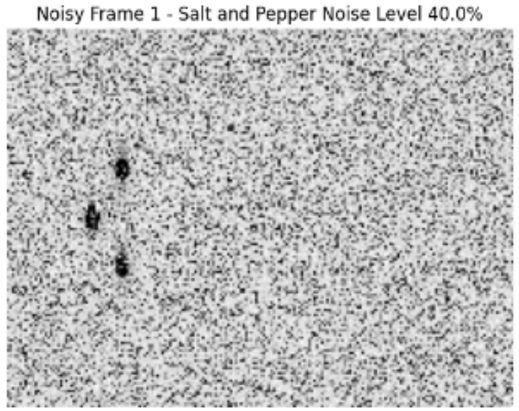


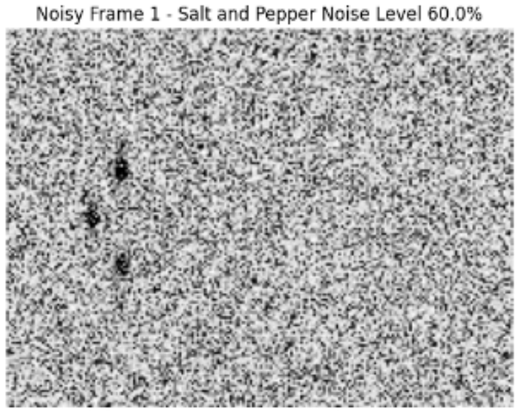
Speckle Noise

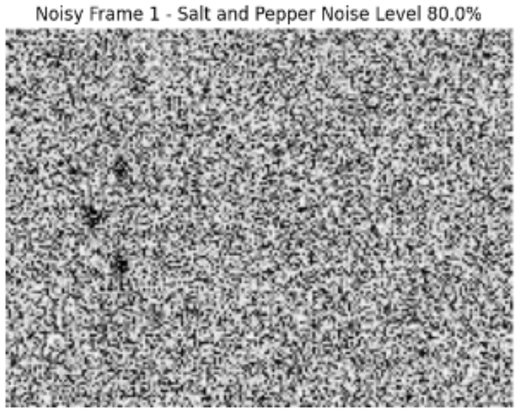
Speckle noise is a type of random noise commonly found in images, characterized by granular patterns that degrade image quality.

