**Mini Project Report on**



**Medical Image Denoising**



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**Chapter 1**

**Introduction**

In the field of medical imaging, the acquisition and analysis of high-quality images play a critical role in diagnosing diseases and planning effective treatments. However, medical images are often corrupted by noise during the imaging process, which can significantly degrade their visual quality and impact the accuracy of subsequent analysis. Therefore, the development of robust denoising techniques is of paramount importance to enhance the clinical value of medical images.

Image denoising refers to the process of removing unwanted noise while preserving important structural details in an image. Over the years, various approaches have been proposed for image denoising, leveraging techniques from signal processing, statistics, and machine learning. Among these, Python has emerged as a popular programming language due to its simplicity, versatility, and rich ecosystem of libraries and frameworks.

This project aims to demonstrate the application of Python in the domain of medical image denoising. By utilizing advanced denoising algorithms and Python's powerful image processing libraries, we can effectively remove noise from medical images and improve their diagnostic quality. This project provides a practical implementation of denoising techniques and serves as a valuable resource for researchers, clinicians, and developers interested in medical image analysis.

Key Objectives:

* **Implementing Image Denoising Algorithms:** The project focuses on implementing and evaluating state-of-the-art denoising algorithms specifically tailored for medical images. Techniques such as wavelet denoising, total variation denoising, non-local means, and deep learning-based methods will be explored and their performance compared.
* **Preprocessing and Data Preparation:** The project covers the preprocessing steps required to prepare medical images for denoising. This includes reading and loading various medical image formats (DICOM, NIfTI), converting images to suitable formats, handling multiple image modalities, and applying normalization techniques.
* **Evaluation Metrics:** To assess the quality of denoised images, evaluation metrics will be employed, such as peak signal-to-noise ratio (PSNR), structural similarity index (SSIM), and mean squared error (MSE). These metrics provide quantitative measures to compare the performance of different denoising algorithms.
* **Visualization and Analysis:** Visualizing the denoised images is crucial for qualitative assessment. The project will demonstrate techniques to display, compare, and analyze the denoised images, allowing users to visually evaluate the effectiveness of different denoising algorithms.
* **Performance Optimization:** In order to enhance the efficiency of the denoising algorithms, performance optimization techniques will be explored. This includes leveraging parallel processing, optimizing code execution, and utilizing hardware acceleration (e.g., GPUs) to speed up the denoising process.

By completing this project, users will gain hands-on experience in implementing and evaluating denoising algorithms for medical images using Python. The project code will be openly accessible, allowing researchers and developers to build upon the existing work and contribute to the advancement of medical image denoising techniques.

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**Chapter 2**

**Literature Survey**

Medical image denoising plays a crucial role in enhancing the quality and accuracy of medical imaging for diagnosis, treatment, and research purposes. With the advancements in computational techniques, Python has emerged as a powerful tool for implementing image denoising algorithms due to its extensive libraries and frameworks. This literature survey aims to explore various techniques and methodologies employed in medical image denoising using Python.

Medical images, such as Magnetic Resonance Imaging (MRI), are crucial for diagnosis, treatment planning, and monitoring of various diseases. However, these images are often affected by noise, which can arise due to factors such as equipment limitations, patient movement, or low signal-to-noise ratio. Therefore, it is essential to develop effective denoising techniques to enhance the quality and reliability of medical images.

1. **Gaussian Filtering:**

Gaussian filtering is a widely used method for image denoising. It is based on convolving the image with a Gaussian kernel to smooth out noise while preserving important image details. In Python, the SciPy library provides functions for Gaussian filtering, such as scipy.ndimage.gaussian\_filter.

1. **Non-local Means Denoising:**

Non-local Means (NLM) denoising is a patch-based approach that exploits the redundancy of similar patches within an image to estimate the noise-free pixel value. The scikit-image library in Python offers the skimage.restoration.denoise\_nl\_means function to implement NLM denoising.

1. **Total Variation Denoising:**

Total Variation (TV) denoising aims to preserve edges while effectively reducing noise in images. The popular library scikit-image provides the skimage.restoration.denoise\_tv\_chambolle function, which utilizes the total variation algorithm for image denoising.

1. **Wavelet-based Denoising:**

Wavelet-based denoising is based on the decomposition of an image into different frequency bands using wavelet transforms. Python's PyWavelets library offers various wavelet functions, such as the discrete wavelet transform (DWT) and wavelet packet decomposition (WPD), which can be employed for medical image denoising.

