A Hybrid Multi-Modal Medical Image Fusion Framework Using Multi-Resolution and Multi-Scale Transforms with Block-Based Enhancement

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Abstract

Medical image fusion is a critical process in clinical diagnostics, enabling the integration of complementary information from multiple imaging modalities into a single, more comprehensive image. This paper proposes a novel hybrid medical image fusion framework that leverages the combined advantages of multi-resolution and multi-scale analysis. The proposed method first generates an initial fused image by applying a multi-resolution technique, the Discrete Wavelet Transform (DWT), followed by a multi-scale technique, the Discrete Ripplet Transform (DRT). To further enhance the quality and preserve salient features from the source images, a block-based matching algorithm is subsequently applied to the initial fused image. This algorithm compares blocks of the fused image with corresponding blocks in the original Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) source images, selectively replacing them to construct a final, enhanced fused image. The performance of the proposed framework was evaluated against other transform-based methods, including DWT, DWT-DRT, and DWT-SVD-DRT, using two datasets of CT and MRI images. Quantitative analysis using metrics such as Peak Signal-to-Noise Ratio (PSNR), Mean Square Error (MSE), Structural Similarity Index Matrix (SSIM), and Entropy demonstrates the superiority of the proposed method. The experimental results show that our framework produces fused images with significantly improved visual quality and quantitative scores, making it a promising approach for enhancing diagnostic accuracy in clinical applications.

1. Introduction

Image fusion is a process of combining two or more input images to create a single high-quality image that retains the most salient features from each source. The resulting fused image contains more complete and accurate information, making it more suitable for human visual perception and subsequent computer processing.[1] this technology finds wide application in diverse fields such as military surveillance, remote sensing, navigation, and medical diagnosis.[1]

In the medical field, image fusion is particularly valuable for integrating information from different imaging modalities like Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), and Single Photon Emission Computed Tomography (SPECT). Each modality provides unique information about the human body; for instance, CT excels at visualizing dense structures like bone, while MRI offers detailed information about soft tissues, organs, and blood vessels.[1] fusing a CT image with an MRI image can provide both anatomical and metabolic information, which is invaluable for surgical planning, detecting brain tumours, and identifying lung cancer.[1]

Image fusion techniques can be broadly categorized into two domains:

The spatial domain and the transform domain. Spatial domain methods, also known as pixel-level fusion, operate directly on the pixel values of the source images. While these methods preserve original information, they often suffer from blurring and contrast reduction.[1]

Transform domain techniques overcome these limitations by first converting the images into the frequency domain. Multi-resolution methods like the Discrete Wavelet Transform (DWT) are popular but can struggle to represent spatial characteristics effectively. To address this, multi-scale geometric analysis (MGA) tools such as Curvelet, Contourlet, and Ripplet transforms have been developed to capture directional information and geometric structures more effectively.[1]

This paper proposes a new medical image fusion method that combines the strengths of both multi-resolution and multi-scale techniques to produce a high-quality initial fused image, which is then refined using a novel image block method to generate a final, superior fused image.[1]

2. Background and Related Work

The foundation of modern image fusion lies in various mathematical transforms that decompose images to separate their features. This section reviews the primary domains and specific transforms relevant to this work.[1]

2.1 Spatial and Transform Domain Fusion

Spatial domain fusion methods include simple techniques like averaging pixel values, the Brovey method, Principal Component Analysis (PCA), and Intensity-Hue-Saturation (IHS).[1] these methods are computationally simple but are prone to spatial distortions.

Transform domain fusion offers more robust performance by operating on the transform coefficients of the images. The general process involves applying a forward transform to the source images, fusing the resulting coefficients according to a specific rule, and then applying an inverse transform to obtain the fused image.[1]

2.2 Multi-Resolution and Multi-Scale Transforms

2.2.1. Discrete Wavelet Transform (DWT): DWT is a multi-resolution analysis tool that decomposes an image into different frequency sub-bands: a low-frequency approximation component (LL) and three high-frequency detail components (LH, HL, HH) representing horizontal, vertical, and diagonal details, respectively. This decomposition can be applied recursively to the LL sub-band to achieve multiple levels of analysis.[1]

2.2.2. Curvelet Transform: The Curvelet transform is a multi-scale geometric analysis tool that represents curves and edges more efficiently than wavelets. It requires fewer coefficients to represent edges, making it highly effective for images with significant curvilinear features.[1]

