دانشگاه بوعلی سینا

Denoising Framework

Digital Image Processing

Fall 2024

1. INTRODUCTION

Extracting meaningful information from images is a critical task in Computer Vision. However, images captured from the real world are often affected by different types of noise. These artifacts can significantly affect Computer Vision systems' performance and visual data quality. In this project, you will develop a noise detection and deduction framework that will equip you with the knowledge and skills necessary to tackle various types of noise in image processing applications.

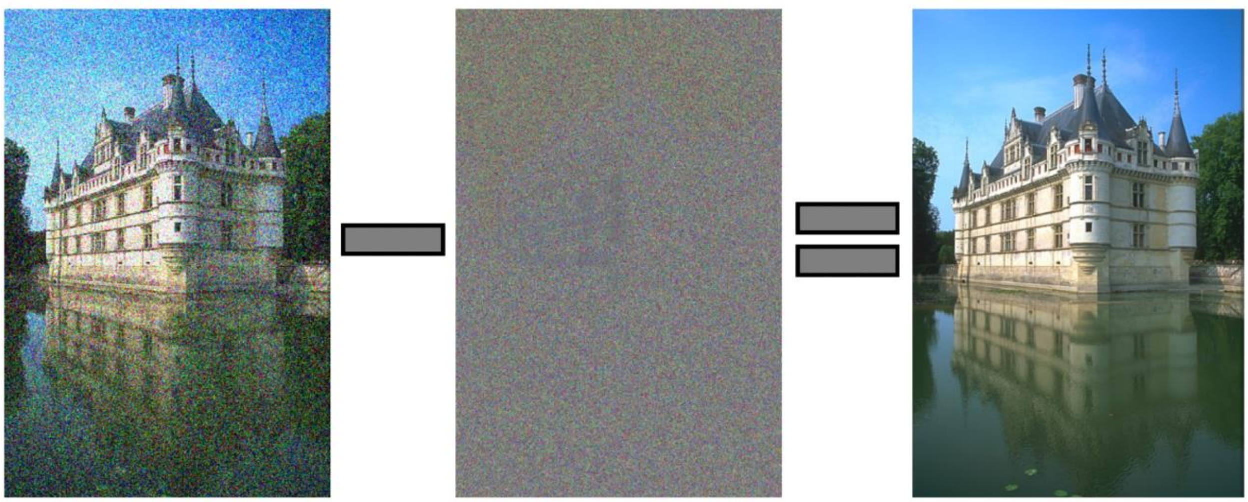

Figure 1. An illustration of removing noise from an image.

2. PREPROCESSING

In data-driven projects, preprocessing is a crucial preparatory step, particularly in vision tasks. By refining raw data, preprocessing enhances its quality and relevance for subsequent analysis and modeling. In the context of vision-based projects, such as image classification, preprocessing becomes pivotal. The objective is to create a clean and standardized dataset, promoting optimal model performance. For your course project, the freedom to choose preprocessing methods is granted.

3. DATASET

The dataset is divided into two parts. Part 1 focuses on defect detection, while Part 2 addresses noise detection and deduction. The dataset is designed for the detection of defects in casting products. Casting is a manufacturing process in which a liquid material is poured into a mold, allowing it to solidify and assume the desired shape. All the images in the dataset depict top views of submersible pump impellers. In Part 1 of the dataset, images are categorized into 1) Defective and 2) Ok. Defective images represent products with defects, while Ok images depict those without defects. Figure. 2 provides a visual representation of the two categories of casting products.

