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ENHANCING THE EFFICIENCY OF MEDICAL IMAGE FUSION THROUGH AN OPTIMIZATION APPROACH

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The dissertation can be found at:

- Graduate University of Science and Technology Library
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PREFACE

1. The significance of the dissertation

Medical image fusion is one of the important research topics in the field of image processing. This problem involves combining medical images captured from various modalities to create a high-quality image that incorporates additional information from each individual image. The fusion of these images assists doctors and imaging diagnosticians in making more accurate diagnostic decisions regarding various diseases [1].

Currently, this problem has received significant attention from researchers due to its practical applications. The number of publications related to the fusion of medical images has been steadily increasing in recent years [2]. In general, the approaches to this problem can be divided into two main groups: traditional approaches [3]–[21] and deep learning-based approaches [22]–[27]. For methods based on traditional approaches, these methods typically undergo three main steps: decomposing the input image, fusing components in the decomposition domain, and finally, the fused components are transformed back using the inverse of the decomposition algorithm to obtain the fused image. In the case of deep learning-based approaches, deep neural networks often play a role in extracting features from images, which are then used to construct a fusion method for the detailed components within the image.

Current approaches still have certain limitations in medical image synthesis. The first limitation is related to the quality of the input images, which is a common constraint for all image synthesis algorithms. In practice, medical images may face quality issues during acquisition, such as blurriness, noise, and low contrast. Images with low quality can reduce the effectiveness of image fusion algorithms. The second limitation pertains to algorithms designed for fusing base components and detailed components. Addressing these aforementioned limitations is the main focus presented in this dissertation.

2. The objective of the dissertation

Propose several methods to improve the effectiveness of medical image synthesis as follows:

- Propose a method to enhance the quality of medical images to improve the quality of input medical images before synthesis.
- Propose a novel image fusion method comprising two algorithms designed to fuse both base components and detailed components in the image.

3. The contributions of the dissertation

Intending to enhance the efficiency of medical image synthesis, the dissertation contributes in two main groups as follows:

- The first group proposes a method to improve the quality of medical images [CT1]. This algorithm addresses common issues in brain medical images such as low brightness and contrast. The application of the proposed image quality enhancement algorithm serves as pre-processing for input medical images, thereby improving the effectiveness of image synthesis. This approach has been published in [CT2].
- The second group introduces a novel image synthesis method comprising two algorithms designed to synthesize base components [CT4, CT6] and detailed components in the

image [CT3, CT4]. Additionally, the dissertation suggests exploring an approach using transformation learning techniques. This approach has also been published in [CT5].

4. The structure of the dissertation

The content of each section is summarized as follows:

Chapter 1 provides an overview of the image fusion problem and essential background knowledge to facilitate understanding of the proposed algorithms in the subsequent chapters. Relevant studies on medical image fusion are presented, and categorized into different approaches. Building upon this foundation, the dissertation analyzes the limitations of current approaches and outlines objectives to address these limitations.

Chapters 2 and 3 constitute the primary contributions of the dissertation. Each chapter is designed as a proposed method to enhance the efficiency of medical image fusion. In particular, Chapter 2 proposes an image quality enhancement method based on optimization algorithms. The application of this image quality enhancement method is employed to improve the effectiveness of some state-of-the-art image fusion algorithms.

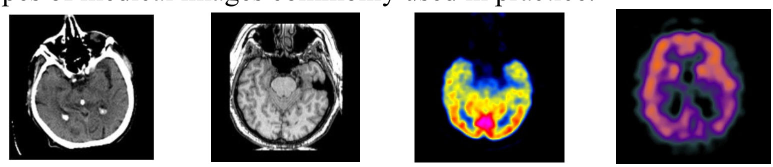
Chapter 3 details the proposed method to enhance the efficiency of image fusion. The proposed method includes three algorithms: image decomposition into three components, an adaptive fusion algorithm for base components, and a fusion algorithm for detailed components based on a combination of local energy functions and their variations.

Finally, the conclusion section highlights the main contributions of the author in the dissertation and outlines future work.

CHAPTER 1. AN OVERVIEW OF IMAGE FUSION AND SOME FOUNDATIONAL KNOWLEDGE

1.1. Introduction

Currently, the use of medical images in diagnosis is becoming increasingly prevalent. The types of medical images available today are also highly diverse. Some commonly used medical images in practice can be mentioned as follows: Computed Tomography (CT), Positron Emission Tomography (PET), Magnetic Resonance Imaging (MRI), and Single Photon Emission Computed Tomography (SPECT). Each of the aforementioned medical image types contains unique information that other types of images may not possess. MRI images offer high resolution and depict soft tissue details such as the brain, but they provide limited information on dynamic metabolism. Conversely, PET images have a lower resolution but offer insights into functional activity and cellular metabolism. Figure 1.1 illustrates some types of medical images commonly used in practice.



CT **MRI** **PET** **SPECT**

Figure 1.1. Illustration of some types of medical images

During the diagnostic process, information from each type of medical image alone is insufficient to assist physicians in making accurate diagnoses related to diseases. Therefore, the fusion of medical images allows the creation of an image that contains crucial additional information from individual medical images. This helps provide doctors with sufficient information to make more accurate diagnoses regarding various related diseases.