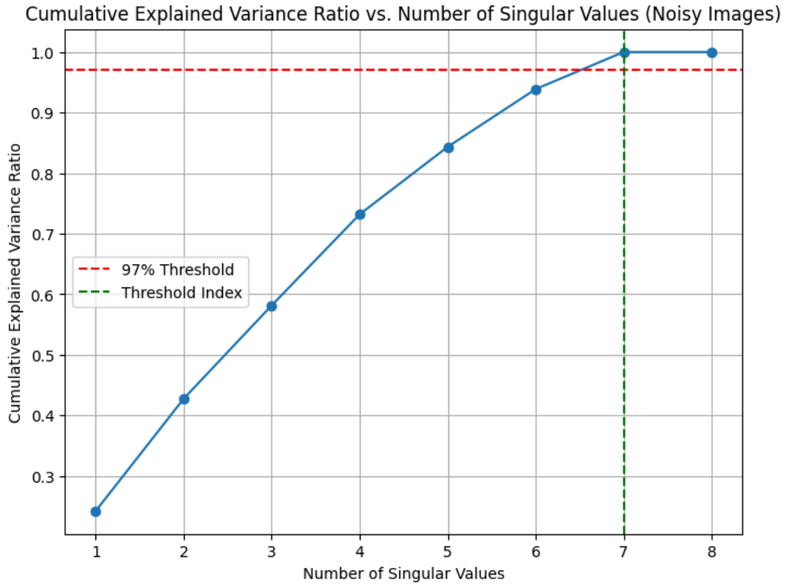
4.1. Adding and Pepper Noise



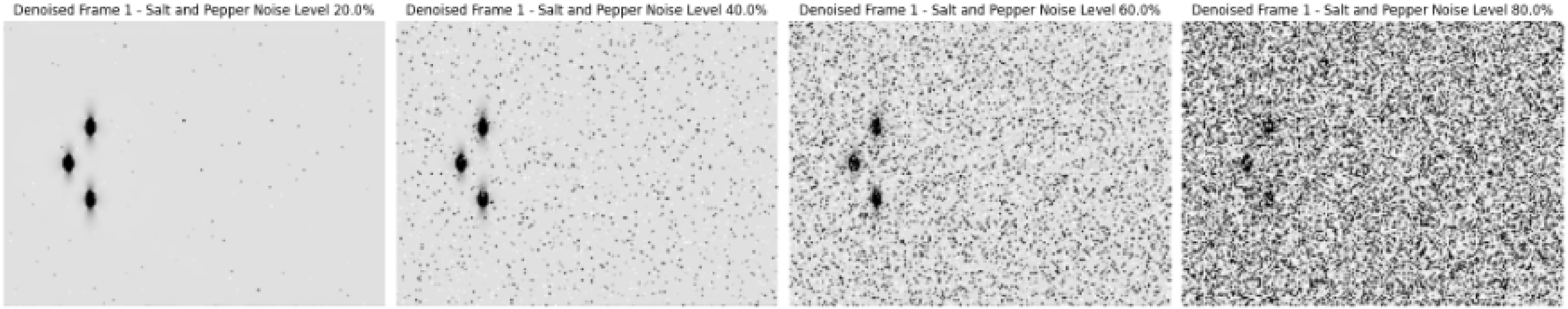








5. Super-Resolving for Salt and Pepper Noise



Median Filter

Salt and Pepper Noise

Salt and pepper noise is a type of random interference in images, manifesting as randomly occurring bright and dark pixels.

NOISES

Gaussian Noise

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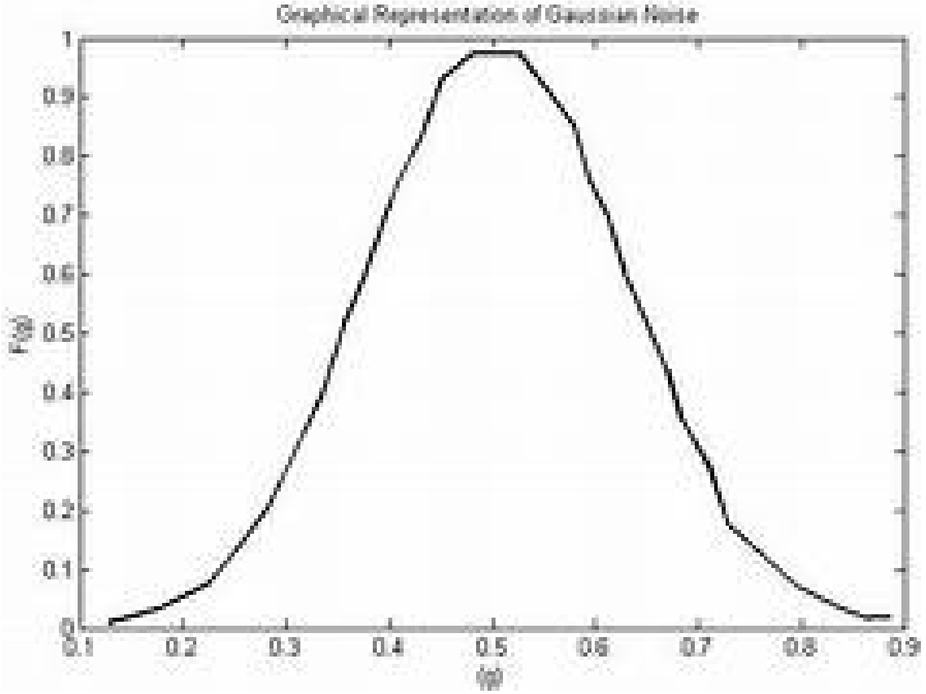