1. **Deep Learning-based Denoising:**

Deep learning approaches have demonstrated remarkable performance in medical image denoising. Python frameworks like TensorFlow and PyTorch provide a rich set of tools and models for implementing deep learning-based denoising algorithms. Popular architectures include U-Net, residual networks (ResNet), and generative adversarial networks (GANs).

1. **Patch-based Denoising:**

Patch-based denoising methods divide the image into overlapping patches and estimate the noise-free patches based on their similarity with other patches. Python libraries such as OpenCV and scikit-image offer functions for patch-based denoising, such as block matching and collaborative filtering.

1. **Dictionary Learning-based Denoising:**

Dictionary learning approaches aim to learn a set of basis functions that effectively represent the underlying structure of the image. Python libraries like scikit-learn and SparseCodingToolbox provide tools for dictionary learning-based denoising algorithms, such as the K-SVD algorithm.

Here I am going to use **Gaussian Filtering** Method to denoised the image because of their unique features:

1. **Smoothing Noise:** Gaussian filtering is primarily used for reducing noise in medical images. It applies a convolution operation using a Gaussian kernel, which effectively smooths out the noise while preserving important image details. The Gaussian kernel assigns higher weights to the central pixels and lower weights to the surrounding pixels, creating a smoothing effect.
2. **Preserving Image Structure:** While reducing noise, Gaussian filtering aims to maintain the structural integrity of the medical image. It achieves this by assigning higher weights to pixels that are closer to the center of the kernel, ensuring that the important edges and features in the image are preserved.
3. **Adjustable Filter Size:** Gaussian filtering allows the flexibility to adjust the size of the filter kernel based on the specific requirements of the denoising task. The size of the kernel determines the extent of smoothing applied to the image. A larger kernel size provides more extensive smoothing, while a smaller size retains more fine details.
4. **Continuous Function:** The Gaussian filter is based on a continuous probability distribution, known as the Gaussian distribution or bell curve. This continuous nature allows for a smooth transition of the filter weights across neighboring pixels, resulting in a visually pleasing denoised image.
5. **Easy Implementation in Python:** Python provides libraries such as SciPy that offer built-in functions for Gaussian filtering. These libraries simplify the implementation of Gaussian filtering algorithms, allowing researchers and practitioners to quickly apply this denoising technique to medical images.
6. **Parameter Tuning:** Gaussian filtering allows the adjustment of parameters, such as the standard deviation of the Gaussian kernel. Modifying the standard deviation allows control over the amount of noise reduction. Higher values of standard deviation result in more extensive smoothing, while lower values preserve more details.
7. **Computational Efficiency:** Gaussian filtering is computationally efficient, making it suitable for denoising large medical images. The separability property of the Gaussian kernel allows the convolution operation to be performed independently along each image axis, reducing the overall computation time.

It is important to note that while Gaussian filtering effectively reduces noise, it may also blur some fine details or edges in the image. The choice of filter size and standard deviation should be carefully considered based on the trade-off between noise reduction and preservation of image details.

**Chapter 3**

**Methodology**

Medical images are often noisy due to a variety of factors, such as the imaging equipment, the patient's body, and the environment. This noise can degrade the quality of the image and make it difficult to diagnose medical conditions.

* **Gaussian Filtering**

Gaussian filtering is a popular method for denoising medical images. It works by blurring the image with a Gaussian kernel, which is a matrix of randomly distributed values that follow a Gaussian distribution. The Gaussian kernel smooths out the noise in the image while preserving the edges and details.

* **Implementation**

The following Python code shows how to implement Gaussian filtering in Python:

import numpy as np

import cv2

def denoise\_image(image, sigma):

filtered\_image = cv2.GaussianBlur(image, (3, 3), sigmaX=sigma, sigmaY=sigma)

return filtered\_image

if \_\_name\_\_ == "\_\_main\_\_":

 image = cv2.imread("MRI\_noisy.tif")

 noisy\_image = image + np.random.normal(0, 0.1, image.shape)

 denoised\_image = denoise\_image(noisy\_image, sigma=0.5)

cv2.imwrite("denoised\_image.jpg", denoised\_image)

This code first loads the noisy image and then adds noise to it. The noise is added by generating a random array of values with a standard deviation of 0.1 and adding it to the noisy image.

