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IMAGE DENOISING AND RECONSTRUCTION IN MEDICAL IMAGING

Khatamov Orif Yusupovich
2st year PhD student of Samarkand State University named after Sharof Rashidov
E-mail: orifxatamov07@gmail.com

Abstract. This article analyzes methods for detecting and effectively removing noise in medical images to restore high-quality diagnostic images. Common noise types such as Gaussian, salt and pepper, and speckle noise are examined in detail due to their frequent occurrence in MRI, CT, and ultrasound modalities. Both classical filtering methods (such as median and Gaussian filters) and advanced techniques (including Non-Local Means, Wavelet Denoising, and Deep Learning-based approaches) are discussed for their effectiveness in enhancing image clarity. Practical implementations using the Python programming language are provided to demonstrate the application of these techniques in real-world scenarios. The study also includes comparative visual results before and after denoising to assess improvements in image quality. This work serves as a practical guide for researchers and developers working on medical image processing and reconstruction.

Key words: noise reduction, medical imaging, reconstruction, Gaussian noise, median filter, Python, denoising, AI, CNN.

Introduction. Images used in medical diagnostics, such as MRI, CT, and X-ray images, are often contaminated with various noises. These noises negatively affect the accuracy of diagnosis. Therefore, the process of cleaning medical images from noise is an important step in improving their quality and ensuring diagnostic reliability.

Medical imaging plays a pivotal role in modern healthcare by enabling accurate and early diagnosis of diseases through visual analysis of internal body structures. However, during image acquisition and transmission, medical images such as MRI (Magnetic Resonance Imaging), CT (Computed Tomography), and ultrasound scans often suffer from various types of noise. This noise - originating from sensor limitations, patient movement, or transmission errors can obscure critical anatomical details, potentially leading to misdiagnosis or the need for repeat examinations.

Common types of noise in medical imaging include gaussian noise, salt and pepper noise, and speckle noise. Each of these noise types has unique characteristics and requires specialized techniques for effective removal. For instance, while Gaussian noise can be smoothed using Gaussian or bilateral filters, salt and pepper noise is more effectively removed using median-based approaches. Speckle noise, particularly prevalent in ultrasound images, requires statistical or wavelet-based filtering methods.

In recent years, alongside traditional image processing techniques, advanced denoising methods such as Non-Local Means (NLM), wavelet transforms, and deep learning-based models like convolutional neural networks (CNNs) have demonstrated superior performance in restoring image quality without compromising diagnostic information.

This study explores a range of noise reduction techniques - ranging from classical filters to state-of-the-art AI models - using practical examples implemented in the Python programming language. The effectiveness of these methods is evaluated visually and quantitatively, highlighting their potential in enhancing diagnostic accuracy. The results and code examples presented aim to serve as a useful guide for researchers, engineers, and healthcare professionals engaged in medical image analysis and reconstruction.

Approaches to noise removal include approaches at different levels, from classical filtering methods to algorithms based on deep learning.[1]

Types of Noise and Methods of Combating Them. Gaussian noise:

Reason: Random movements in digital sensors.

Solution: Gaussian filter, Bilateral filter, DnCNN model.

Salt & Pepper Noise (Salt & Pepper):

Reason: Transmission errors.

Solution: Median filter, Adaptive Median Filter.

Speckle noise:

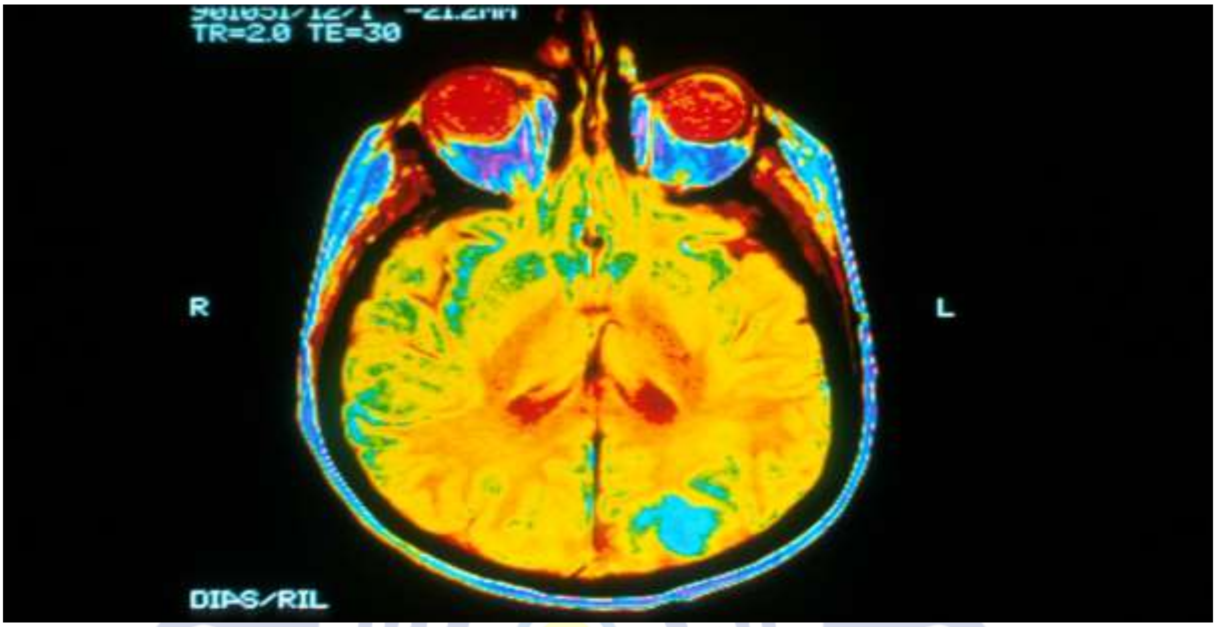
Reason: Long-distance echo and wave interference.

Solution: Lee, Frost and Kuan filters, Wavelet Transform.

Practical Examples in Medical Imaging Libraries used in the program:

```
import cv2
```

```
import numpy as np
import matplotlib.pyplot as plt
from skimage.restoration import denoise_nl_means, estimate_sigma
```



Adding and cleaning Gaussian noise:

```
 # Tasvirni yuklash
i = cv2.imread('brain_mri.png', cv2.IMREAD_GRAYSCALE)
img = cv2.resize(i, (256, 256))
# Gauss shovqini qo'shish
mean = 0
var = 0.01
sigma = var**0.5
gauss = np.random.normal(mean, sigma, img.shape)
noisy = img + gauss*255
noisy = np.clip(noisy, 0, 255).astype(np.uint8)
 # Non-Local Means Denoising
sigma_est = np.mean(estimate_sigma(noisy, multichannel=False))
den = denoise_nl_means(noisy, h=1.15 * sigma_est, fast_mode=True)
den = (den * 255).astype(np.uint8)
 # Vizualizatsiya
plt.figure(figsize=(12,4))
plt.subplot(1,3,1); plt.imshow(img, cmap='gray'); plt.title('Asl')
```

```
plt.subplot(1,3,2); plt.imshow(noisy, cmap='gray'); plt.title('Gauss shovqinli')
plt.subplot(1,3,3); plt.imshow(den, cmap='gray'); plt.title('Denoised')
plt.show()
```

Image Results

Original MRI Image	**Gaussian Noise Image**	**Denoising Result**
Clear in original condition	Contrast lost due to noise	Smoothed, contrast restored

These results show that the accuracy of medical MR images can be significantly improved by removing noise.

Conclusion. Medical image restoration and denoising algorithms are of great importance in the healthcare industry. A good denoising algorithm increases diagnostic accuracy, helps in early detection of disease, and reduces the need for redundant analysis. Practical approaches in the Python programming language are an effective tool for achieving advanced results in this field.

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