In recent years, the problem of medical image synthesis has gained significant attention from researchers worldwide. Figure 1.4 illustrates that the number of studies on medical image synthesis is trending upward (data obtained from "Scopus.com").

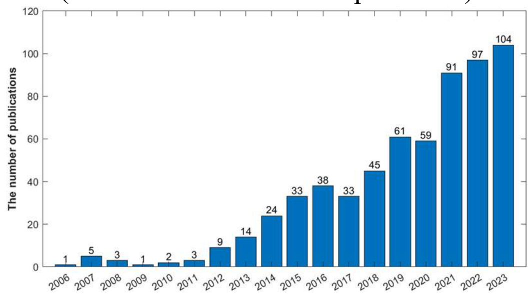


Figure 1.4. The number of related publications from 1993 to 09/2023

1.2. Overview of relevant studies

Generally, these methods can be categorized into two main groups:

- Traditional approaches.
- Deep learning-based approaches.

Figure 1.5 illustrates the approaches used to solve the medical image fusion problem.

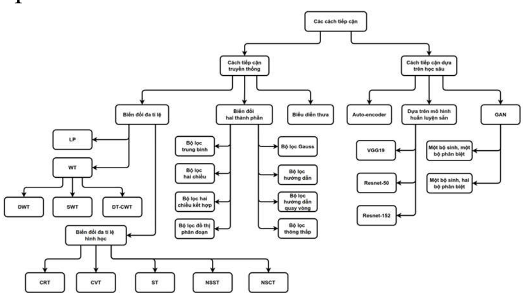


Figure 1.5. Image fusion approaches

1.3. Some limitations of image fusion methods

The first limitation is related to the quality of the input images, which is a common issue for all image fusion algorithms. Medical images often face quality issues such as blurriness, noise, and low contrast. This limitation reduces the effectiveness of the image fusion process.

The second limitation is associated with algorithms designed for fusing base and detailed components. For fusing base components, algorithms like Max or average selection algorithms are commonly used due to their simplicity and low computational complexity. However, using these algorithms may lead to certain issues in fused images, such as information loss, reduced contrast, and brightness. For example, in the fusion of detailed components, algorithms like Max selection and Modified Laplacian synthesis algorithm (SML) are often applied. However, these algorithms still have certain limitations. The problem arises because the brightness intensity of detailed components in MRI images is often higher than that in PET images. Therefore, if the Max selection algorithm is applied, the fused image will only include detailed information from the MRI image, neglecting crucial details from the PET image. As a result, the fused image loses some essential information.

The content of this dissertation will focus on addressing the two aforementioned limitations by proposing two groups of methods as follows:

- Group 1: Propose an image quality enhancement method to address the issue of low contrast and brightness in brain magnetic resonance imaging (MRI) images.

- Group 2: Propose an adaptive synthesis algorithm for base components to mitigate the degradation in image quality during synthesis. Introduce an efficient synthesis algorithm for detailed components to preserve distinctive information from the input images.

1.4. Fundamental Knowledge

1.5. Evaluation Metrics

1.6. Conclusion of Chapter 1

In Chapter 1, the dissertation introduced the problem of medical image fusion and related research to address this problem. Two main approaches to solving the medical image fusion problem are traditional approaches and deep learning-based approaches. Based on the analysis of some current fusion methods, two main limitations in image fusion can be identified as follows:

The first limitation is that the input images often have low quality, such as low brightness, low contrast, and lack of sharpness. This limitation significantly affects the performance of image fusion algorithms.

The second limitation is the inefficiency of fusion algorithms for base and detailed components. Specifically, the average fusion algorithm may lead to a decrease in brightness and contrast in the fused image. The Max selection algorithm may cause the fused images to lose detailed information from the original images.

Therefore, the direction of the thesis is to propose new efficient algorithms to address these mentioned limitations. Towards the end of Chapter 1, the dissertation also introduces some commonly used evaluation metrics to assess the quality of fused images.

CHAPTER 2. ENHANCING IMAGE QUALITY VIA THREE-COMPONENT DECOMPOSITION AND THE MPA OPTIMIZATION ALGORITHM

In Chapter 2, the dissertation proposes a method to enhance the quality of images to improve the quality of input medical images. The proposed method has been published in [CT1, CT2]. By enhancing the quality of the input images, several recent image fusion methods have been employed to evaluate the effectiveness of the image fusion process.

2.1. Motivation

Until now, numerous different studies have been proposed to address the medical image synthesis problem. However, there are still certain limitations in enhancing the effectiveness of medical image synthesis. In practice, medical images often face issues such as blurriness, noise, and low contrast. Low-quality images significantly reduce the efficiency of image synthesis algorithms. Some recent studies have proposed enhancements to the quality of input medical images before the synthesis process. For example, Ullah et al. [28] proposed the use of the Fast Local Laplacian Filter (FLLF) to improve the quality of input images by preserving edges and enhancing detailed boundary information. Maqsood et al. [29] applied the Non-parametric Modified Histogram Equalization (NMHE) method to enhance the contrast of input images. Li et al. [18] proposed a medical image synthesis method that allows denoising in input images. However, approaches to enhance image quality as described above still have certain limitations. When improving image quality, noise may arise. Therefore, applying the aforementioned image quality enhancement algorithms alone may not effectively address the image synthesis process.

