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Impact of Gaussian Noise on the Optimization of Medical Image Registration

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Abstract: Gaussian noise often poses a significant challenge to medical image registration, impacting the accuracy and reliability of alignment across varying imaging modalities. The research investigates the effect of Gaussian noise on medical image registration by comparing four optimization techniques: a direct approach, an optimization using FMINCON, a multiscale approach, and a combined optimization strategy that integrates FMINCON and the multiscale approach. The comparative analysis assesses each method's robustness against Gaussian noise, evaluating registration accuracy through three key similarity metrics: Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index Measure (SSIM). The results reveal that while each approach demonstrates a degree of resilience to noise, the combined optimization method significantly outperforms the others, achieving the lowest MSE, highest PSNR, and superior SSIM. These findings suggest that the combined approach effectively enhances the optimization process by leveraging the strengths of both FMINCON and multiscale frameworks, thus providing a more accurate and noise-resistant solution for medical image registration. The analysis highlights the necessity of image filtering techniques to mitigate noise interference and improve the image registration process in clinical applications.

Keyword: Gaussian noise, FMINCON, optimization, MSE, PSNR, SSIM

Introduction

Medical image registration plays a crucial role in diagnosis, treatment planning, functional studies, computer-assisted therapies, and medical research. This process involves the transformation of different images with common content into a unified coordinate system. The main purpose of the registration is to determine the optimal geometric transformation that approximates the content of an image with the corresponding area of the other. An important challenge in image processing is to identify this optimal transformation, which is obtained through optimization methods guided by a similarity measure that determines the degree of similarity between two images [1]. Image registration is used in surgical and therapeutic applications such as multimodal medical image fusion, treatment planning, disease diagnosis, and surgical medical care. In addition to clinical applications, image registration can be used in remote sensing and computer vision [2]. Today, medical imaging systems play a key role in clinical workflow, thanks to their ability to represent anatomical and physiological features that are otherwise inaccessible for inspection, thus providing useful and accurate imaging information. Digital imaging in the medical realm poses a significant challenge due to image clarity and noise effects [3]. Medical images convey an amount of information primarily related to high image resolution and high pixel depth that can overwhelm the ability of human vision to distinguish dozens of gray levels. Therefore, improving the appearance and visual quality of medical images is essential to provide doctors with valuable information that would not be immediately apparent in the original image, helping to detect, diagnose and treat abnormalities [4]. Different imaging modalities such as MRI, X-rays, mammography, and CT scans, often present challenges due to overlapping structures and complexities, which can hinder accurate diagnosis [5].

This study focuses on assessing the effects of Gaussian noise on medical image registration to improve alignment accuracy across different imaging modalities. By examining four optimization methods, a straightforward approach, FMINCON optimization, a multiscale technique, and a combined FMINCON multiscale approach. The research evaluates each method's resilience to noise using Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index Measure (SSIM) as performance indicators. The main contribution is the identification of the combined optimization technique as the most effective technique that provide enhanced noise resistance and precision, thus offering a promising solution for more accurate clinical image registration.

Materials and Methods

The research methodology comprises of four different stages with an ENTERIX image. In the first stage, the image is transformed, and the image is registered using optimization approach of FMINCON (Original) approach. The second stage comprises of a multiscale approach as an image registration technique to register the image. In the third stage, a combined approach that involved FMINCON and multiscale approach was used to optimize the image registration process and lastly, the registration of the noisy image using a noisy image transformation and direct image registration without any optimization.

Medical images are often corrupted by noise and affected by artifacts. These phenomena are specific to a particular imaging modality. In Magnetic Resonance Imaging (MRI), noise is produced by the stochastic movement of free electrons in the coils of the radiofrequency receiver and by eddy current losses in the patient. Optical imaging is affected by optical detector noise, which typically exhibits a Poisson or

Gaussian distribution. In Computed Tomography (CT) scan, Poisson Noise is caused by the statistical error of the small number of photons in the detectors. In ultrasound imaging, the superposition of acoustic echoes with random phases and amplitudes produces speckle noise [6]. Ultrasound (US) imaging is widely used in cardiology and obstetrics for producing high-resolution images without ionizing radiation. It works by sending high-frequency sound pulses (1 to 5 MHz) into the body, which reflect off tissue boundaries to create images. MRI generates detailed internal body images using magnetic fields and radio waves. When the body is placed in a magnetic field, hydrogen atoms align with it, and a radio frequency pulse disrupts this alignment. As the atoms return, energy is released, forming images. CT scans capture cross-sectional images by taking X-rays from multiple angles, which are then processed into 3D data, useful for detecting hemorrhages, tumors, and lesions. Positron Emission Tomography (PET) is a functional imaging method that detects gamma rays from radioactive substances injected into the body, providing insights into metabolic processes [7]. Figure 1 depicts the process of image modalities in medical diagnosis.

