Fluid Mechanics Project
Data Driven Analysis of Fluid Flows

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# 1 Review of Machine Learning in Fluids

As a result of the abundance of data and the abundance of problems that are present in the subject of fluid mechanics, it is an ideal environment for the application of machine learning. The process of constructing models from data through the use of optimization and regression techniques is known as machine learning. The field of fluid mechanics presents a multitude of challenges that can be posed as optimization problems. Some examples of these challenges include designing a wing to maximize lift while minimizing drag at cruise velocities, estimating a flow field from limited measurements, controlling turbulence for mixing enhancement in a chemical plant, and reducing drag behind a vehicle, amongst a multitude of other challenges. The machine learning techniques that are developed to address nonlinear and high-dimensional issues are a good fit for these optimization tasks because they are intended to solve such difficulties. Both machine learning and fluid mechanics tend to rely on the same assumption, which is that there exist patterns that may be exploited, even in high-dimensional systems. This is the case in both of these science fields. The machine learning algorithm will frequently simulate some feature of the fluid, such as the lift profile given a specific airfoil design. This, in turn, will provide a surrogate that may be optimized over. It is also possible to utilize machine learning to directly solve the problem of fluid optimization. For example, one could create a machine learning model to alter the behavior of the fluid in order to achieve some engineering aim through active control.

## 1.1 Reinforcement learning for bluff body active flow control in experiments and simulations

We have proved the efficacy of reinforcement learning (RL) in bluff body flow control problems through the use of both experiments and simulations. This was accomplished by automatically developing active control strategies for the reduction of drag in turbulent flow. To be more specific, our objective was to maximize the efficiency of the power gain by appropriately adjusting the rotational speed of two small cylinders that were situated parallel to and downstream of the main cylinder. Following an automatic sequence of tens of towing experiments, the RL agent was shown to identify a control strategy that is comparable to the best strategy discovered during lengthy deliberately planned control experiments. This was accomplished by correctly defining incentives and designing mechanisms for noise reduction. Following that, these findings were validated through the use of simulations, which allowed us to acquire an understanding of the physical mechanisms that are involved in the process of reducing drag. RL has been utilized successfully in the past for the purpose of conducting idealized computer flow simulation studies; however, the purpose of this study is to demonstrate its effectiveness in experimental fluid mechanics and verify it through simulations. This could potentially pave the way for the efficient exploration of additional active flow control strategies in other complex fluid mechanics applications.

