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PERFORMANCE ANALYSIS OF CONVENTIONAL AND DEEP LEARNING IMAGE FUSION METHODS

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ABSTRACT

This paper presents a comparative study of three different image fusing techniques such as hybrid image fusion designed using conventional image fusion technique, enhancement of low dose Computerized Tomography (CT) image and fusing with Magnetic Resonance Imaging (MRI) image, and Deep Learning (DL) based image-fusing technique. Firstly, it is observed that the hybrid method of image fusion outperforms single mode of image fusion such as Discrete Wavelet Transform (DWT) or Principal Component Analysis (PCA)-based image fusion. Secondly, it is worth noting that the performance of image fusion applied to enhanced low dose CT and MRI images are on par with fused normal dose CT & MRI images based on results obtained with the standard fusion quality metrics. Finally, the performance of Deep Learning (DL)-based image fusion developed using Convolution Neural Network (CNN) is evaluated. The Peak Signal to Noise Ratio (PSNR) of the DL based image fusion is more than 25 dB that of the conventional methods of image fusion. From that, it can be concluded that DL based image fusion technique will be the advanced form of medical image fusion to obtain a proper diagnosis of different diseases.

Keywords: *Discrete Wavelet Transform; Principal Component Analysis;Image Fusion; Deep Learning; Convolutional Neural Network, Multi Modal Images*

A) INTRODUCTION

Medical imaging is a modern way of treating patients using non-invasive methods. There are different modalities in medical imaging which are used to obtain information about the body organ/ tissue. The CT (Computed Tomography) images provide information about the hard tissues in the body like bone structures and implants, whereas MRI provides information about the soft tissues in the body. The SPECT scan gives the 3-D information i.e., functional information of any organ in the body [1]. It is essential to integrate important information from different sources into a composite image for performing the precise diagnosis. The process of image fusion can achieve this target. Image fusion integrates the salient features of various images into a composite image [2]. This composite image helps the doctors in diagnosis for determining the growth of a tumor, and to find the exact boundaries of the tumor [3]. Image fusion can be done at the pixel, region, or reference image level to form the composite image [4].

Image fusion algorithms can be categorized into two types: spatial domain and transform domain [3]. The spatial domain fusion algorithms can be sub-grouped into pixel-based, feature-based, and decision-based algorithms. When a special medical diagnosis requirement is present, they are ideal for combining images of the same modality. They usually suffer from block and region artefacts as image fusion accomplished here by combining the most salient regions. Hence, images are converted to features through transform domain and are applied to fusion algorithms to integrate the features in transform domain [5-8]

The pixel - based image fusion can be done with or without the use of Multi Scale Decomposition (MSD).

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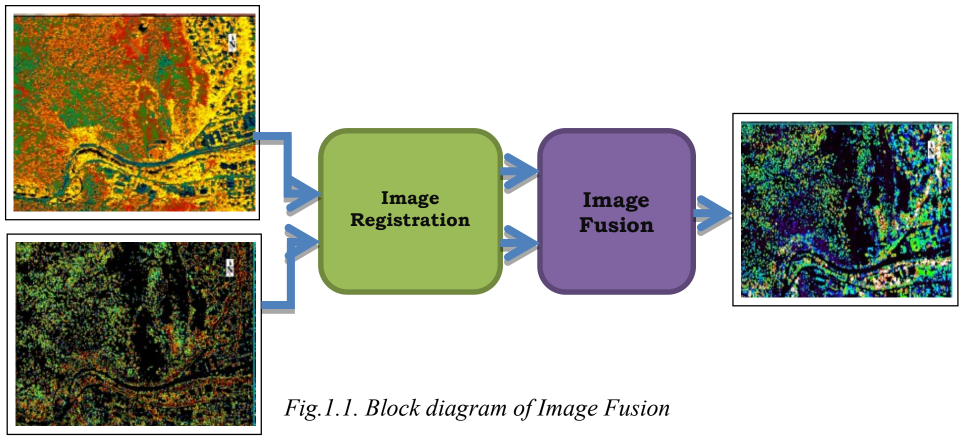

Fig.1.1. Block diagram of Image Fusion

It is found that MSD extracts and combines the salient features at different scales. Hence, the MSD produces the composite image with greater information compared to the Non-MSD [5]. The feature level fusion combines adaptively the extracted features of different modalities using Gabor Wavelet transform [5]. The decision level fusion is used to optimally fuse the decisions received from multiple classifiers to improve the overall classification based on pattern of modalities and complementarities of source [6]. It is reported that the pixel level fusion is better than other two fusion methodologies and it is computationally efficient[5].