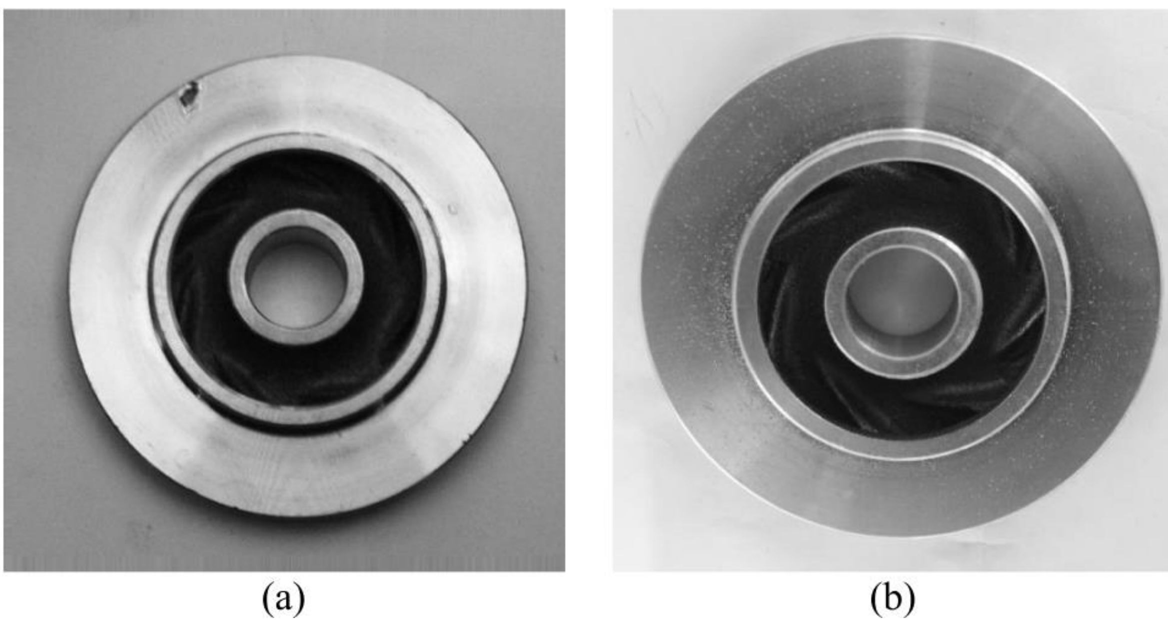

Figure 2. An example for category: a) Defective, b) Ok.

Part 2 of the dataset is synthesized to introduce a diverse range of noises commonly encountered in real-world scenarios, including Salt and Pepper noise, Gaussian noise, and Periodic Noise. Figure. 3 provides a visual representation of the different noises after synthesizing.

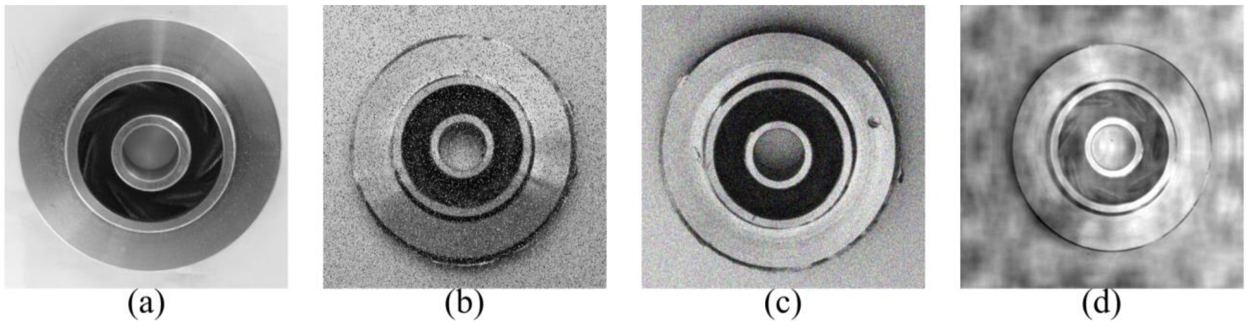

Figure 3. An example of dataset categories after synthesizing: a) Noise-free, b) Salt and Pepper, c) Gaussian, and d) Periodic.

4. Project Overview and Experimental Guidelines

This project unfolds in three phases, each addressing specific aspects of the denoising framework development and its impact on the classification task. In Phase 1, a binary classification task is undertaken, utilizing noisy images to detect defects in disks. Phase 2 sees the development of a denoising framework, encompassing a noise classification module to identify types of noises, followed by targeted denoising processes. This leads to the generation of denoised images. Finally, Phase 3 revisits the binary classification task, applying the denoising framework to the initially noisy images in Phase 2. The comparison between Phase 1 and Phase 3 results is a comprehensive evaluation, showing the impact of denoising on different classification metrics. Evaluation metrics such as classification accuracy and denoising quality metrics are employed, providing a thorough understanding of the framework's effectiveness in enhancing image analysis tasks by mitigating noise artifacts.