NOISES

Salt and Pepper Noise

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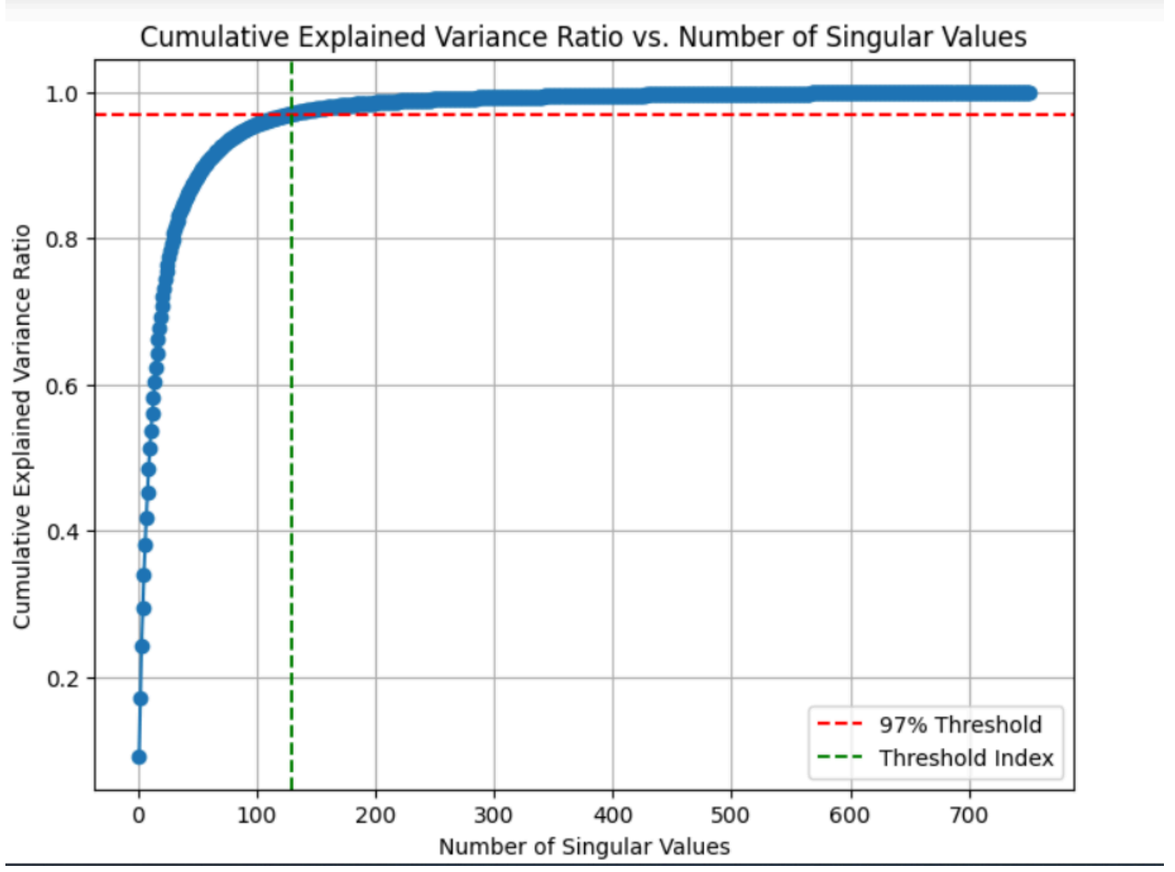