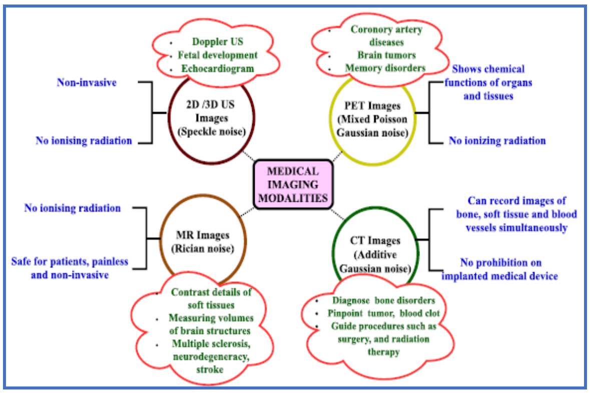


Figure 1: Medical Image Modalities [7]

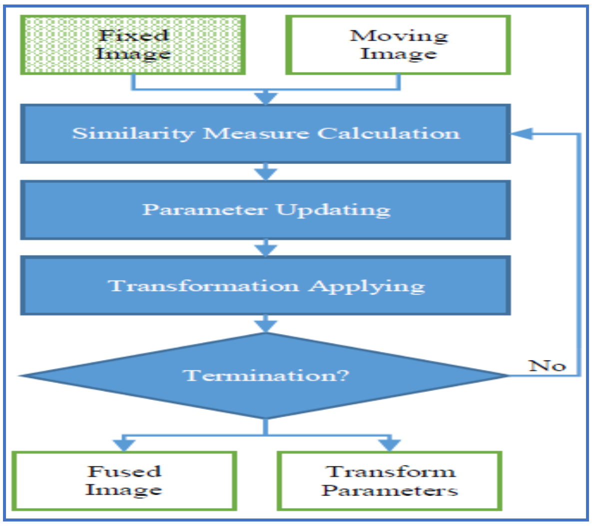


Figure 2: The workflow of conventional image registration techniques based on optimization procedures [12]

For Positron Emission Tomography (PET), a Gaussian-Poisson mixed noise model is considered more accurate and noise reduction is usually achieved with Gaussian smoothing and local adaptive filtering. One of the main challenges is to choose the spatial width of the Gaussian filter to balance the spatial resolution and the signal-to-noise ratio (SNR) [7]. Noise in medical images can also be caused by various sources, including many reasons external to environmental factors and transmission systems, such as Poisson noise, Gaussian noise, fuzzy noise, salt noise and of pepper, and the noise speckle. For example, in the medical field, ultrasound imaging is widely used to capture the details of body parts such as the liver, spleen, uterus, heart, heart and others. A common confound in ultrasound imaging is speckle noise, the noise created by the techniques used for imaging, which may depend on coherent waves [8]. UI quality and contrast are degraded by speckle noise. Radiologists have great difficulty in accurately diagnosing diseases caused by speckle noise. In fact, it hides grayscale functions and image changes. Due to the speckle noise, the structural information present in the user interface is corrupted. Speckle noise degrades image resolution, resulting in poor user interface quality. Therefore, in situ noise reduction is a desirable preprocessing step user interface diagnostics [9]. Furthermore, Poisson Noise is a fundamental form of uncertainty associated with light measurement, inherent in the quantized nature of light and the independence of photon detection. Its expected amplitude depends on the signal and is the dominant source of image noise except in low-light conditions [10]. The performance of the image denoising method is measured with important factors such as the mean pixel intensity, the standard deviation, the mean squared error, the mean squared error, the mean absolute error, the maximum signal-to-noise ratio, structural similarity, universal image quality index. and entropy [11]. Conventional image registration is an iterative optimization process involving feature extraction, similarity measure selection (to assess registration quality), transformation model choice, and a search mechanism as shown in Figure 2.

The process begins by inputting two images, with one fixed and the other moving. Optimal alignment is achieved by iteratively adjusting the moving image over the fixed one. Initially, the similarity measure assesses the correspondence between the images. An optimization algorithm updates transformation parameters, which are then applied to the moving image to produce a potentially better-aligned version. The process continues iteratively until the alignment criteria are met or no further improvement is possible. The system ultimately outputs either the transformation parameters or the final interpolated fused image [12].