4.1 Phase 1: Binary Classification

In the initial phase of the project, your task involves conducting binary classification on a noisy dataset. You have the flexibility to employ any recognized classification method, ranging from traditional techniques to those based on deep learning approaches. It is essential to provide a comprehensive evaluation of your model's performance on the test set, comprising a minimum of 10% of the dataset. This evaluation should be presented in a table, reporting metrics such as Accuracy, Sensitivity, Specificity, and F-1 Score. Additionally, include a visualization of the confusion matrix and ROC curve for the test set to provide a detailed overview of the classification performance.

4.2 Phase 2: Denoising Framework

The second phase involves the development of a denoising framework consisting of two main parts: **1) Noise Detection** and **2) Noise Deduction**.

Initially, the framework incorporates a noise classifier module to identify the type of noise present in the input images, including Gaussian Noise, Salt and Pepper Noise, and Periodic Noise. Similar to Phase 1, any classification method can be employed for the classifier module.

Once the noise type is detected, the framework proceeds to the Noise Deduction stage, where an appropriate denoising method is applied to remove the identified noise artifacts. The denoising methods may range from traditional techniques like Median and Mean Filters to deep learning methods such as Autoencoder architectures.

To assess the performance of the Noise Classifier module, evaluation metrics, including Accuracy, Sensitivity, Specificity, and F-1 Score, should be reported in a table. Also, the Denoiser module should be evaluated using metrics discussed in Section 5, including Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Learned Perceptual Image Patch Similarity (LPIPS).

The output of this framework is a denoised image. Figure 4 visually represents the denoising framework, highlighting the sequential processes involved in noise classification and subsequent denoising.

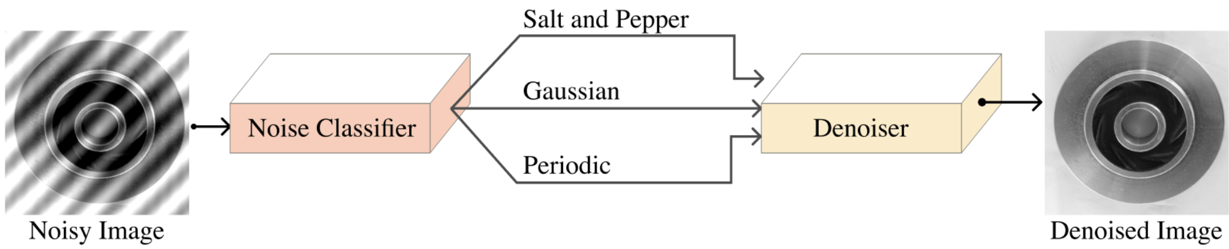

Figure 4. An illustration of the denoising framework for noise detection and deduction.

4.3 Phase 3: Final Lap

Great progress! You've reached the final phase of the project. In this third and concluding phase, your objective is to apply the denoising framework developed in Phase 2 to clean all the images within the initially provided noisy dataset, which was used for binary classification in the project's initial phase. Once the denoising process is complete, you are tasked with performing the same binary classification on this newly refined dataset. The evaluation criteria remain consistent with those outlined in Phase 1, encompassing metrics such as Accuracy, Sensitivity, Specificity, and F-1 Score, along with the presentation of the confusion matrix and ROC curve for the test set. It is crucial to meticulously compare the results obtained from the denoised dataset with the original classification outcomes and engage in a comprehensive discussion regarding the impact and effectiveness of your denoiser model on the overall classification task.

5. EVALUATION METRICS

To evaluate the performance of the denoising framework developed in this project, you will focus on quantifying the performance of the denoising methods in terms of *Peak Signal-to-Noise Ratio (PSNR)*, *Structural Similarity Index (SSIM)*, and *Learned Perceptual Image Patch Similarity (LPIPS)*.

The evaluation process will involve comparing the denoised images against noise-free images, measuring the extent of noise reduction, and quantifying the perceptual similarity between the denoised and noise-free images. These metrics collectively provide a comprehensive understanding of the denoising framework's effectiveness in preserving image quality and mitigating various types of noise.