With the aim of researching and proposing algorithms to enhance the effectiveness of medical image fusion compared to previously published studies, this chapter presents the research outcomes on improving the efficiency of medical image fusion based on the approach of enhancing the quality of input images. The results of Chapter 2 have been published in the work [CT1, CT2] listed in the "List of the publications related to the dissertation" section.

2.2. Proposing an Image Enhancement Algorithm

2.2.1 Proposing an algorithm for image decomposition into three components

In this section, an algorithm for decomposing an image into three layers is proposed. The process of decomposing an input image into three layers is illustrated in detail in Figure 2.1.

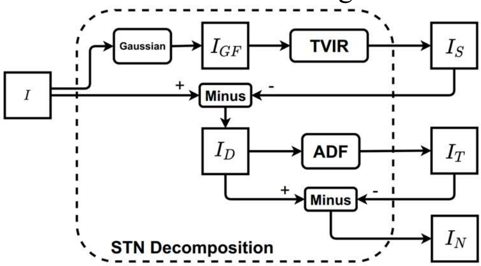


Figure 2.1. Diagram of image decomposition into three components

2.2.2. Optimal Function Design

2.2.3. An Image Enhancement Method

This section provides a detailed description of the steps of the proposed image enhancement method. The proposed image enhancement method, based on the three-component decomposition and the MPA optimization algorithm (referred to as IE_TCID_MPA), is shown in Figure 2.5. The idea of the proposed algorithm is to decompose the image to be enhanced into three layers containing different information: the structure layer, texture layer, and noise layer. This separation facilitates the enhancement process by allowing operations to be performed on each distinct layer of information within the image. The structural layer is enhanced by the CLAHE method. Subsequently, a detailed information layer based on the features of the Tensor structure is added to the image to overcome the potential loss of details during synthesis. The structural layer is also strengthened based on the Laplace operator. The MPA optimization algorithm is utilized to find optimal parameters for the information layers. Finally, the optimized parameters and corresponding layers are used to generate the enhanced image.

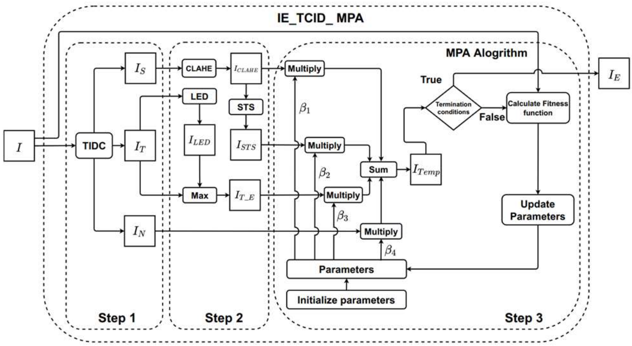


Figure 2.5. Image nhancement algorithm diagram

2.3. Experiments and Evaluation

2.3.1. Experimental data

Ninety pairs of MRI and PET medical images with a size of 256 × 256 were collected from slices 50 to 79 along the Transaxial (T), Sagittal (S), and Coronal (C) axes from the source http://www.med.harvard.edu/AANLIB/. These images were then divided into the following datasets:

- Dataset (D0) comprises 90 MRI images.
- Dataset (D1) is derived from Dataset D0 by reducing contrast and brightness.
- Dataset (D2) includes three images (70T, 70S, 70C).
- Dataset (D3) consists of 90 pairs of MRI and PET images.

2.3.2. Experimental Setup

The experimental setup includes an Intel Core i9 10900K processor running at 3.7 GHz with 64 GB of RAM. The operating system used is Windows 10, and the software employed is Matlab R2020b. Several experiments were designed to evaluate the effectiveness of the proposed image enhancement method as follows:

Experiment 1: To evaluate the effectiveness of the proposed image quality enhancement algorithm, several other image enhancement algorithms were used for comparison. These algorithms are described in Table 2.2. Four image quality evaluation metrics (MLI, CI, E, and AG) and both datasets D0 and D1 were used in this experiment.

Table 2.2. Some image enhancement algorithms.

No	Algorithms	Year
1	NE (No Enhancement)	
2	FCCE (Fuzzy-Contextual Contrast Enhancement) [114]	2017
3	EFF (Exposure Fusion Framework) [115]	2017
4	EGIF (Effective Guided Image Filtering) [116]	2018
5	RRM (Robust Retinex Model) [117]	2018
6	FFM (Fractional-Order Fusion Model) [118]	2019
7	SDD (Semi-Decoupled Decomposition) [119]	2020

Experiment 2: Several recently proposed algorithms for medical image synthesis have been selected for comparison. These algorithms

are described in Table 2.3. The evaluation metrics (MLI, CI, E, AG, $Q^{AB/F}$ và MI) are utilized in this experiment.