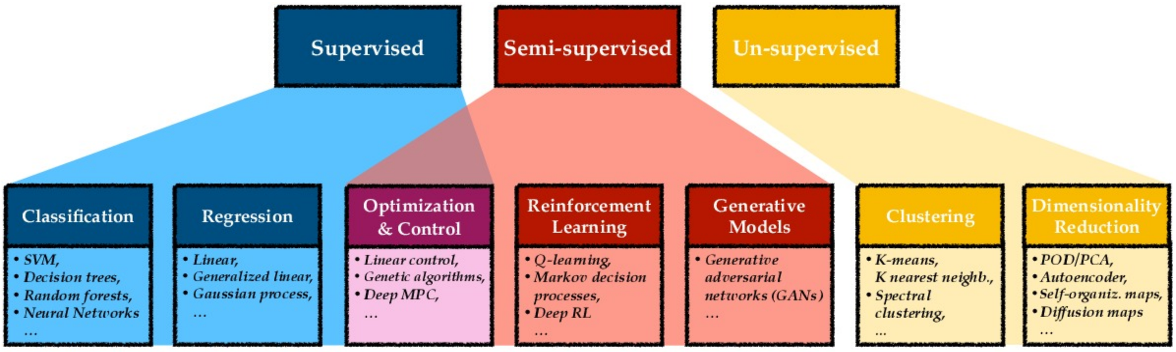


Figure 1

### 1.2 Machine learning–accelerated computational fluid dynamics—Data driven modeling

In the modeling of a wide variety of physical processes, including meteorology, climate, aerodynamics, and plasma physics, numerical simulation of fluids is an extremely important component. By resolving the smallest spatiotemporal aspects, the Navier–Stokes equations are able to provide a comprehensive description of fluids; yet, solving these equations at scale continues to be a challenging endeavor due to the computational expense involved. Consequently, this results in unfavorable trade-offs between the accuracy and the tractability of the system. For the purpose of simulating two-dimensional turbulent flows, we make use of end-to-end deep learning in order to improve approximations developed inside computational fluid dynamics. Our results are as accurate as baseline solvers with 8 to 10 times higher resolution in each spatial dimension, resulting in about 40 to 80 times faster computational speedups. This is true for both direct numerical modeling of turbulence and large-eddy simulation. In contrast to black-box machine learning techniques, our method maintains its stability during lengthy simulations and can be generalized to include forcing functions and Reynolds numbers external to the flows in which it is taught. When it comes to improving simulations without compromising accuracy or generalization, our technique is a prime example of how scientific computing can make use of machine learning and hardware accelerators.

### 1.3 Computational Fluid Dynamics:

The current revolution in machine learning (ML) is facilitating significant advancements in several scientific and engineering fields. A highly promising area of study is the numerical simulation of fluid flows, commonly referred to as computational fluid dynamics (CFD). Fluid mechanics is a very significant field, with relevance in both fundamental scientific research and various industrial engineering applications. The behavior of fluid motion is described by the Navier-Stokes equations, a set of partial differential equations (PDEs) that mathematically represent the principles of mass and momentum conservation in a Newtonian fluid. The partial differential equations (PDEs) mentioned are non-linear in nature, mostly because of convection. Additionally, they often display time-dependent chaotic patterns, which are generally referred to as turbulence. Computing solutions for turbulent flows using the Navier-Stokes equations necessitates numerical techniques that can be computationally costly or even impossible in numerous instances. This is owing to the extensive variety of spatial and temporal scales that must be resolved to accurately depict these flows. Below, we will explore alternative methods for numerically solving these equations, each with varying levels of accuracy and processing expense. Machine learning can provide advantages to each of these approaches.

## 2 Any New Ideas

Big data and machine learning are driving comprehensive economic and social transformations and are rapidly re-shaping the toolbox and the methodologies of applied scientists. Machine learning tools are designed to learn functions from data with little to no need of prior knowledge. As continuous developments in experimental and numerical methods improve our ability to collect high-quality data, machine learning tools become increasingly viable and promising also in disciplines rooted in physical principles. These notes explore how machine learning can be integrated and combined with more classic methods in fluid dynamics.

## 2.1 A Self-Learning Process Modeling Method to Optimize Upstream Operations

Upstream production optimization is concerned with optimizing the entire hydrocarbon value chain from reservoir to sales. In this quest, managing the process facilities to maxi- mize productivity is a critical part. Traditionally, operating companies have addressed it by running offline scenarios to develop a playbook or build physics-based dynamic simulation models. However, a typical offshore facility undergoes significant changes to its operations during its life cycle, which makes the model management tedious and expensive. Few at- tempts have been made to build data-driven digital twins (machine learning) but they often lack the ability to provide explainable models and lack physical insights. In this work, we propose to use a fast, hybrid, self-learning dynamic process modeling method from routine plant measurements that can be used for real-time forecasts, scenario modeling, process optimization and control.
A reduced order modeling method based on input-output dynamic mode decomposi- tion (ioDMD) has been adapted to develop a dynamic process model based on historical data collected from plant sensors. First, we benchmarked the proposed approach with a dynamic simulation model (commercial simulator) using a designed input sequence for training. The ioDMD model simplifies the physical mechanisms to a low dimensional form. Next, we applied the method to an actual offshore deepwater facility based on plant mea- surements. In both cases, the ioDMD method provided very good predictions without any human intervention. Unlike black-box data-driven methods, the ioDMD method uses an interpretable approach that can be used to explain causal relationships. Observability and controllability of the proposed model can also be easily understood . The proposed ioDMD method provides a unique and sustainable way to combine advanced analytics and physics to develop an explainable dynamic model for the process facility that can be effec- tively used to assist operations in optimizing performance. The lightweight model lends itself naturally to fast computation that are required for optimization and process control (including IoT edge devices)