2.2.3. Contourlet Transform: The Contourlet transform provides a multi-scale and directional representation of an image. It uses a two-stage process involving a Laplacian pyramid for multi-scale decomposition and directional filter banks to capture geometric structures and contours.[1]

2.2.4. Discrete Ripplet Transform (DRT): Proposed by Jun Xu et al., the Ripplet Transform (RT) is a higher-dimensional generalization of the Curvelet transform designed to overcome the limitations of Fourier and Wavelet transforms in handling discontinuities like edges. It represents 2D signals at different scales and directions and has been shown to outperform the Contourlet transform in fusion tasks.[1]

2.2.5. Singular Value Decomposition (SVD): SVD is a linear algebra technique that decomposes a matrix into three other matrices. In image processing, it is used to reduce data dimensionality and expose the most significant variations within the data, making it a useful tool for feature extraction and fusion.[1]

3. Proposed Fusion Methodology

The proposed framework integrates multi-resolution and multi-scale transforms with a novel block-based enhancement method to produce a high-quality fused medical image. The process is illustrated in Figure 3.1 and detailed in the subsequent steps.[1]

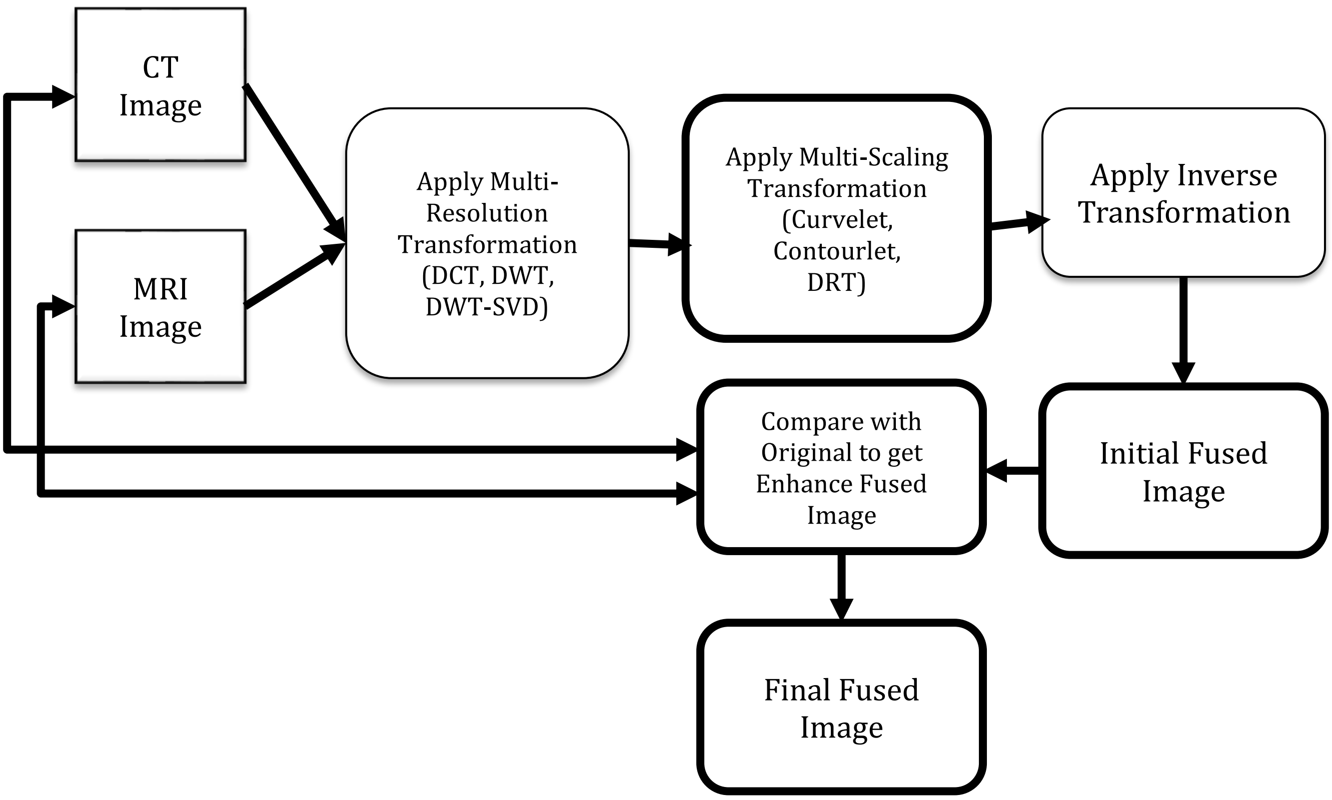

Figure: 3.1 BLOCK DIAGRAM OF PROPOSE IMAGE FUSION MEHOD

The steps of the proposed method are as follows:

1. **Image Registration:** The source CT and MRI images are registered to ensure that corresponding pixels are spatially aligned.[1]
2. **Multi-Resolution Transformation:** A multi-resolution technique, such as DWT or DWT-SVD, is applied to both the CT and MRI images. This decomposes each image into its wavelet coefficients, separating high-resolution and high-spectral quality content.[1]
3. **Multi-Scale Transformation:** A multi-scale transform, such as DRT, is then applied to the approximation coefficients obtained from the previous step. The detail coefficients are fused using an absolute maximum fusion rule.[1]
4. **Inverse Transformation:** An inverse transform is applied to the fused coefficients to generate an initial fused image, denoted as .[1]

5. **Image Block Method for Enhancement:** The core of the proposed enhancement is the Image Block Method. The source images (CT, MRI) and the initial fused image () are divided into equal-sized square blocks of size. The similarity measure (SM) between the blocks of the source images and the initial fused image is calculated.[1] the final fused image, F, is constructed by checking for consistency. If a pixel block in has a higher similarity to the corresponding block in the MRI image, that block is selected for the final image. Otherwise, the block from the CT image is selected. This ensures that each block in the final fused image is an original block from one of the source images, thereby improving visual quality.[1]

4. Experimental Setup and Performance Metrics

4.1 Implementation and Datasets

The proposed framework and all comparative methods were implemented using MATLAB. The experiments were conducted on five different datasets, each containing a pair of registered CT and MRI medical images.[1]

4.2 Comparative Methods

The performance of the proposed method (DWT-DRT-BLOCK BASED) was compared against three other transform-based fusion techniques:

- Discrete Wavelet Transform (DWT)
- DWT combined with Discrete Ripplet Transform (DWT-DRT)
- DWT combined with Singular Value Decomposition and DRT (DWT-SVD-DRT) [1]

4.3 Performance Metrics

Four quantitative metrics were used to evaluate the quality of the fused images:

1. **Entropy:** Measures the amount of information contained in the fused image. A higher value indicates a more information-rich image.[1]
2. **Mean Square Error (MSE):** Calculates the cumulative squared error between the reference image and the fused image. A lower value indicates a better result.[1]
3. **Peak Signal-to-Noise Ratio (PSNR):** Represents the ratio between the maximum possible power of a signal and the power of corrupting noise. A higher PSNR value indicates better fusion quality.[1]
4. **Structural Similarity Index Matrix (SSIM):** Measures the similarity between two images based on luminance, contrast, and structural changes. An SSIM value closer to 1 indicates a higher similarity to the source images.[1]

5. Results and Analysis

The experimental results are presented through both qualitative visual comparisons and quantitative metric evaluations.

5.1 Qualitative Analysis

Figures 5.1.1 through 5.2.4 show the fused images generated by the different methods for one of the datasets. Visually, the images produced by the proposed DWT-DRT-BLOCK BASED method are superior. They exhibit better contrast, sharper edges, and retain more detailed information from both the CT and MRI source images compared to the other methods.[1]