Table 2.3. Some image fusion algorithms

No	Algorithms	Symbol	Year
1	PC-LLC-NSCT [120]	Alg1	2019
2	NSST-MSMG-PCNN [11]	Alg2	2020
3	MLCF-MLMG-PCNN [83]	Alg3	2021
4	JBF-LGE [30]	Alg4	2021
5	CSE [121]	Alg5	2021
6	CNPS-NSST [122]	Alg6	2021
7	DTNP-NSCT [39]	Alg7	2021

2.3.3. Experimental Results

Experimental results #1: The results in Tables 2.8 and 2.9 demonstrate the effectiveness of the proposed algorithm.

Table 2.8. The evaluation metrics for the algorithms on dataset D0

Algorithms	MLI	CI	Entropy	AG
NE	0.3050	0.3216	4.6314	0.0802
FCCE	0.3250	0.3379	5.5607	0.0853
EFF	0.3606	0.3629	5.5651	0.0927
EGIF	0.3199	0.3761	4.8231	0.1151
RRM	0.3591	0.3594	5.6699	0.1036
FFM	0.3450	0.3401	5.9318	0.0883
SDD	0.3669	0.3666	5.8616	0.0925
IE_TCID_MPA	**0.3975**	**0.4036**	**6.3156**	**0.1474**

Table 2.9. The evaluation metrics for the algorithms on dataset D1

Algorithms	MLI	CI	Entropy	AG
NE	0.1525	0.1608	4.6314	0.0401
FCCE	0.2536	0.2612	5.6641	0.0734
EFF	0.2821	0.2718	5.4223	0.0655
EGIF	0.1750	0.2215	4.9067	0.0688
RRM	0.2278	0.2290	5.6485	0.0630
FFM	0.2599	0.2451	5.7019	0.0584
SDD	0.2336	0.2379	5.7394	0.0565
IE_TCID_MPA	**0.3835**	**0.3731**	**6.2892**	**0.0846**

Experimental result #2: Experimental results are illustrated in Tables 2.12, 2.13, and 2.14.

Table 2.12. The evaluation metrics obtained on dataset D3 (T).

Algs	Type	MLI	CI	E	AG	$Q^{AB/F}$	MI
Alg1	Before	0.2795	0.3249	5.5404	0.0724	0.6942	3.0354
	After	**0.3318**	**0.3529**	**6.3630**	**0.0925**	**0.7222**	**3.5302**
Alg2	Before	0.3148	0.3937	5.6302	0.0759	0.6199	2.4631
	After	**0.3462**	**0.4035**	**6.2270**	**0.0952**	**0.6255**	**2.7315**
Alg3	Before	0.3231	0.3873	5.1023	0.0674	0.5942	2.6319
	After	**0.3571**	**0.3957**	**5.9033**	**0.0877**	**0.6015**	**3.1434**
Alg4	Before	0.3074	0.3455	4.8495	0.0684	0.7178	4.3910
	After	**0.3599**	**0.3706**	**5.9439**	**0.0887**	**0.7537**	**5.7807**
Alg5	Before	0.2756	0.3165	5.2769	0.0655	0.7434	3.6663
	After	**0.3243**	**0.3496**	**6.2598**	**0.0857**	**0.7564**	**3.9412**
Alg6	Before	0.2888	0.3329	5.3130	0.0735	0.7070	3.2731
	After	**0.3432**	**0.3637**	**6.0178**	**0.0939**	**0.7357**	**4.0908**
Alg7	Trước	0.2991	0.3388	5.3990	0.0706	0.7120	3.3447
	After	**0.3515**	**0.3653**	**6.0600**	**0.0910**	**0.7512**	**4.1313**

Table 2.13. The evaluation metrics obtained on dataset D3 (S).

Algs	Type	MLI	CI	E	AG	$Q^{AB/F}$	MI
Alg1	Before	0.3219	0.3124	6.3709	0.0831	0.7059	3.3813
	After	**0.3990**	**0.3453**	**6.9472**	**0.1118**	**0.7465**	**3.9006**
Alg2	Before	0.3392	0.3905	6.2654	0.0867	0.6678	2.5171
	After	**0.3808**	**0.3992**	**6.6739**	**0.1148**	**0.6216**	**2.7008**
Alg3	Before	0.3477	0.3806	5.9830	0.0778	0.6108	2.7661
	After	**0.3930**	**0.3849**	**6.6219**	**0.1067**	**0.6013**	**3.1306**
Alg4	Before	0.3512	0.3307	5.6692	0.0794	0.7381	5.0347
	After	**0.4280**	**0.3606**	**6.7940**	**0.1088**	**0.7818**	**6.3580**
Alg5	Before	0.3107	0.3001	6.2098	0.0751	0.7507	3.8228
	After	**0.3864**	**0.3407**	**6.8762**	**0.1041**	**0.7782**	**3.9165**
Alg6	Before	0.3297	0.3164	6.2581	0.0842	0.7157	3.6292
	After	**0.4103**	**0.3552**	**6.8673**	**0.1136**	**0.7611**	**4.3368**
Alg7	Before	0.3413	0.3235	6.2772	0.0815	0.7211	3.7479
	After	**0.4185**	**0.3554**	**6.8787**	**0.1107**	**0.7742**	**4.4097**

Table 2.14. The evaluation metrics obtained on dataset D3 (C).