Results and Discussions

The ENTERIX image contains noise of varying degree with Gaussian noise at (20, 40, 60 and 80%). The image containing the noise was transformed at different degree of transformation and used in image registration. The results of Gaussian noise effects on the image registration are represented in Table 1 with the application of different optimization approach and direct image method. The similarity metrics results obtained shows that the combined approach outperformed other techniques in terms of having higher accuracy in MSE.

Table 1: Similarity metrics of Gaussian noise of varying degree with different approach

Noise Level	Approach Type	MSE	PSNR	SSIM
20%	Original (with noise)	0.1244	9.0491	0.0776
	Multiscale (with noise)	0.0770	11.1310	0.2278
	Combined (with noise)	**0.0574**	**12.4070**	**0.2784**
	No Optimization (with noise)	0.1653	7.8169	0.0055
40%	Original (with noise)	0.1331	8.7573	0.0964
	Multiscale (with noise)	0.0901	10.4520	0.2240
	Combined (with noise)	**0.0813**	**10.8950**	**0.2547**
	No Optimization (with noise)	0.2058	6.8643	0.0042
60%	Original (with noise)	0.1524	8.1701	0.0982
	Multiscale (with noise)	0.0986	10.057	0.2394
	Combined (with noise)	**0.0865**	**10.629**	**0.2423**
	No Optimization (with noise)	0.2290	6.3935	0.0029
80%	Original (with noise)	0.1490	8.2677	0.0873
	Multiscale (with noise)	0.1135	9.4470	0.203
	Combined (with noise)	**0.0945**	**10.2420**	**0.2359**
	No Optimization (with noise)	0.2467	6.0769	0.0037

Figure 3 depicts the input and output image registration with the addition of 20% gaussian noise using the original (with noise), multiscale (with noise), combined (with noise) and no optimization (with noise). Figure 4a, 4b, and 4c denotes the chart of MSE, PSNR, and SSIM with an addition of 20% gaussian noise to the image registration. The result obtained indicated that the combined approach outperformed both original (with noise), multiscale (with noise) and no optimization (with noise) at the lowest MSE value of 0.05745, higher PSNR value of 12.407 and higher SSIM value of 0.27841, respectively.