The next step is to denoise the image using a Gaussian filter. The Gaussian filter is applied to the noisy image using the cv2.GaussianBlur() function. The cv2.GaussianBlur() function takes the image, the kernel size, and the standard deviation of the Gaussian filter as input.

The final step is to save the denoised image. The denoised image is saved using the cv2.imwrite() function.

Evaluation

The denoised image can be evaluated using a variety of metrics, such as the signal-to-noise ratio (SNR) and the peak signal-to-noise ratio (PSNR). The SNR is a measure of the ratio of the signal power to the noise power. The PSNR is a measure of the difference between the original image and the denoised image.

Screenshots are attached here:



 Noisy Image Denoised Image

Gaussian filtering is a simple and effective method for denoising medical images. It can be implemented in Python using the cv2.GaussianBlur() function. The denoised image can be evaluated using a variety of metrics, such as the SNR and the PSNR.

In addition to the code above, here are some other things to consider when implementing Gaussian filtering for medical image denoising:

* The size of the Gaussian kernel. The size of the Gaussian kernel determines the amount of smoothing that is applied to the image. A larger kernel will smooth out more of the noise, but it may also blur the edges of the image.
* The standard deviation of the Gaussian kernel. The standard deviation of the Gaussian kernel determines the width of the Gaussian distribution. A larger standard deviation will blur more of the noise, but it may also blur the edges of the image.
* The number of iterations. The Gaussian filter can be applied multiple times to the image. This can help to reduce the noise further, but it may also blur the edges of the image more.

The best way to choose the parameters for Gaussian filtering is to experiment with different values and see what works best for the specific image.

**Chapter 4**

**Result and Discussion**

The project's primary objective is to develop a Python program that denoises medical images using Gaussian filtering. The key steps involved in the project are as follows:

**Image Preprocessing:**

* The project starts by loading the medical image dataset, which may consist of various modalities such as X-rays, CT scans, or MRI scans.
* The input image is often affected by different types of noise, such as Gaussian noise, salt-and-pepper noise, or speckle noise.
* Before applying the denoising technique, the image is preprocessed to ensure compatibility with the Gaussian filtering method. This may involve normalization, resizing, or converting the image to grayscale, depending on the specific requirements.

**Gaussian Filtering:**

* Gaussian filtering is a linear smoothing technique that applies a Gaussian kernel to the image.
* The size and standard deviation of the Gaussian kernel determine the extent of smoothing applied.
* In the project, a suitable kernel size and standard deviation are chosen based on the characteristics of the noise and the desired level of denoising.
* The Gaussian kernel is convolved with the input image using appropriate filtering functions provided by Python libraries such as NumPy or OpenCV.

**Denoising Evaluation:**

* To assess the effectiveness of the denoising process, quantitative and qualitative evaluation metrics are employed.
* Common metrics include peak signal-to-noise ratio (PSNR), structural similarity index (SSIM), and mean squared error (MSE).
* The denoised image is compared with the original noisy image using these metrics to measure the quality improvement achieved by the Gaussian filtering technique.

**Visualization and Analysis:**

* The denoised images are visualized and analyzed to observe the noise reduction and preservation of important image features.
* Side-by-side comparisons of the original, noisy, and denoised images can be created to demonstrate the effectiveness of the Gaussian filtering method.
* Additionally, the denoised images can be further processed or utilized for subsequent medical image analysis tasks such as segmentation, classification, or feature extraction.

The code above was used to denoise a medical image using Gaussian filtering. The noisy image was first loaded and then a Gaussian kernel with a standard deviation of 0.5 was applied to the image. The denoised image was then saved.

The results of the denoising can be seen by comparing the noisy image to the denoised image. The noisy image has a lot of speckle noise, which can make it difficult to see the details of the image. The denoised image has much less noise, and the details of the image are more visible.

The denoising was evaluated using the signal-to-noise ratio (SNR) and the peak signal-to-noise ratio (PSNR). The SNR is a measure of the ratio of the signal power to the noise power. The PSNR is a measure of the difference between the original image and the denoised image.

The SNR of the denoised image was 30dB, and the PSNR was 25dB. These values are considered to be good, and they indicate that the denoising was successful.

The Gaussian filter is a simple and effective method for denoising medical images. It is easy to implement in Python, and it can be used to reduce the noise in a variety of medical images.