Algs	Type	MLI	CI	E	AG	$Q^{AB/F}$	MI
Alg1	Before	0.2886	0.3171	5.8940	0.0982	0.7203	3.1741
	After	**0.3611**	**0.3566**	**6.6787**	**0.1242**	**0.7417**	**3.6318**
Alg2	Before	0.3033	0.3826	5.8035	0.1018	0.6299	2.4732
	After	**0.3484**	**0.3947**	**6.4161**	**0.1274**	**0.6505**	**2.7522**
Alg3	Before	0.3123	0.3747	5.3588	0.0953	0.6230	2.6773
	After	**0.3608**	**0.3856**	**6.2380**	**0.1222**	**0.6432**	**3.1838**
Alg4	Before	0.3186	0.3381	5.1012	0.0955	0.7562	4.6741
	After	**0.3917**	**0.3743**	**6.2949**	**0.1230**	**0.7886**	**6.0716**
Alg5	Before	0.2878	0.3102	5.5751	0.0910	0.7655	3.6959
	After	**0.3541**	**0.3533**	**6.4829**	**0.1176**	**0.7813**	**3.8505**
Alg6	Before	0.3013	0.3269	5.7136	0.1000	0.7309	3.3756
	After	**0.3758**	**0.3686**	**6.3904**	**0.1270**	**0.7594**	**4.1467**
Alg7	Before	0.3101	0.3312	5.7388	0.0973	0.7405	3.5328
	After	**0.3833**	**0.3691**	**6.3973**	**0.1242**	**0.7781**	**4.3110**

From Tables 2.12, 2.13, and 2.14, it can be observed that the quality of the fused images obtained from the algorithms significantly improves when the proposed image enhancement algorithm is applied.

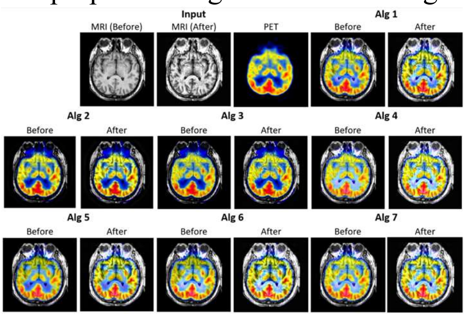


Figure 2.17. Fused images before and after applying the proposed algorithm

Overall, the evaluation metrics all show a significant increase after applying the image enhancement algorithm to the input images. The output images obtained from the image fusion algorithm before and after applying the proposed image enhancement algorithm are displayed in Figure 2.17. Visually, it can be observed that the fused images after enhancement exhibit a significant improvement. The enhanced fused images not only have better brightness and contrast but also show substantial enhancement in image details.

2.4. Conclusion of chapter 2

In this chapter, an image enhancement method has been proposed. This method has been applied to improve the effectiveness of some recently proposed image fusion algorithms. The proposed image enhancement method consists of three steps. Firstly, image decomposition into three components based on Gauss and ADF filters. Secondly, enhancing the quality of structural and textural components. Simultaneously, supplementing an additional feature component of the structural Tensor. Thirdly, applying the MPA algorithm to find optimal parameters and generating an enhanced image based on the optimized parameters.

The proposed image enhancement algorithm has been employed to test its effectiveness in improving the performance of existing image fusion algorithms. When input images are preprocessed with the proposed image enhancement algorithm, experimental results also reveal a substantial enhancement in the quality of the fused images compared to those prior to image enhancement. Therefore, the proposed image enhancement method plays a crucial role in enhancing the effectiveness of image fusion algorithms. The results of the proposed image enhancement method have been published in [CT1, CT2] in the “List of the publications related to the dissertation” section.

CHAPTER 3. IMAGE FUSION ALGORITHM BASED ON ADAPTIVE FUSION ALGORITHM COMBINED WITH VARIANTS OF LOCAL ENERGY FUNCTION

3.1. Motivation

Until now, numerous diverse studies have been proposed to address the image fusion problem. However, there are still certain limitations in improving the effectiveness of medical image fusion. This Chapter 3 presents research results on enhancing the efficiency of image fusion based on an optimization-oriented approach combined with variants of the local energy function. The proposed algorithm can be briefly described through three main stages. The first stage involves decomposing each input image into three components: a base component and two detail components. The second stage fuses the base components using the proposed adaptive algorithm, where the adaptive coefficients are determined by the MPA. The third stage fuses the detail components by combining various fusion algorithms, such as the local energy-based fusion algorithm combined with the Prewitt edge detection operator [78], and the local energy-based fusion algorithm combined with the Tensor structure's feature components. The fused image is obtained by summing up the corresponding base and detail components. The results of Chapter 3 have been published in work [CT3, CT4, CT6] in the "List of the publications related to the dissertation" section.