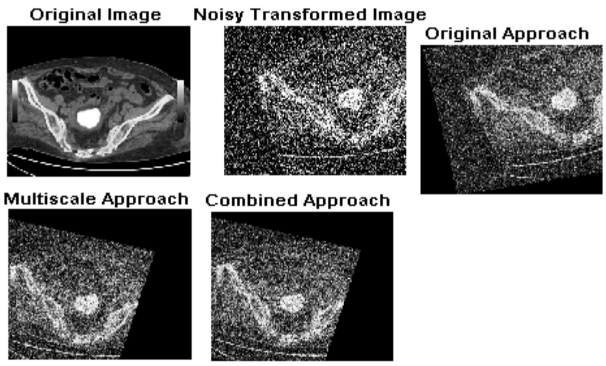


Figure 3: Image registration at 20% Gaussian noise

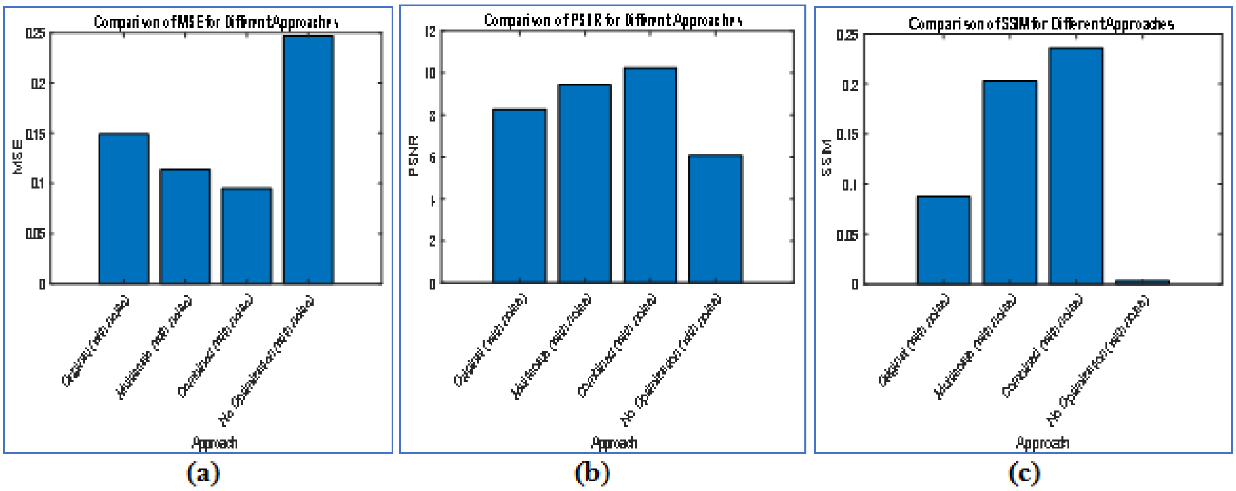


Figure 4a, b & c: MSE, PSNR and SSIM at 20% Gaussian noise

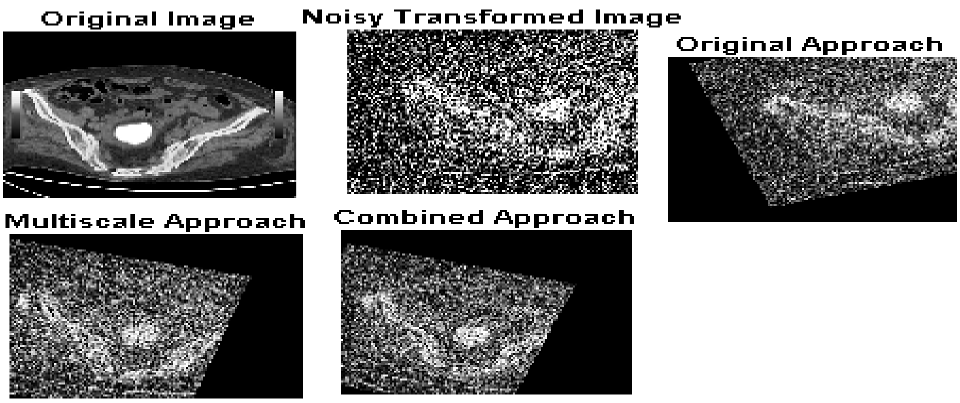
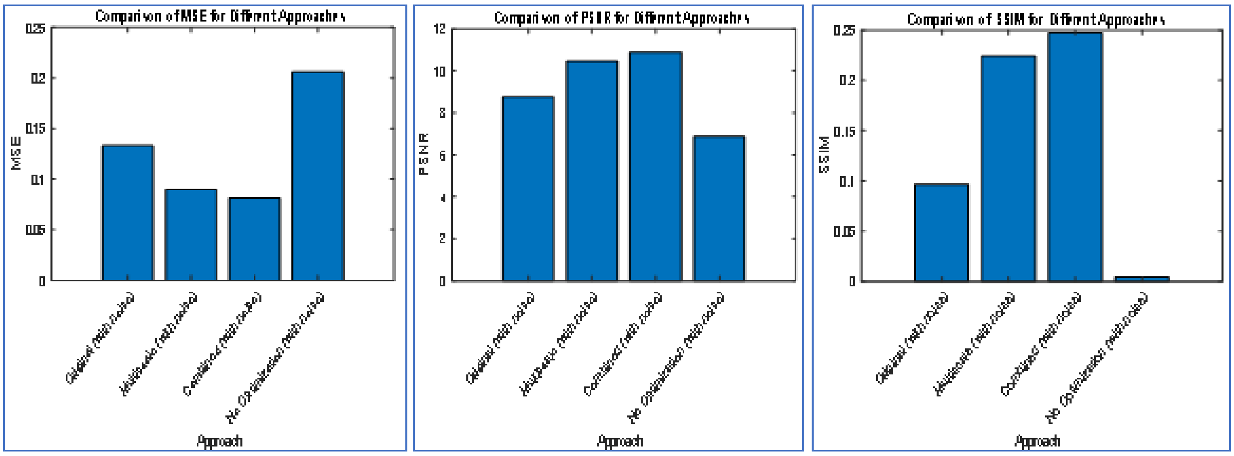


Figure 5: Image registration at 40% Gaussian noise

The Figure 5 illustrate the input and output image registration with the addition of 40% gaussian noise using the original (with noise), multiscale (with noise), combined (with noise) and no optimization (with noise).

