Brain Image Fusion Techniques to Enhance the Neurological Visualization: A practical Approach

[1]Miss. Sonali B. Anantkar ,   [2]Prof. S.R.Khot
[1]Student, DYPCOE, Kolhapur, India
[2] Associate Professor, DYPCOE, Kolhapur, India
Email - sonalibanantkar@gmail.com

Abstract: *Brain image fusion plays a crucial role in integrating complementary information from multiple modalities to enhance diagnostic accuracy and facilitate comprehensive neuroimaging analysis. This paper explores a practical approach to brain image fusion using four distinct techniques: simple intensity averaging, intensity hue saturation, wavelet transformation, and principal component analysis (PCA). Each technique contributes unique advantages in combining structural and functional information from MRI, CT modalities. The proposed method aims to improve image clarity, contrast, and spatial resolution while preserving relevant features critical for accurate clinical interpretation. Experimental results demonstrate the effectiveness of the fusion techniques in enhancing neurological visualization, thereby offering valuable insights for medical practitioners and researchers in the field of neuroimaging.*

Key Words: *Brain image fusion, Intensity averaging, Hue saturation, Wavelet transformation, Principal component analysis (PCA)*

1. INTRODUCTION:

Medical imaging, particularly in neurology, relies heavily on the complementary strengths of CT and MRI scans to provide comprehensive insights into brain tumors. CT scans offer detailed structural information through X-ray imaging, highlighting dense tissues and calcifications, while MRI scans provide superior soft tissue contrast, revealing intricate details of brain anatomy and pathology.

However, each imaging modality possesses inherent limitations in terms of spatial resolution, contrast enhancement, and sensitivity to specific types of abnormalities. Image fusion techniques aim to overcome these limitations by combining the strengths of multiple modalities into a single, more informative image. This process not only enhances visualization but also aids in accurate localization, characterization, and treatment planning for brain tumors.

The details of some general methods used for image fusion are as below,

- Simple Intensity Averaging Fusion:

This method blends CT and MRI images by averaging pixel intensities across corresponding image regions.It is straightforward and computationally efficient, providing a fused image that incorporates intensity information from both modalities.

- Intensity Hue Saturation Fusion:

This technique integrates intensity information from CT with color components (hue and saturation) from MRI. It enhances visual interpretation by preserving color contrast while combining structural details from CT with tissue-specific information from MRI.

- Wavelet Transformation Fusion:

Wavelet transformation decomposes CT and MRI images into frequency components at multiple scales. By fusing these components selectively based on their significance, wavelet fusion retains fine details from modalities, improving spatial resolution and feature localization.

- PCA Fusion:

Principal Component Analysis reduces the dimensionality of CT and MRI images by extracting principal

components that capture the most significant variations. PCA-based fusion combines these components to create a composite image that emphasizes shared features while minimizing noise and irrelevant information.

In summary, image fusion plays a pivotal role in advancing neuroimaging capabilities, offering robust solutions for analyzing complex brain pathologies such as tumors. The methods discussed—simple intensity averaging, intensity hue saturation fusion, wavelet transformation fusion, and PCA fusion—illustrate diverse approaches to enhance image quality and information extraction in clinical practice.

2. LITERATURE SURVEY:

Brain image fusion techniques are essential for integrating diverse neuroimaging modalities, thereby improving diagnostic accuracy and enabling comprehensive insights into neurological conditions. This section reviews the literature on various image fusion techniques employed in neuroimaging research. The review begins by highlighting a hybrid approach combining Discrete Wavelet Transform (DWT) and Principal Component Analysis (PCA) for image fusion, discussed in [1]. This method aims to maximize relevant information while minimizing redundancy across fused images, demonstrating its effectiveness in preserving spectral details and enhancing overall image processing applications. Different fusion methods categorized into spatial and frequency domains are compared and evaluated across various studies ([2] and [3]). Spatial fusion directly combines pixel values, while frequency fusion decomposes images into coefficients for synthesis. Techniques such as Intensity Hue Saturation (IHS), Weighted Average, PCA, and transforms are assessed using diverse quality measures, emphasizing their role in optimizing information extraction and reducing redundancy from multiple input images.