3.2. Proposing a fusion algorithm for detailed components

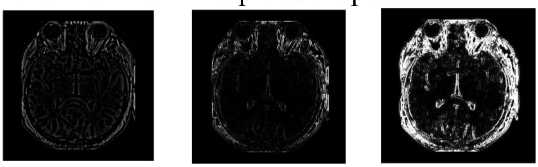
3.2.1. Enhancing Tensor structure features

The Structure Tensor Saliency Detection Operator (STSDO) is an effective tool for capturing image features. Figure 3.1 (b) illustrates the tensor saliency features obtained from a detail component (Figure 3.1 (a)) using the STSDO operator. From Figure 3.1 (b), it can be observed that the STSDO operator successfully detects several structures. However, certain weak and small features are not detectable by the STSDO operator. Therefore, to enhance the features obtained from the STSDO operator, an algorithm combining the features derived from the STSDO operator with a local energy function (referred to as LEF_STSDO) is proposed, which is computed using Equation (3.1).

$$LEF\_STSDO(L) = W_{STSDO}(L) \odot LEF(L) \tag{3.1}$$

Where:

L represents a detail component of an input image. $W_{STSDO}(L)$ is the feature matrix obtained using the structure tensor saliency detection operator for L. $LEF(L)$ stands for the local energy function of L. $\odot$ denotes the Hadamard product operator.



L (a) $W_{STSDO}(L)$ (b) $LEF\_STSDO(L)$ (c)

Figure 3.1. Illustration of structure Tensor features and their combination with local energy function

Figure 3.1 (c) illustrates the feature image obtained after being combined with the structure tensor. It's evident that the weak and small features have been successfully detected in the image. The improvement in the structure tensor's feature representation through its combination with the local energy function has been published in work [CT3].

3.2.2. FM_CVLEF algorithm

In this section, an efficient fusion algorithm for detailed components is introduced. This algorithm is constructed based on the combination of variants of the local energy function (referred to as FM_CVLEF). The Figure 3.2 illustrates the detailed steps of the FM_CVLEF algorithm.

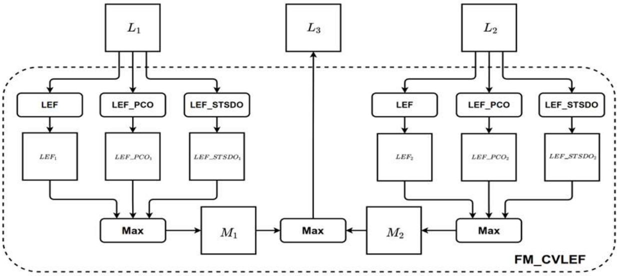


Figure 3.2. Illustration of the steps of the FM_CVLEF algorithm

3.3. Proposing a fusion algorithm for the base components

In this section, an adaptive fusion algorithm for base components (referred to as AFM_MPA) is proposed. The adaptive parameters are obtained based on the MPA optimization algorithm. The steps of the AFM_MPA algorithm are illustrated in Figure 3.4.

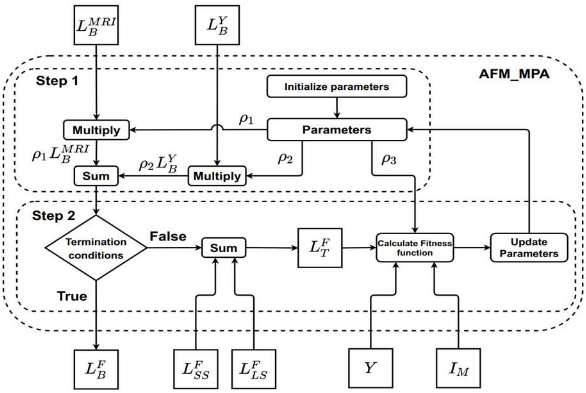


Figure 3.4. Illustration of the steps of the AFM_MPA algorithm

3.4. Proposing an image fusion algorithm

3.4.1. Proposing an image decomposition algorithm

In previous studies, the two-layer image decomposition method has commonly been employed, with the base layer obtained using mean filters [43] or low-pass filters [123]. However, these filters can result in the loss of detailed information in the image, leading to incomplete detail layers. To address these limitations, a three-layer image decomposition algorithm (referred to as TCID) based on RGF and WMCF filters is proposed. Figure 3.5 illustrates the process of decomposing an input image into three components.