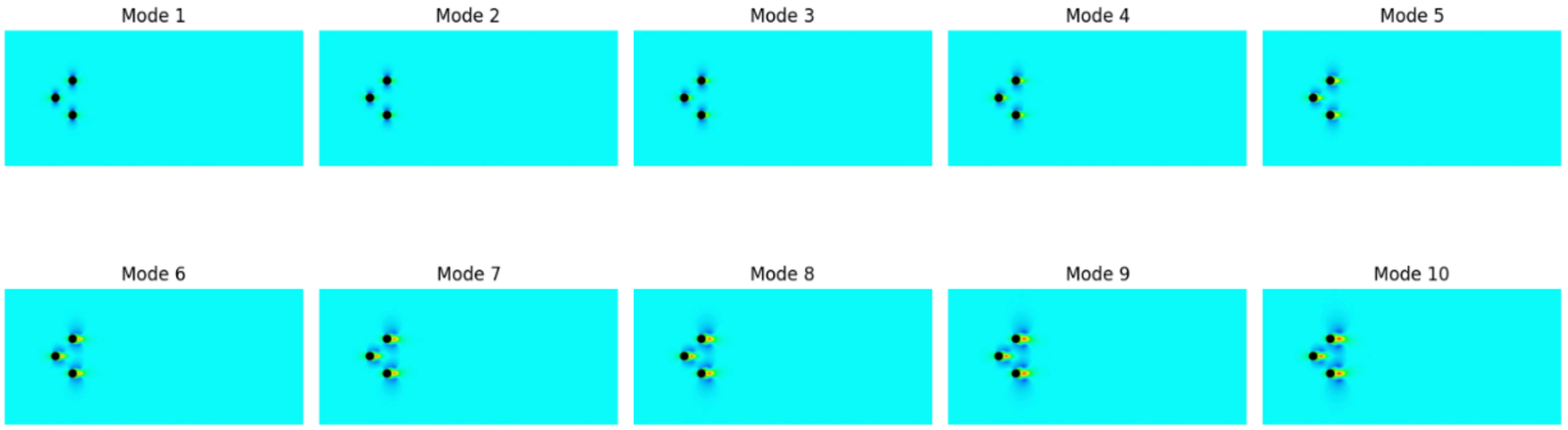
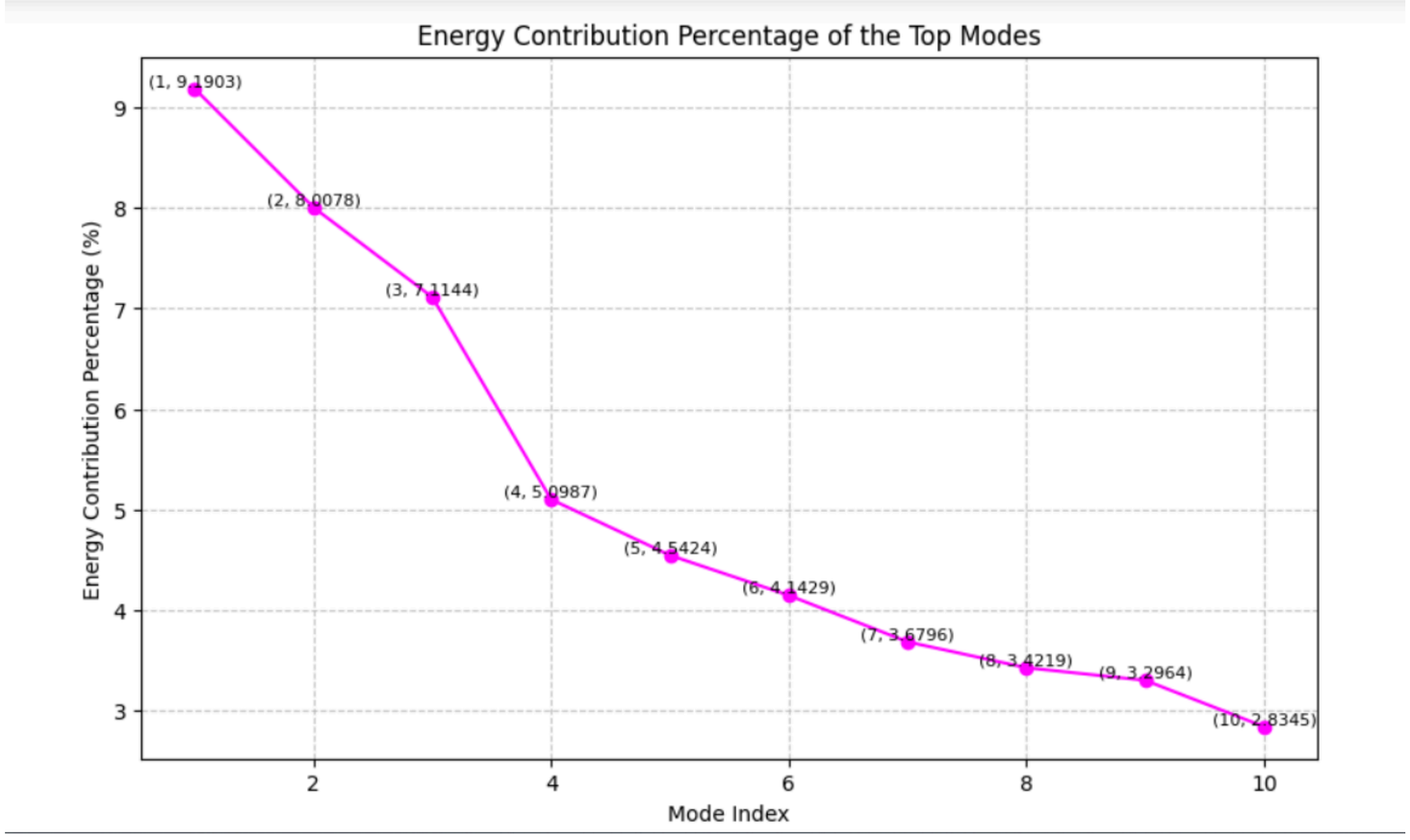
THANK YOU