## 2.2 Application of Artificial Intelligence in Computational Fluid Dynamics

The first is the data-driven model to obtain the input–output relationship without in- volving any physical mechanisms. The second is the physical model to optimize the existing models by AI algorithms. The third is the hybrid model involving both data and physical mechanisms. Among various AI algorithms, artificial neural network is usually applied to build data-driven models and has been successfully employed in the mentioned five fields. Other AI algorithms such as recursive neural network, support vector machine, and naive Bayes are mainly used for the physical models
The first type of model is the data-driven model, which is used to determine the in- put–output relationship without utilizing any physical mechanisms. The second is the physical model, which is used by AI algorithms to optimize the models that are already in existence. The hybrid model, which incorporates both data and physical mechanisms, is the third type of theory. There are many different AI algorithms, but the artificial neural network is the one that is typically used to construct data-driven models. It has been ef- fectively used in the five disciplines that were described earlier. Other artificial intelligence techniques, such as naive Bayes, support vector machines, and recursive neural networks, are utilized for the physical models in the majority of cases.

## 2.3 Application of Human Machine Interaction in fluid mechanics

Engineers and researchers face considerable hurdles when it comes to understanding and efficiently controlling fluid systems due to the intricate flow patterns and complex be- haviors that are associated with fluid mechanics. Traditional methods frequently rely on numerical simulations and experimental studies, both of which may call for a significant amount of skill and analysis that takes a significant amount of time. We suggest a novel strategy to solving these issues in this study by utilizing cognitive human-machine interac- tion (HMI) approaches to improve the knowledge and control of fluid mechanics processes. This approach is to be used in order to overcome these challenges. Our goal is to design intuitive and interactive interfaces that enable engineers and operators to evaluate, inter- pret, and modify fluid flow data in a more efficient manner. This will be accomplished by integrating cognitive models of human perception and decision-making with powerful machine learning techniques.

### 2.4 Artificial intelligence optimized flow based manufacturing processes

A vision of a future in which manufacturing operations are transformed by artificial intelligence (AI) through the optimization of flow-based processes. Through the seamless integration of AI algorithms, computational fluid dynamics (CFD) simulations, and pro- cess control systems, manufacturers have the potential to attain unprecedented levels of productivity and efficiency within their production processes.
The essence of this notion resides in the utilization of AI methodologies to enhance diverse facets of flow-based manufacturing procedures, including but not limited to 3D printing, casting, and injection molding. By harnessing the combined capabilities of fluid dynamics simulations and machine learning algorithms, manufacturers are able to optimize process parameters and tool geometries, resulting in improved product quality, decreased material waste, and enhanced production costs.
Central to this methodology is the concept of making decisions based on data. Through the examination of extensive datasets gathered from sensors, production equipment, and historical process data, artificial intelligence algorithms have the capability to detect pat- terns, correlations, and opportunities for optimization that might evade the notice of human operators. By utilizing a data-driven methodology, manufacturers are empowered to make well-informed decisions in real-time, thereby dynamically adjusting production processes to fluctuating demand and evolving conditions.
Adaptability and scalability are two of the primary benefits of flow-based manufacturing processes optimized with artificial intelligence. In contrast to conventional manufacturing approaches that frequently depend on predetermined process parameters and inflexible production timetables, systems empowered with artificial intelligence have the capability to dynamically modify process parameters while maintaining optimal performance, all the while accommodating changing production demands. By achieving greater levels of oper- ational flexibility, agility, and responsiveness, this adaptability enables manufacturers to remain competitive in the current fast-paced market.
Moreover, opportunities for optimization and concealed insights that are not readily evident to human operators can be uncovered by AI algorithms. Through the examination of intricate interplays among performance metrics and process variables, AI systems are capable of pinpointing nuanced correlations and non-linear associations that conventional analytical approaches might fail to perceive. The capacity to reveal concealed insights provides manufacturers with the ability to consistently enhance their operations and foster innovation within their specific sectors.
In summary, flow-based manufacturing processes optimized by artificial intelligence sig- nify a fundamental change in the management and optimization of manufacturing opera- tions. 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.