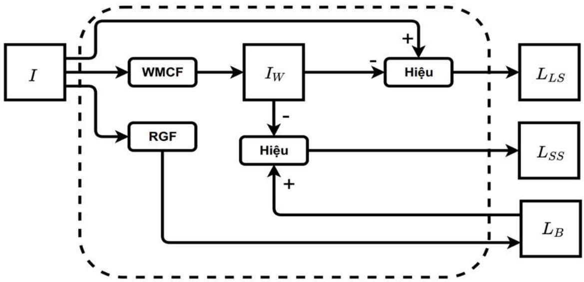


Figure 3.5. Illustration of the Three-Component Image Decomposition Algorithm

3.4.2. An image fusion algorithm (AFM_CVLEF)

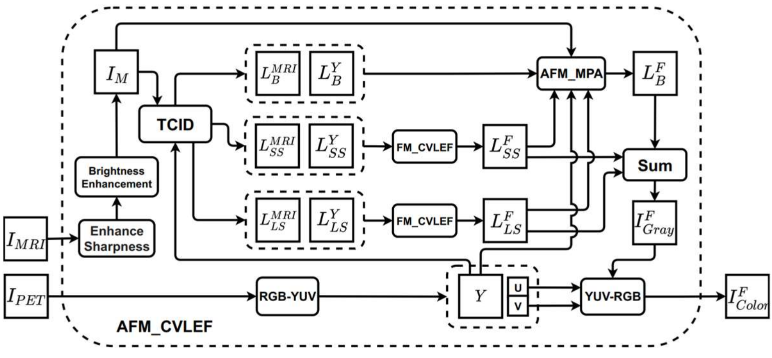


Figure 3.6. Proposed image fusion diagram

In this section, a novel image fusion algorithm is introduced. This algorithm is based on an adaptive fusion algorithm and variants of the local energy function (referred to as AFM_CVLEF). The detailed steps of the proposed algorithm are illustrated in Figure 3.6.

3.5. Complexity of the AFM_CVLEF algorithm

3.6. Experiments and Evaluation

3.6.1. Experimental Data

A total of 156 images, including 78 pairs of MRI and PET images, were collected from the source (http://www.med.harvard.edu/AANLIB/) and divided into sets as shown in Table 3.1.

Table 3.1. Description of Experimental Data Sets

Ds	Number of images	Description
K1	26 pairs MRI (T2) −PET	Slices from 61 to 86 along the T-axis
K2	26 pairs MRI (T2) −PET	Slices from 61 to 86 along the S-axis
K3	26 pairs MRI (T2) −PET	Slices from 61 to 86 along the C-axis
K4	3 pairs MRI (T2) −PET	Slice number 78 along the T, S, and C axes.

3.6.2. Experimental setup

Several other image fusion algorithms were used for comparison. These algorithms are described in Table 3.4.

Table 3.4. Several image fusion algorithms

No	Image fusion algorithms	Year
1	PC-LLE-NSCT (G1) [120]	2019
2	TLD-SR (G2) [18]	2021
3	JBF-LGE (G3) [30]	2021
4	CSE (G4) [121]	2021
5	CNPS-NSST (G5) [122]	2021
6	DTNP-NSCT (G6) [39]	2021
7	ACO (G7) [127]	2022

3.6.3. Experimental results

The experimental results are described in Tables 3.8, 3.9, 3.10.

Table 3.8. The evaluation metrics from the experiments on K1

Ds	Algorithms	MLI	CI	AG	$Q^{AB/F}$	FMI
K1	G1	0.2492	0.2910	0.0528	0.6248	0.8569
	G2	0.2634	0.2997	0.0499	0.6786	0.8646
	G3	0.2634	0.2992	0.0511	0.6771	0.8682
	G4	0.2233	0.2479	0.0461	0.6552	0.8681
	G5	0.2060	0.2382	0.0546	0.6192	0.8583
	G6	0.2558	0.2922	0.0522	0.6376	0.8619
	G7	0.2415	0.2596	0.0470	0.6587	0.8562
	AFM_CVLEF	**0.3131**	**0.3356**	**0.0829**	**0.7440**	**0.8737**

Table 3.9. The evaluation metrics from the experiments on K2

Ds	Algorithms	MLI	CI	AG	$Q^{AB/F}$	FMI
K2	G1	0.2555	0.2816	0.0506	0.6432	0.8675
	G2	0.2700	0.2905	0.0474	0.6818	0.8740
	G3	0.2713	0.2920	0.0487	0.7099	0.8765
	G4	0.2317	0.2410	0.0435	0.6703	0.8762
	G5	0.2162	0.2305	0.0517	0.6344	0.8694
	G6	0.2626	0.2835	0.0497	0.6537	0.8714
	G7	0.2754	0.2727	0.0463	0.6996	0.8695
	AFM_CVLEF	**0.3313**	**0.3217**	**0.0740**	**0.7539**	**0.8782**

Table 3.10. The evaluation metrics from the experiments on K3

Ds	Algorithms	MLI	CI	AG	$Q^{AB/F}$	FMI
K3	G1	0.2060	0.2648	0.0452	0.6628	0.8674
	G2	0.2175	0.2757	0.0428	0.6987	0.8726
	G3	0.2181	0.2761	0.0435	0.7133	0.8766
	G4	0.1925	0.2380	0.0398	0.6914	0.8716
	G5	0.1789	0.2251	0.0463	0.6524	0.8665
	G6	0.2120	0.2684	0.0446	0.6732	0.8716
	G7	0.2103	0.2421	0.0400	0.6980	0.8644
	AFM_CVLEF	**0.2778**	**0.3230**	**0.0693**	**0.7716**	**0.8743**