5.2 Quantitative Analysis

5.1.1-DATASET1

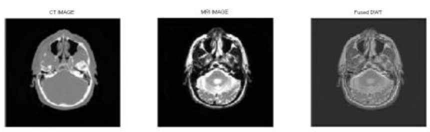

Figure-5.1.1(a) DWT Fused image

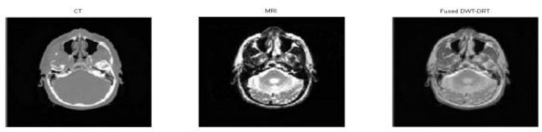

Figure-5.1.1(b) DWT-DRT Fused image

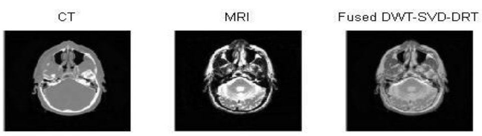

Figure-5.1.1(c) DWT-SVD-DRT Fused image

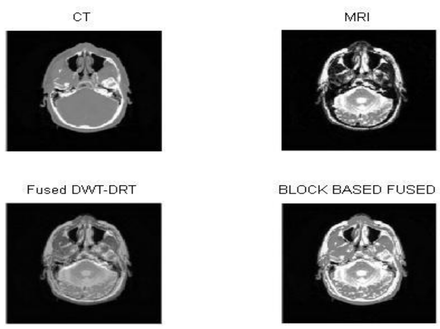

Figure-5.1.1(d) DWT-DRT-BLOCK BASED Fused image

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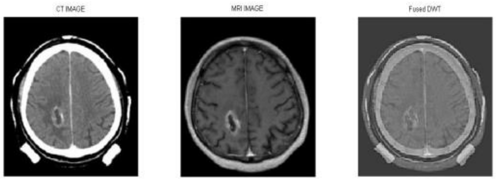
5.1.2. DATASET2



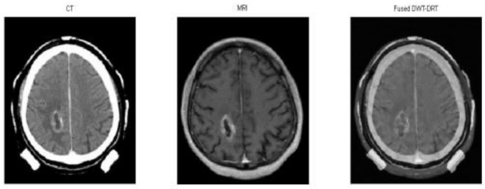


Figure-5.1.2(a) DWT Fused image

Figure-5.1.2(b) DWT-DRT Fused image

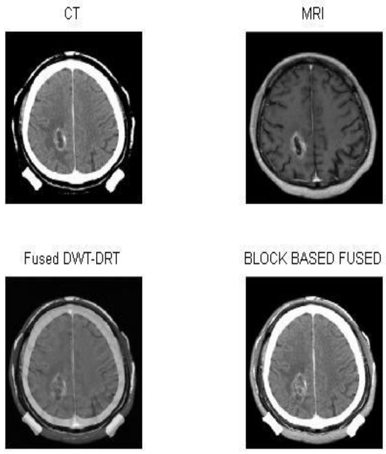


Figure-5.1.2(c) DWT-SVD-DRT Fused Image

Figure-5.1.2(d) DWT-DRT-BLOCK BASED Fused image

The quantitative results for two datasets are summarized in Table 1. The data clearly indicates that the proposed method consistently outperforms the other techniques across all metrics. For every dataset, the proposed method achieves the highest PSNR and SSIM values and the lowest MSE values when compared to both source images. It also yields the highest Entropy, signifying that the final fused image contains the most information from the source images.[1] For instance, in Dataset 1, the proposed method achieved a PSNR of 65.35 (vs. CT) and 62.84 (vs. MRI), and an SSIM of 0.998 and 0.996, respectively, which are significantly higher than the values obtained by the other methods.[1]

Table 1: Comparison of Performance Metrics across Different Fusion Methods for two Datasets [1]

DATASETS	METHODS	CT IMAGES			MRI IMAGES			FUSED IMAGES
		PSNR	MSE	SSIM	PSNR	MSE	SSIM	ENTROPHY
DATASET1	DWT	17.2698	1219.3	0.7058	18.5227	913.7110	0.8209	0.6152
	DWT-DRT	**20.5551**	**572.23**	**0.6982**	**17.2508**	**1224.6**	**0.6279**	**5.2378**
	DWT-SVD-DRT	20.4629	584.5067	0.8194	17.4075	1181.2	0.7909	5.2296
	PROPOSED	**65.3528**	**0.0190**	**0.998252**	**62.8483**	**0.0337**	**0.996394**	**5.4670**
DATASET2	DWT	15.7994	1710.6	0.7242	14.6970	2204.9	0.5839	1.1976
	DWT-DRT	**16.9966**	**1298.4**	**0.5308**	**14.4097**	**2355.6**	**0.3890**	**6.1707**

	DWT-SVD-DRT	17.3392	1199.9	0.7945	14.2666	2434.5	0.6141	5.7445
	PROPOSED	**64.0249**	**0.0257**	**0.996541**	**58.9549**	**0.0827**	**0.988950**	**5.7605**

6. Conclusion

This paper has presented a novel hybrid medical image fusion method that effectively combines multi-resolution (DWT) and multi-scale (DRT) transforms, enhanced by a block-based matching algorithm. The experimental results confirm that the proposed framework is superior to other existing transform-based methods, delivering fused images with higher informational content and structural integrity. The block matching algorithm, in particular, proves effective in preserving the original features from the source images, leading to significant improvements in both visual quality and quantitative evaluation metrics.[1]

7. References

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