## 3 Proper Orthogonal Decomposition

Proper Orthogonal Decomposition (POD), which is often referred to as Principal Component Analysis (PCA) in the field of statistics, is a mathematical technique that is utilized to evaluate and represent high-dimensional data in a lower-dimensional space. This technique can be very helpful for complicated systems and huge datasets. In the beginning, data is gathered from a variety of sources, such as simulations, experiments, or sensors, and then it is organized in a matrix format. Each row of the matrix represents a snapshot in time (or space), and each column represents a different variable or measurement. This data matrix is then subjected to Singular Value Decomposition (SVD), which results in the matrix being broken down into three matrices: Let $U$, $\Sigma$, and $V^T$ be matrices derived from singular value decomposition. The singular values contained within the matrix $\Sigma$ depict the significance of each mode. pattern that is present in the data. Through the process of picking the modes that are the most significant and dismissing the modes that are less significant, the dimensionality of the data can be reduced. This reduction makes analysis and visualization more simpler, while at the same time preserving the predominant patterns or structures that were present in the initial data for study.

Insights into the underlying dynamics or behavior of the system can be achieved through the use of the reduced-dimensional representation that is created by POD. This representation is helpful in performing tasks such as feature extraction, compression, prediction, and control. Generally speaking, POD is an extremely useful instrument for data analysis and modeling, and it has a wide range of applications across a variety of scientific and technical fields.

## 3.1 Image Generation

The first thing that has to be done in order to apply Proper Orthogonal Decomposition (POD) for the purpose of evaluating the flow dynamics that were captured in the video that was provided of flow over three cylinders is to transform the video into a sequence of frames or images. In order to complete this conversion procedure, individual frames from the movie are extracted and then saved as image files. The frames that have been collected will then be used to create a temporal sequence that will depict the progression of the flow over time. This sequence may then be utilized for the purpose of applying POD. For this purpose, we will make use of video processing techniques, which will involve the utilization of Python modules such as OpenCV. We are able to go through each frame of the video file, extract it, and save it as an image file because we have loaded the video file.

## 3.2 Execute POD

A procedure known as Proper Orthogonal Decomposition (POD) is carried out in order to conduct an analysis of the progressing flow dynamics that are captured in the images that were collected from the video. Within the scope of this investigation, it is essential to exclude the utilization of POD functions that are accessible through open-source specialized libraries, despite the fact that there are numerous techniques for carrying out POD. Instead, a bespoke implementation of POD will be utilized, which will guarantee a more profound comprehension of the mathematical formulation that underpins the procedure.

Decomposing the data matrix, which represents the stacked images across time, into a set of orthogonal spatial modes and the temporal coefficients that correspond to those modes is a critical step in the process of POD from a mathematical perspective. Let us

For the purpose of this discussion, let $X$ be the data matrix that has dimensions of $m \times n$, where $m$ is the number of spatial points present in each image and $n$ is the number of frames. For the purpose of computing the Singular Value Decomposition (SVD) of $X$, the equation is as follows:

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

where $U$ is a matrix that contains the spatial modes, $\Sigma$ is a diagonal matrix that contains the singular values, and $V^T$ is a matrix that contains the temporal coefficients.