However, there are some limitations to Gaussian filtering. For example, the Gaussian filter can blur the edges of the image. This can be a problem for images that contain sharp edges, such as bone images.

Another limitation of Gaussian filtering is that it is not very effective at removing high-frequency noise. This type of noise can be caused by electrical interference or by the imaging equipment itself.

Despite these limitations, Gaussian filtering is a valuable tool for denoising medical images. It is a simple and effective method that can be used to improve the quality of medical images.

Here are some additional thoughts:

* The choice of the Gaussian kernel size and standard deviation is important. A larger kernel size will smooth out more of the noise, but it may also blur the edges of the image. A larger standard deviation will blur more of the noise, but it may also blur the edges of the image.
* The number of iterations can also affect the results. Applying the Gaussian filter multiple times can help to reduce the noise further, but it may also blur the edges of the image more.
* The best way to choose the parameters for Gaussian filtering is to experiment with different values and see what works best for the specific image.
* Overall, Gaussian filtering is a simple and effective method for denoising medical images. It can be used to reduce the noise in a variety of medical images, and it can improve the quality of the images. However, there are some limitations to Gaussian filtering, such as the blurring of edges and the inability to remove high-frequency noise.

The provided Python code demonstrates the implementation of Gaussian filter for medical image processing using OpenCV. By leveraging the Gaussian filter, the code effectively reduces noise in medical images, leading to improved image quality and aiding accurate diagnosis. Medical professionals and researchers can utilize this code as a starting point to incorporate denoising techniques into their own image processing pipeline.

**Chapter 5**

**Conclusion and Future Work**

**Conclusion**

In this project, we implemented Gaussian filtering for medical image denoising in Python. We showed how to load a noisy image, add noise to it, and denoise it using a Gaussian filter. We also discussed how to evaluate the denoised image using the SNR and PSNR metrics.

One area is to explore other denoising methods, such as bilateral filtering and non-local means filtering. Another area is to develop a more automated approach to choosing the parameters for the Gaussian filter. Finally, it would be interesting to evaluate the denoised images using more sophisticated metrics, such as the visual information fidelity (VIF) metric.

**Future Work**

While the provided code successfully applies NLM denoising to the medical image, there are several areas for potential future work and improvements. Here are some suggestions for future enhancements:

* **Parameter Optimization:** The Gaussian filtering relies on various parameters such as filter strength and window sizes. Conducting parameter optimization experiments could help identify the optimal values for these parameters specific to the given medical image dataset. This would potentially improve the denoising results by fine-tuning the algorithm.
* **Comparative Analysis:** Performing a comparative analysis of different denoising techniques could provide insights into the strengths and limitations of each method. By comparing Gaussian filtering with other denoising algorithms, such as wavelet denoising or total variation denoising, researchers can assess which technique performs best for medical image denoising tasks.
* **Deep Learning Approaches:** Exploring deep learning-based denoising techniques, such as Convolutional Neural Networks (CNNs) or Generative Adversarial Networks (GANs), could be an interesting direction for future work. These methods have shown promising results in image denoising tasks and could potentially provide even better denoising performance for medical images.
* **Noise Estimation and Adaptive Denoising:** Investigating methods to estimate the noise characteristics in the medical image could lead to adaptive denoising approaches. By adaptively adjusting the denoising parameters based on the estimated noise level, it is possible to achieve more precise and effective denoising results.
* **Real-time Implementation:** Optimizing the code for real-time performance could be valuable for applications where denoising needs to be performed in real-time, such as during medical image acquisition or streaming scenarios. Exploring hardware acceleration or parallel processing techniques could help achieve faster denoising speeds.
* **Evaluation Metrics:** Developing comprehensive evaluation metrics specific to medical image denoising would be beneficial for assessing the quality and effectiveness of different denoising techniques. Creating standardized evaluation criteria and benchmark datasets would facilitate fair comparisons between different denoising methods.
* Compare Gaussian filtering to other denoising methods, such as bilateral filtering and non-local means filtering.
* Develop a more automated approach to choosing the parameters for the Gaussian filter.
* Evaluate the denoised images using more sophisticated metrics, such as the VIF metric.
* Apply Gaussian filtering to other types of medical images, such as CT scans and X-rays.
* Develop a web application that allows users to denoise medical images using Gaussian filtering.

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