Cumulative Explained Variance Ratio vs. Number of Singular Values
Cumulative Explained Variance Ratio
1.0
0.8
0.6
0.4
0.2
0
100
200
300
400
500
600
700
Number of Singular Values
97% Threshold
Threshold Index


Mode 1
Mode 2
Mode 3
Mode 4
Mode 5
Mode 6
Mode 7
Mode 8
Mode 9
Mode 10


Energy Contribution Percentage of the Top Modes
Energy Contribution Percentage (%)
Mode Index
(1, 9.1903)
(2, 8.0078)
(3, 7.1144)
(4, 5.0987)
(5, 4.5424)
(6, 4.1429)
(7, 3.6796)
(8, 3.4219)
(9, 3.2964)
(10, 2.8345)
9
8
7
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2
4
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8
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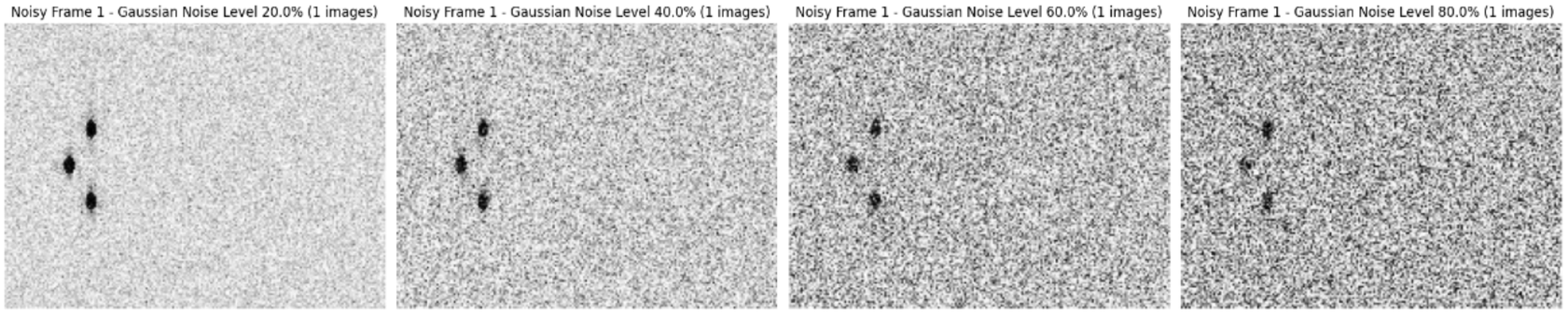
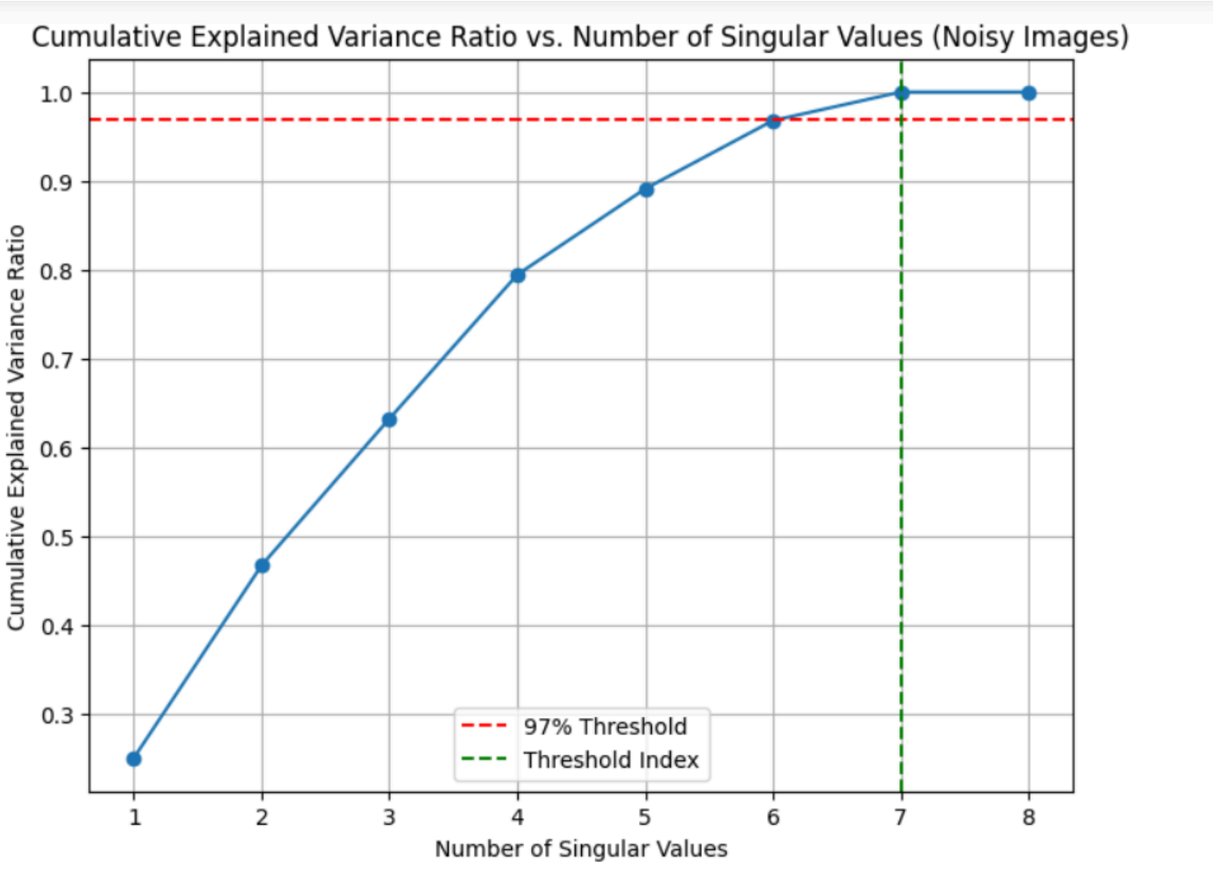
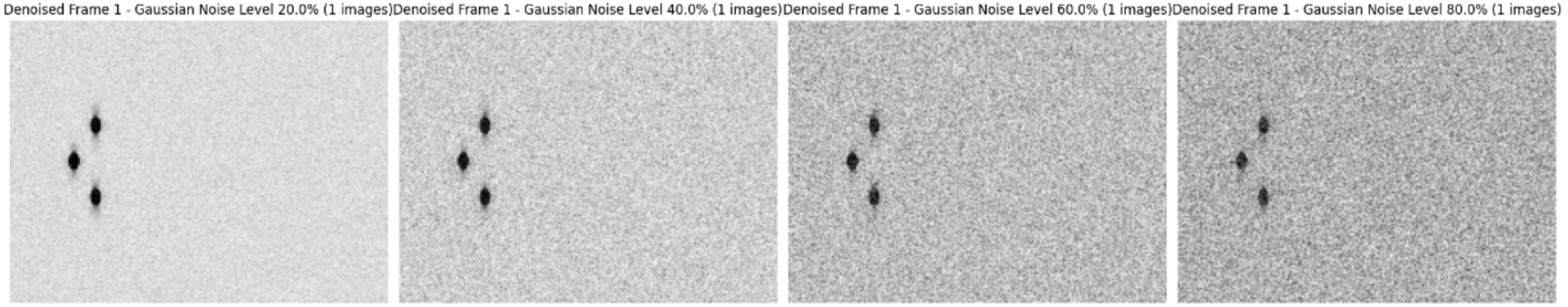
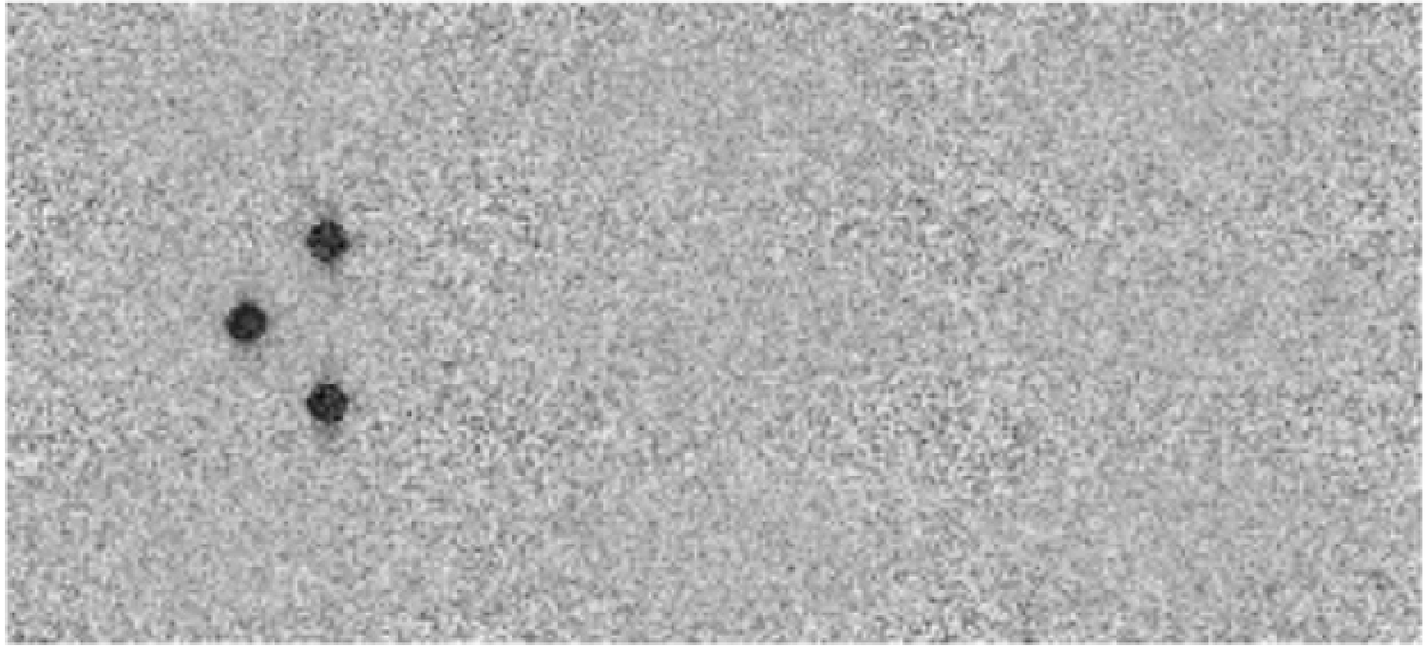
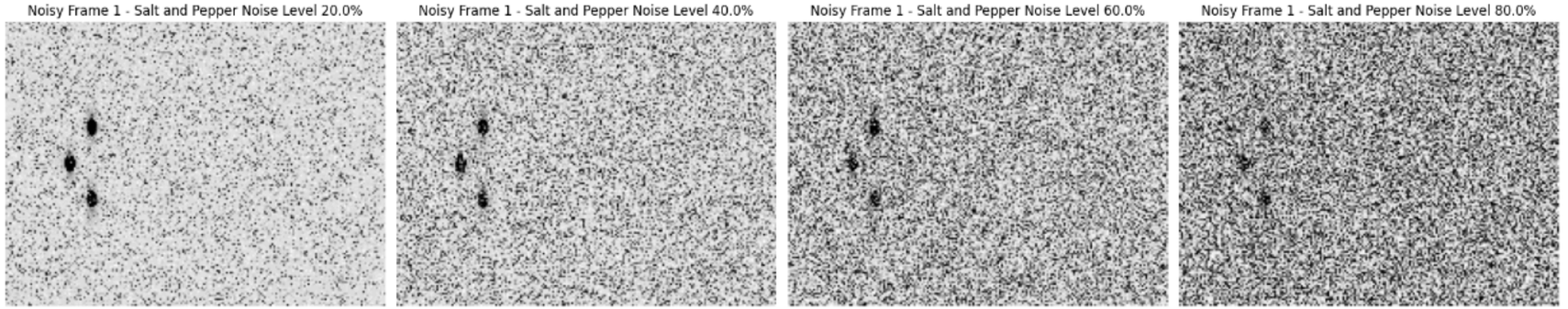

Noisy Frame 1 - Gaussian Noise Level 20.0% (1 images)
Noisy Frame 1 - Gaussian Noise Level 40.0% (1 images)
Noisy Frame 1 - Gaussian Noise Level 60.0% (1 images)
Noisy Frame 1 - Gaussian Noise Level 80.0% (1 images)


Cumulative Explained Variance Ratio vs. Number of Singular Values (Noisy Images)
Cumulative Explained Variance Ratio
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
97% Threshold
Threshold Index
1
2
3
4
5
6
7
8
Number of Singular Values


Denoised Frame 1 - Gaussian Noise Level 20.0% (1 images)
Denoised Frame 1 - Gaussian Noise Level 40.0% (1 images)
Denoised Frame 1 - Gaussian Noise Level 60.0% (1 images)
Denoised Frame 1 - Gaussian Noise Level 80.0% (1 images)

Mean Noisy Image




Noisy Frame 1 - Salt and Pepper Noise Level 20.0%
Noisy Frame 1 - Salt and Pepper Noise Level 40.0%
Noisy Frame 1 - Salt and Pepper Noise Level 60.0%
Noisy Frame 1 - Salt and Pepper Noise Level 80.0%