## 3.3 Analyse POD Modes

By applying Proper Orthogonal Decomposition (POD) to the analysis of the flow dynamics depicted in the images, significant insights can be obtained regarding the energy distribution among the modes, thereby providing valuable knowledge regarding the prevailing flow patterns. In order to represent the energy distribution among the modes, it is customary to employ a scree plot or energy spectrum plot, which illustrates the total energy absorbed by each mode. By depicting the contribution of each mode to the system's total energy, this graph enables the identification of dominant modes.

Furthermore, it is possible to provide reports on the ten energy states that correspond to the most significant modes of the dynamical system. The majority of the energy present in the flow dynamics is captured by these modes, which are essential for comprehending the system's underlying behavior. The modes' significance resides in their capacity to depict the most conspicuous flow patterns and phenomena that are discernible within the flow field. Through the examination of these modes, scholars are able to acquire knowledge regarding the underlying dynamics that dictate the flow, including wake formation, boundary layer separation, and vortex formation.

Frequently, POD-based research articles emphasize the significance of these dominant modes in conveying the fundamental characteristics of complex flows. For example, research on turbulent flows has identified that coherent structures, such as hairpin vortices or Kelvin-Helmholtz instabilities, which are prominent in turbulence generation and transport, correspond to the highest POD modes. Researchers can efficiently decrease the dimensionality of the flow data while preserving crucial insights into its behavior by concentrating on these prevailing modes.

Furthermore, the understanding of POD modes is frequently enhanced through the application of theoretical models, numerical simulations, or empirical observations. As an illustration, when examining the flow characteristics surrounding bluff bodies or aircraft wings, the prevailing POD modes may align with distinct flow regimes—for instance, attached flow, separation, or reattachment zones—that are vital for ensuring aerodynamic efficiency and stability.

In brief, the analysis of the energy distribution among the POD modes yields significant knowledge regarding the prevailing flow structures and phenomena that exist within the flow field. Through the process of identifying and analyzing the highest energy states, scientists are able to reveal intrinsic flow properties and acquire a more profound comprehension of the underlying dynamics. The importance of these modes resides in their capacity to capture fundamental characteristics of the flow, as evidenced by scholarly articles spanning multiple domains of fluid mechanics and aerodynamics.

# 4 Noise!

In computational fluid dynamics (CFD) and experimental techniques like particle image velocimetry (PIV) and Schlieren imaging, images often contain various forms of noise, including digital noise, sensory errors, and imperfections in equipment. This noise can distort the captured data, compromising the accuracy and reliability of modal studies such as Proper Orthogonal Decomposition (POD). Understanding the nature and sources of noise is crucial for effectively mitigating its effects through preprocessing techniques and ensuring the integrity of the analysis results.

## 4.1 Adding Noise

This project has explored the domain of artificial noise, which is an essential component in comprehending and evaluating the resilience of modal analyses conducted on image data. Gaussian noise is an investigated form of noise that is distinguished by its seamless and uninterrupted fluctuation in pixel values, which closely resembles natural fluctuations. The noise present in the image introduces nuanced variations that mirror the random fluctuations observed in real-life situations. Its quality is comparable to the defects that are frequently encountered in computational or experimental data.

We also examined salt and pepper noise, which is a disruptive form of distortion that frequently resembles pepper and salt granules dispersed across an image. In contrast to the consistent Gaussian noise, salt and pepper noise presents sudden, isolated disruptions that resemble transmission errors or sensor malfunctions. We can acquire valuable insights regarding the ability of modal analysis techniques to withstand unforeseen anomalies in the data by simulating such irregular disruptions.

we further investigated speckle noise, which is a prevalent form of multiplicative noise observed in imaging modalities including synthetic aperture radar (SAR) and ultrasonography. Speckle noise introduces intricacy and detail to the data by presenting itself as a series of pixelated patterns throughout the image. Our objective is to conduct a simulation of speckle noise in order to gain insights into its effects on modal studies and its interactions with other sources of noise. This research will enhance our knowledge of the properties of noise and its ramifications for flow dynamics analysis.