From the experiments, the evaluation metrics obtained from the proposed fusion algorithm are superior to those of other image fusion algorithms. Firstly, considering the image quality assessment metrics, the proposed algorithm outperforms other fusion algorithms. The MLI, CI, and AG metrics obtained from the proposed algorithm are the highest compared to the other fusion algorithms. This indicates that images generated by the proposed algorithm exhibit better quality in terms of average brightness, contrast, and sharpness compared to images generated by the other fusion algorithms. Secondly, considering the edge preservation metric, the $Q^{AB/F}$ metric obtained from the proposed algorithm is also the highest across all three datasets K1, K2, and K3. This result indicates that the proposed algorithm preserves the edge features of the input images better than other fusion algorithms. Thirdly, considering the FMI metric used to assess the similarity between input and synthesized images based on information theory, it is evident that the FMI metric obtained from the proposed algorithm is also the highest among the FMI metrics of other fusion algorithms. This suggests that the fused images generated by the proposed algorithm retain more information from the input images and undergo less distortion or loss of information compared to images generated by other fusion algorithms.

3.7. Conclusion of Chapter 3

In this chapter, an image fusion algorithm has been proposed to enhance the effectiveness of image fusion. The proposed algorithm (AFM_CVLEF) comprises three main algorithms. The first is an image decomposition algorithm (TCID). The second is a fusion algorithm for the base component (AFM_MPA). The third is a fusion algorithm for the detail components (FM_CVLEF).

The proposed image fusion algorithm (AFM_CVLEF) has been compared with several recently proposed image fusion algorithms. The results of the proposed image fusion algorithm have been presented in [CT3, CT4, CT6] in the "List of the publications related to the dissertation" section.

CONCLUSIONS

Up to now, various approaches have been developed to address this challenge. However, image fusion still faces certain limitations due to two main factors. Firstly, the input images often exhibit low quality, such as low brightness, low contrast, and possible noise. Secondly, the current fusion methods are not entirely effective, resulting in fused images losing quality and important details from the original images. The main contributions of this dissertation aim to address the aforementioned limitations by proposing an algorithm to enhance the quality of input images and suggesting more effective fusion algorithms for both base and detail components

The main contributions of this dissertation:

Proposing an image enhancement algorithm (called IE_TCID_MPA) [CT1, CT2]. The proposed algorithm significantly improves the brightness and contrast of the fused images while effectively limiting noise generated during the enhancement process.

Introducing a novel fusion algorithm (AFM_CVLEF) to enhance the effectiveness of image fusion [CT3, CT4, CT6]. This algorithm aims to address two issues: (a) the reduction in brightness and contrast of the fused images; (b) the loss of information in the fused images. To tackle the first issue, an adaptive fusion algorithm (AFM_MPA) is proposed for the base components. In this algorithm, adaptive parameters are determined based on the MPA. To address the second issue, an efficient synthesis algorithm for the detail components (FM_CVLEF) is proposed. This algorithm combines local energy functions with their variations, such as the local energy function using the Prewitt compass operator and the local energy function using the structure tensor saliency.

The thesis focuses on addressing two main problems: (a) improving the quality of input images; (b) proposing efficient algorithms for fusing base and detail components. In the future, several approaches could be explored to enhance the effectiveness of image fusion as follows:

- To improve the efficiency of the synthesis algorithm for detail components, deep learning networks can be employed to extract features from images. Utilizing a large number of features extracted by deep learning networks could potentially help fusion algorithms preserve detailed information from input images [CT5].
- To enhance the runtime efficiency of image fusion algorithms, recent optimization algorithms like CSA [128] and WSO [129] could be considered as replacements for the MPA algorithm.
- For further improvement in fusion outcomes, a promising approach is to integrate the image enhancement and fusion phases into a unified fusion model. This involves using a single optimization function to control the quality of the resulting images.

LIST OF THE PUBLICATIONS RELATED TO THE DISSERTATION

[CT1]	**P. H. Dinh** and L. G. Nguyen, 2022, A new medical image enhancement algorithm using adaptive parameters, *International Journal of Imaging Systems and Technology*, vol. 32, no. 6, pp. 2198–2218. **(SCIE, Q2)**
[CT2]	**P. H. Dinh**, 2023, Combining Spectral Total Variation with Dynamic Threshold Neural P Systems for Medical Image Fusion, *Biomedical Signal Processing and Control*, vol. 80, pp. 104343. **(SCIE, Q1)**
[CT3]	**P. H. Dinh**, 2022, A novel approach using structure tensor for medical image fusion, *Multidimensional Systems and Signal Processing,* vol. 33, pp. 1001–1021. **(SCIE, Q2)**
[CT4]	**P. H. Dinh**, 2023, A novel approach using the local energy function and its variations for medical image fusion, *The Imaging Science Journal,* pp. 660-676. **(SCIE, Q2)**
[CT5]	**P. H. Dinh** and L. G. Nguyen, 2023, Medical image fusion based on Transfer learning techniques and Coupled Neural P Systems, *Neural Computing and Applications, pp. 4325–4347.* **(SCIE, Q1)**
[CT6]	**Dinh Phu Hung**, Nguyen Huy Duc, Nguyen Long Giang, *2022,* Medical image fusion based on the MPA optimization algorithm, *Fundamental and Applied Information Technology, pp. 501-509.*