The importance and applications of image fusion in enhancing scene description beyond individual images are explored in [4], detailing its benefits for human and machine perception, as well as for tasks like segmentation, feature extraction, and object recognition. Moreover, the review discusses the critical role of image fusion in image processing and computer vision applications, such as feature extraction and target recognition ([5]). It delves into advanced methods like multi- resolution fusion using multi-scale decomposition, emphasizing their impact on improving fused image quality and performance across different fusion techniques.

Furthermore, challenges in brain tumor detection and characterization using wavelet-based approaches are addressed, such as the integration of Non-Subsampled Contourlet Transform (NSCT) with sparse representation (SR) to improve diagnostic accuracy ([6]). These methods show significant advancements in clinical applications by enhancing the quality of fused CT and MRI images. The review also highlights specific methodologies for brain tumor detection and segmentation using fused MRI and PET images ([7]). Techniques involving DWT and novel fusion rules are discussed, alongside the application of Deep Neural Networks (DNNs) and weighted k-means for precise tumor diagnosis. Additionally, the effectiveness of wavelet-based image fusion in enhancing tumor detection efficiency for MR and CT images is examined ([8] and [9]). These studies evaluate various wavelet transform parameters and methodologies, emphasizing metrics like Peak Signal-to-Noise Ratio (PSNR) and computational efficiency in accurately estimating tumor characteristics. Lastly, innovative approaches in medical image fusion are presented, such as combining PCA with wavelets to improve spatial resolution and diagnostic quality ([10] and [11]). These methods leverage human visual system characteristics and physical wavelet coefficients to achieve homogenous fused images with reduced noise, demonstrating their efficacy in both simulated and real medical imaging scenarios.

3. METHODOLOGY:

This methodology section provides a comprehensive framework for implementing and evaluating various fusion techniques for brain tumor CT scan and MRI image fusion. In this study, we employed several fusion techniques to integrate CT and MRI images of brain tumors, aiming to enhance diagnostic accuracy and information richness. The first method utilized was Simple Intensity Averaging Fusion, where corresponding pixel intensities from CT and MRI images were averaged to produce a fused image. This straightforward approach involved calculating the average intensity for each pixel, thereby blending the structural details from both modalities effectively. Mathematically, the average intensity fusion is represented as:

$$I_{avg(x,y)} = \frac{I_{CT(x,y)} + I_{MRI(x,y)}}{2}$$

$$\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.1)$$

Where,

- $I_{avg(x,y)}$: Average intensity at pixel *(x, y)* in the fused image.
- $I_{CT(x,y)}$: Intensity at pixel *(x, y)* in the CT image.
- $I_{MRI(x,y)}$: Intensity at pixel *(x, y)* in the MRI image.

Next, we implemented Intensity Hue Saturation (IHS) Fusion, which involved transforming the intensity components of CT and MRI images into the IHS color space. By fusing these components, including potentially the hue and saturation, and subsequently inverse transforming them, we obtained a fused image that aimed to leverage color information for enhanced visualization and analysis. Mathematically, the fusion step can be expressed as a combination of the intensity, hue, and saturation components. One common approach is to combine intensity and possibly hue and saturation components linearly:

$$I_{fused(x,y)} = \alpha \cdot I_{CT(x,y)} + (1 - \alpha)I_{MRI(x,y)}$$

…………….………………… (3.2)

Where,

- $I_{fused(x,y)}$: Intensity at pixel *(x, y)* in the fused image.
-    : Weighting factor that determines the contribution of the CT image intensity $I_{CT(x,y)}$ relative to the MRI image intensity $I_{MRI(x,y)}$.

Additionally, Wavelet Transformation Fusion was employed, which included decomposing CT and MRI images into wavelet coefficients using selected wavelet functions such as Daubechies or Haar. By applying fusion rules—such as maximum selection or weighted averaging—to corresponding coefficients at each decomposition level, we reconstructed a fused image that aimed to preserve both low-frequency structural details and high- frequency textural information.