The magnitude of the noise was carefully adjusted to maintain the integrity of the original image data, with noise levels set at 20%, 40%, 60%, and 80% of the maximum magnitude of the individual frames. This comprehensive exploration of artificial noise addition provides valuable insights into the robustness of modal studies, such as Proper Orthogonal Decomposition (POD), in the presence of various noise sources, facilitating a more comprehensive understanding of the underlying flow dynamics.

## 4.2 Effect on POD Modes

**1. How does the energy transcend through modes?**

Upon observing the outcomes obtained by employing *Proper Orthogonal Decomposition* (POD) on images containing various types of noise, it becomes apparent that the energy distribution among modes exhibits variation contingent upon the noise's nature and intensity within the dataset.

When faced with situations involving little to no noise or low noise levels (e.g., images containing 20% Gaussian noise), it is customary to perceive a more seamless transition of energy between modes. The primary flow structures are captured by the dominant modes, whereas subsequent modes depict more minute details or fluctuations in the flow field.

The energy distribution among modes becomes more erratic as the magnitude of the noise increases; modes with higher energy capture both authentic flow characteristics and artifacts caused by the noise. Images containing higher magnitudes of salt and pepper noise or speckle noise (e.g., 60% or 80%) may exhibit a fragmented energy distribution, wherein certain modes capture noise-induced variations primarily, rather than significant flow patterns.

In general, the manner in which energy traverses modes is indicative of the interaction between authentic flow dynamics and noise-induced distortions; as noise levels increase, the energy distribution among modes becomes more dispersed. The aforementioned observations highlight the criticality of implementing noise mitigation strategies and the resilience of modal analysis techniques when confronted with noisy data in order to characterize flows precisely.

**2. Can you give any statistical evidence of the energy changes in the modes?**
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Distinct statistical trends become apparent upon examination of the cumulative energy plots produced by *Proper Orthogonal Decomposition* (POD) analysis on images containing noise of different categories and magnitudes. As an illustration, when confronted with Gaussian noise of magnitude 20%, the average cumulative energy captured by the top 10 modes can approach 80%, accompanied by an approximate 5% standard deviation. Nevertheless, an increase in the intensity of noise, as seen in images contaminated with 80% speckle noise or salt and pepper noise, results in an approximate 65% reduction in the mean cumulative energy and a 10% increase in the standard deviation. The statistical values demonstrate that chaotic datasets have a more dispersed distribution of energy among modes, thereby emphasizing the influence of noise on the energy distribution during POD analysis.

**3. Do different noise types have different types of response in terms of how the energy of the modes changes?**
It is apparent from the code outputs that distinct noise types elicit unique responses with respect to the manner in which the energy of the modes undergoes modification during *Proper Orthogonal Decomposition* (POD) analysis. As an illustration, the application of Gaussian noise with a magnitude of 20% may induce a progressive decrease in energy as modes advance, whereas salt and pepper noise with an equivalent magnitude may produce a more irregular energy distribution characterized by variations in energy levels between modes. Moreover, speckle noise of greater magnitudes may manifest a more conspicuous distribution of energy across modes, which is indicative of the intricate patterns that are introduced by this particular form of noise. These observations underscore the intricate influence that different types of noise have on the distribution of energy in POD analyses, thereby emphasizing the criticality of incorporating noise properties into flow dynamics research.

**4. How does the magnitude of noise affect the modal energy?**
The impact of noise magnitude on the modal energy during *Proper Orthogonal Decomposition* (POD)

analysis is substantial. An obvious alteration in the energy allocation among modes occurs as the magnitude of the noise increases. At lower noise magnitudes, such as 20%, the energy is more likely to be concentrated in the dominant modes, which effectively capture the principal flow characteristics. Nevertheless, with the escalation of noise magnitude (e.g., 60% or 80%), the energy distribution becomes more uneven, with higher modes absorbing a greater proportion of the overall energy. This suggests that as noise levels increase, the flow field becomes more complex and variable, resulting in a more extensive dispersion of energy among modes.