5.1 Peak Signal-to-Noise Ratio (PSNR):

PSNR is a classic metric widely used to measure the quality of denoised images by comparing them to the original, noise-free images. It is defined as the ratio of the maximum possible power of a signal to the power of the noise that affects the fidelity of its representation. Higher PSNR values indicate better image quality. The formula for PSNR is given by:

$$PSNR = 10 \cdot log_{10}(\frac{MAX_I^2}{MSE})$$

where $\underline{MAX}$ represents the maximum pixel value of the image (e.g., 255 for an 8-bit image) and $\underline{MSE}$ is the mean squared error between the denoised image and the noise-free reference image.

5.2 Structural Similarity Index (SSIM):

SSIM is a perceptual metric that assesses the structural similarity between the original and denoised images. It considers luminance, contrast, and structure, providing a more nuanced evaluation of image quality than PSNR. SSIM values range from -1 to 1, with 1 indicating perfect similarity. The formula for SSIM is given by:

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1) + (\sigma_x^2 + \sigma_y^2 + C_2)},$$

where x and y represent the enhanced and ground truth reference images, respectively. μ_x and μ_y are the average values of x and y, σ_x^2 and σ_y^2 are their variances, and σ_{xy} is the covariance of x and y. $C_1$and $C_2$are small constants used to stabilize the division.

5.3 Learned Perceptual Image Patch Similarity (LPIPS):

LPIPS is a perceptual metric that leverages deep neural networks to evaluate the perceptual similarity between images. It considers human visual perception to assess the quality of denoised images, making it particularly relevant for evaluating the performance of advanced denoising techniques. Lower LPIPS scores correspond to higher perceptual similarity. You **must** use **AlexNet** for your evaluations.

GRADING CRITERIA

- Phase 1 (15%)
- Phase 2 (35%)
- Phase 3 (20%)
- Report (30%)
- Best Implementation (+10%)
- Three Most Accurate Results (+15%, +10%, +5%)

Projects must be submitted in person, and the final evaluations, as well as comparisons between projects, are conducted using a test set that is not accessible to students. Therefore, all students must be prepared to assess their models with the provided test data during the delivery session.

CONTACT

You can reach out to the course teaching assistants for any project-related inquiries through the following means:

Mahdie Behrooz	Email: Sarabehrooz1376@gmail.com Telegram: @br_s1997
Hanie Zomorodi	Email: zomorrodi.hanie@gmail.com Telegram: @hanie_zmrd
Alireza Maleki	Email: Alirezamalekiiiii78@gmail.com Telegram: @allirezamaleki

Good luck with your project!

Appendix. Guide to Writing Your Course Project Report

Importance of the Report

Your course project report is a pivotal piece of your academic journey. It's more than just an assignment; it's an opportunity to demonstrate your understanding of the subject matter and your ability to conduct meaningful research. A well-crafted report can positively impact your academic path and contribute to your overall success.

Abstract

The abstract is a succinct summary of your entire report.

1. **Purpose:** Clearly state the objective or purpose of your research.
2. **Methodology:** Briefly describe your research methods.
3. **Results:** Summarize the key findings.
4. **Conclusion:** Provide a concise overview of your conclusions.

Experiments

The experiments section explains the specifics of your experimental work.

1. **Setup:** Clearly explain your experimental design or setup.
2. **Procedure:** Provide a step-by-step account of the experiments conducted.
3. **Control Measures:** Discuss any controls in place to ensure accurate results.

Results

In the results section, present your findings clearly and organized.

1. **Data Presentation:** Use tables, graphs, or charts for effective data representation.
2. **Statistics:** If relevant, include statistical analyses.
3. **Findings:** Summarize key findings and trends observed in your experiments.

Conclusion

The conclusion section wraps up your report, providing a thoughtful reflection on your research.

1. **Summarize Findings:** Revisit the main findings from the results section.
2. **Interpretation:** Discuss the implications of your findings.
3. **Limitations:** Acknowledge any limitations in your study.
4. **Future Research:** Suggest areas for future research.

References

The references section is crucial for giving credit to your sources and maintaining academic integrity.

1. **Format:** Use the citation style specified for your course (APA, MLA, etc.).
2. **Accuracy:** Ensure proper citation of all sources consulted during your research.
3. **Consistency:** Maintain a consistent format throughout your reference list.