Finally, Principal Component Analysis (PCA) Fusion was implemented to extract and combine principal components from both CT and MRI images. This technique involved performing PCA separately on each image set, selecting principal components based on variance or other criteria, and then combining these components to reconstruct a fused image that aimed to capture the most significant features from both modalities. Each fusion technique was evaluated quantitatively using metrics Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), Entropy, Fusion Quality Index (FQI).. The implementation utilized MATLAB with appropriate libraries for image processing, ensuring robust evaluation and comparison of the fusion techniques in the context of enhancing diagnostic capabilities for brain tumor imaging.

4. RESULT AND DISCUSSION:

The GUI image of a project designed in MATLAB encapsulates both the functionality and user interface design principles necessary to create an effective tool for data analysis, simulation, or any other computational tasks. Each element is carefully crafted to ensure usability, clarity, and efficiency in achieving the project's objectives.
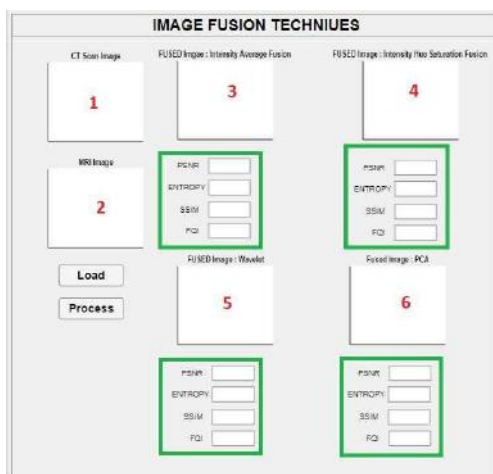

Figure 4.1 Components in designed GUI and their functions

The figure 4.1 shows the Graphical User Interface designed to show the implementation of image fusion techniques. The different fields are described as in table 4.1.

Table 4.1 Components in designed GUI and their functions

Sr. No	Component	Name	Function
1	Button_1	Load	Load images to be fused
2	Button_2	Process	Process the loaded images
3	Axes_1	-	Display CT scan brain image
4	Axes_2	-	Display MRI image
5	Axes_3	-	Display fused image
6	Axes_4	-	
7	Axes_5	-	
8	Axes_6	-	
9	Text Fields	-	Display the Performance parameters

The implemented project incorporates several image fusion techniques including simple intensity averaging, intensity hue saturation fusion, wavelet transformation, and Principal Component Analysis (PCA). Figure 4.2 illustrates the functionality of the 'Load' button within the graphical user interface (GUI). Upon clicking the 'Load' button, the GUI initiates the process of loading CT (Computed Tomography) scanned images and MRI (Magnetic Resonance Imaging) images of the brain into designated areas:

* Axes_1 (Top Axes): Displays the loaded CT scanned image of the brain.
* Axes_2 (Bottom Axes): Displays the loaded MRI image of the brain.

This user action enables users to visually compare and analyze the CT and MRI images simultaneously, facilitating subsequent image fusion processes. The GUI's design ensures clarity and ease of interaction, supporting effective utilization of the implemented fusion techniques for enhanced image analysis and interpretation.
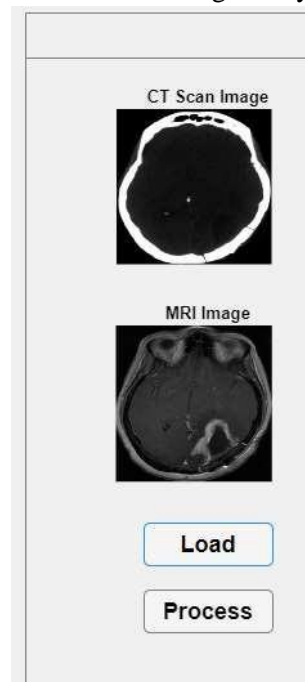