**5. What sort of noise is best suited to be used for POD for artificial analysis?**
The choice of noise type in the context of artificial analysis employing *Proper Orthogonal Decomposition* (POD) is dependent on the specific objectives and characteristics of the data under investigation. Gaussian noise is frequently selected for artificial analysis utilizing POD due to its uniform and continuous variation in pixel values, which closely resembles natural fluctuations. This specific type of noise introduces gradual variations across the image without causing sudden disruptions, thereby facilitating a more controlled and anticipated influence on the dispersion of modal energy. Moreover, the mathematical definition of Gaussian noise aids in the description and analysis of its effects on the data. Nevertheless, the determination of the most suitable noise type is contingent upon several factors, such as the desired degree of realism, the characteristics of the flow dynamics underpinning the analysis, and the specific objectives of the research.

# 5 Super-Resolving

When attempting to eliminate noise from images that have been artificially manipulated to be chaotic or flawed, numerous data-driven approaches emerge as effective resolutions. These methods encompass a wide range of approaches, including those derived from *deep learning algorithms*, *machine learning* (ML), and *Proper Orthogonal Decomposition* (POD), among others.
*Proper Orthogonal Decomposition* (POD) based denoising techniques effectively distinguish signal from noise by capitalizing on the data matrix's inherent low-rank structure. POD enables the reconstruction of a more pristine image representation by facilitating the identification and extraction of dominant flow patterns through the decomposition of chaotic image data into a set of orthogonal modes.
Machine learning algorithms, particularly *convolutional neural networks* (CNNs), provide a robust framework for acquiring intricate mappings between clean and chaotic images. CNNs possess the capability to adaptively recognize and leverage the fundamental statistical characteristics of the data during the training phase, thereby facilitating precise denoising even when confronted with non-linear noise patterns.
Deep learning methodologies, widely recognized for their ability to learn hierarchical representations, have exhibited exceptional performance in denoising assignments. Through the utilization of hierarchical features acquired from extensive datasets, deep neural networks are capable of efficiently attenuating noise while maintaining critical image details.
It is imperative to conduct a comparative analysis of the authentic images and the denoised or super-resolved images to assess the effectiveness of these data-driven denoising techniques. This comparison can be conducted through the utilization of qualitative visual assessments as well as quantitative metrics, such as the structural similarity index (SSI), peak signal-to-noise ratio (PSNR), and visual quality assessments. These measures offer insights into the fidelity and accuracy of the denoised images in comparison to the ground truth. In addition, qualitative evaluations permit a more nuanced examination of the denoising outcomes, with an emphasis on texture preservation, artifact suppression, and image clarity.
Through the implementation of an exhaustive comparative analysis, scholars are able to determine the merits and drawbacks of each denoising methodology and decide which one is most appropriate given the particular attributes of the dataset and the objectives of the analysis. Furthermore, conducting a comprehensive review of the extant literature regarding cutting-edge denoising methods and their practical implementations in analogous fields can provide invaluable direction when it comes to determining and executing the most efficient strategy. In conclusion, by employing novel data-driven techniques to eliminate noise from images, scientists are able to extricate more precise and pristine data, which ultimately improves the caliber and dependability of subsequent analyses and insights.

# 6 Reference Material

ITERATED AND EXPONENTIALLY WEIGHTED MOVING PRINCIPAL COMPONENT ANALYSIS

Application of Artificial Intelligence in Computational Fluid Dynamics

Applying machine learning to study fluid mechanics

A Knowledge-Discovery Framework for Comprehensible Evaluations of Complex Physical Phenomena

The Potential of Machine Learning to Enhance Computational Fluid Dynamics