Figure 6a, 6b, and 6c represents the chart of MSE, PSNR, and SSIM with an addition of 40% gaussian noise to the image registration. The findings indicate that the combined approach outperformed the other methods, achieving the lowest MSE value of 0.0813, the highest PSNR value of 10.8950, and the highest SSIM value of 0.2547. The Figure 7 depicts the input and output image registration with the addition of 60% gaussian noise using the original (with noise), multiscale (with noise), combined (with noise) and no optimization (with noise). Figure 8a–c indicates the chart of MSE, PSNR, and SSIM with an addition of 60% gaussian noise to the image registration. The results indicate that the combined approach outperformed the other methods, achieving the lowest MSE value of 0.0865, the highest PSNR value of 10.629, and the highest SSIM value of 0.2423.



(a) (b) (c)

Figure 6a, b & c: MSE, PSNR, and SSIM at 40% Gaussian noise

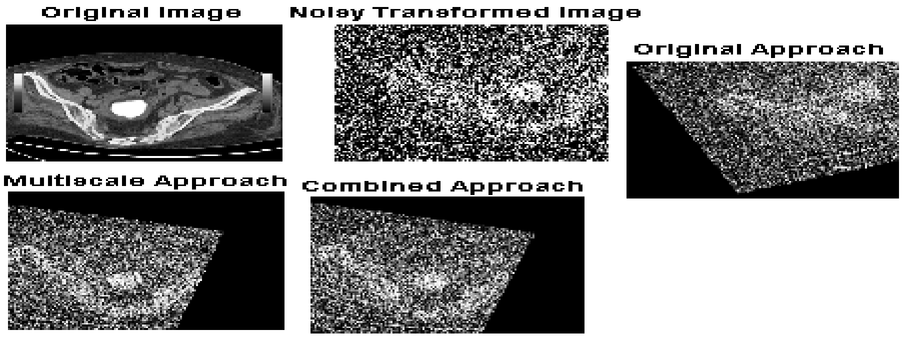
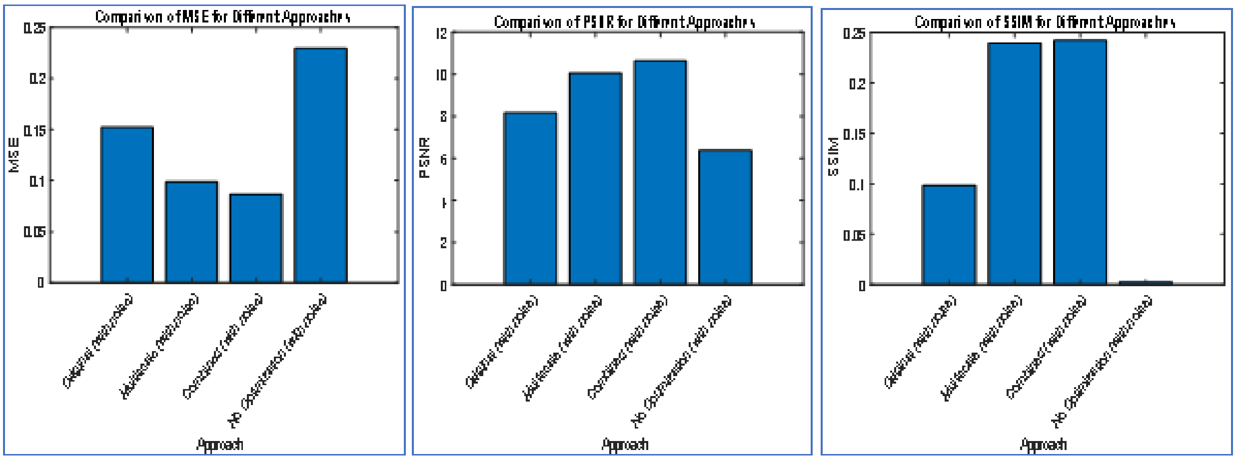


Figure 7: Image registration at 60% Gaussian noise



(a) (b) (c)