Figure 4.2: Image Loading of CT and MRI Scans

After loading the CT and MRI images into the GUI by clicking the 'Load' button, users can initiate image fusion processes by clicking the 'Process' button. This triggers the application of various fusion techniques discussed earlier.
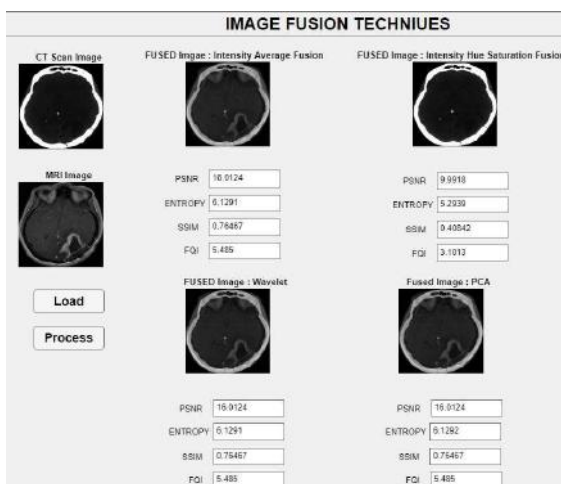

Figure 4.3: Visual Results of Image Fusion Techniques

In Figure 4.3, the GUI displays the visual outcomes of different image fusion techniques:
-     Axes_3: Demonstrates the result of the simple intensity averaging technique.
-     Axes_4: Shows the fused image obtained using the intensity hue saturation fusion method.
-Axes_5: Illustrates the outcome of image fusion through Wavelet transformation.
-     Axes_6: Displays the result achieved via Principal Component Analysis (PCA).

Each fusion technique is applied to combine the loaded CT and MRI images, presenting users with comparative visual representations in Axes_3 to Axes_6.

Additionally, the GUI dynamically evaluates performance parameters after each fusion process such as Peak Signal-to-Noise Ratio (PSNR),Structural Similarity Index (SSIM), Entropy, Fusion Quality Index (FQI).These metrics are calculated and displayed in respective text boxes within the GUI interface. They provide quantitative insights into the quality and effectiveness of each fusion technique applied, aiding users in evaluating and comparing the results for further analysis or decision-making.

This structured approach ensures that users can seamlessly navigate the image fusion process, interpret visual outcomes, and assess performance metrics to achieve informed conclusions about the fusion techniques' applicability and efficacy. Table 4.2 presents the outcomes linked with each fusion technique.

Table 4.2 Results of Fusion Techniques

Evaluation Parameter \ Fusion Method	Simple Intensity Averaging Fusion	Intensity Hue Saturation Fusion	Wavelet Transformation Fusion	PCA Fusion
PSNR	16.04	10.02	16.04	16.04
Entropy	6.22	5.29	6.22	6.22
SSIM	0.72	0.31	0.72	0.72
FQI	5.45	3.07	5.45	5.45

Based on the performance parameters provided for different image fusion techniques, here are some observations:
–   Intensity Averaging vs. Other Techniques:
Intensity Averaging shows varying performance depending on the instance:
First instance: Peak-SNR = 16.04, SSIM = 0.72, Entropy = 6.22, FQI = 5.4594 Second instance: Peak-SNR = 10.02, SSIM = 0.31, Entropy = 5.29, FQI = 3.07

In both instances, Intensity Averaging tends to have lower SSIM and Peak-SNR compared to Wavelet Transformation Fusion and PCA, indicating potentially inferior image quality in terms of structural similarity and signal-to-noise ratio.

− Consistency in Wavelet Transformation Fusion and PCA:

Wavelet Transformation Fusion and PCA show identical performance across all parameters (Peak-SNR, SSIM, Entropy, FQI) with values of 16.04, 0.72, 6.22, and 5.4594 respectively. This suggests that these methods produce consistent results in terms of image quality metrics.

− Entropy and FQI:

Entropy and FQI values are consistent across all methods, indicating similar levels of information contentand fusion quality index.

5. CONCLUSION:

Wavelet Transformation Fusion and PCA appear to be more reliable than Intensity Averaging based onthe provided metrics. They consistently achieve higher SSIM and Peak-SNR, which are indicators of better image quality and fidelity. If these metrics (SSIM and Peak-SNR) are crucial for the application, then Wavelet Transformation Fusion or PCA would be preferred over Intensity Averaging. However, the choice should also consider specific application requirements beyond these metrics, such as computational complexity and implementation feasibility.

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