Figure 8a, b & c: MSE, PSNR, and SSIM at 60% Gaussian noise

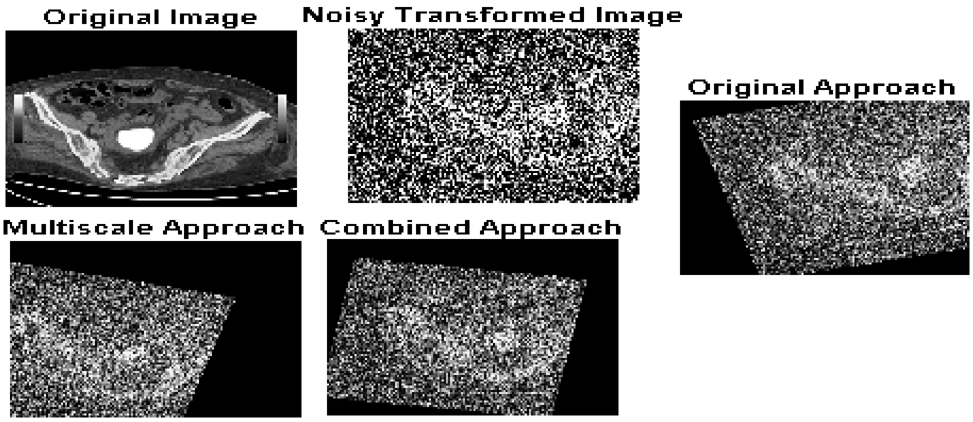


Figure 9: Image registration at 80% Gaussian noise

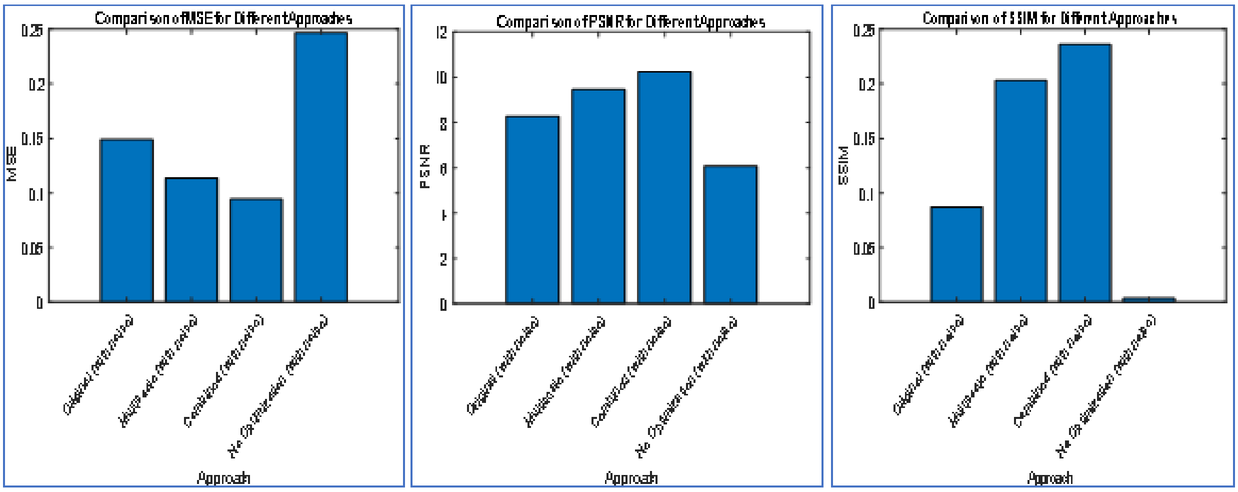


Figure 10a, b & c: MSE, PSNR, and SSIM at 80% Gaussian noise

The Figure 9 illustrate the input and output image registration with the addition of 80% gaussian noise using the original (with noise), multiscale (with noise), combined (with noise) and no optimization (with noise). Figure 10a–c indicates the chart of MSE, PSNR, and SSIM with an addition of 80% gaussian noise to the image registration. The findings revealed that the Combined approach outperformed the other methods, achieving the lowest MSE value of 0.0945, the highest PSNR value of 10.2420, and the highest SSIM value of 0.2359.

Conclusion and future work

This study results highlight the significant impact of Gaussian Noise on the accuracy of medical image registration, emphasizing the need for robust optimization methods. Among the four approaches examined, the direct method, FMINCON optimization, multiscale optimization, and a combined strategy merging FMINCON with the multiscale approach. The combined method consistently delivered superior performance. It achieved the lowest Mean Squared Error (MSE), highest Peak Signal-to-Noise Ratio (PSNR), and optimal Structural Similarity Index Measure (SSIM) across noisy medical images, reflecting improved accuracy and resilience. The combined approach's effectiveness is attributed to the strengths of its components, with FMINCON ensuring precise local optimization and the multiscale method providing stability across various image scales. These findings underscore the practical benefits of blending optimization techniques for medical image registration, particularly in clinical settings where noise poses a frequent obstacle. Future research could enhance this combined approach by adapting it to other noise types and incorporating additional similarity metrics to further establish its versatility and effectiveness across a range of medical imaging scenarios.

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