A CNN based medical image fusion algorithm is proposed by Kunpeng Wang et al., in which they trained Siamese convolutional network to fuse the pixel activity information of source image. A contrast pyramid algorithm has been utilised to decompose the source images and based on the different frequency bands a weighted fusion operator has been utilised to integrate the images [9].

Yi Li et al.,[10] proposed a multimodal medical image fusion with CNN and supervised learning in batch processing mode. This method improved the fusion effect, image detail clarity, and time efficiency effectively by overcoming the traditional fusion problem that can only be solved by single image fusion. Shubam Dwivedi et al., proposed an effective fusion methodology using deep learning for early detection of Alzheimers disease. They fused the MRI and PET scan images and found that it is beneficial for health professionals in diagnosing Alzheimers at early stage.[11]

Shihabudeen et al., proposed an image fusion technique for the infrared and visible images using deeplearning L2 norm. They integrated the L2 norm information with the complementary information from both the image modalities [12]. Weisheng Li proposed an image fusion algorithm using multiple salient features with guided image filter to prevent the problem of low contrast detail [13]As illustrated in Fig. 1.1, medical image fusion is a three-step procedure that includes picture pre-processing, image registration, and lastly image fusion.

The first step of medical image fusion called image pre-processing involves i) bringing images to same size and resolution and ii) possibility of removal of noise & then enhancement. Image registration, the second step in medical image fusion, entails spatial manipulation of one image to achieve the same region as another image's equivalent point. Picture fusion, the third phase in medical image fusion, is explained here using two different methods of image fusion.

1.Principal Component Analysis Method for Image fusion

It is a method, which determines the Eigen vectors called Principal Components and Eigen values to form a sample of Covariance matrix for the given image. Suppose that two images of different characteristics have to be fused. Assume that Image-1 is having rich spectral information and low spatial resolution and Image-2 is having opposite characteristics.

In the PCA, method of fusion the image, having higher spatial resolution is divided into sub images and PC is determined for each sub image. Now, new image is created for Image-1 and using histogram to match the PC of the sub

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image. Now, PC of the sub image is injected to newly created image. This process will be done for all sub images as shown in Fig1.2 and finally apply inverse PCA to generate composite image.

2. Wavelet Transform Method for Image Fusion: Here also we consider Image-1 & 2 mentioned above for the persistence of image fusion..

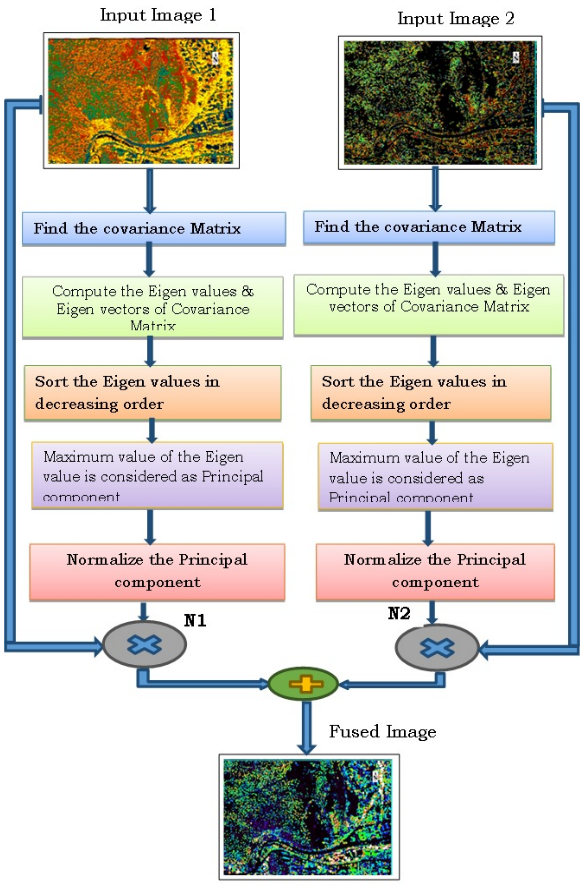

Fig.1.2. Block Diagram of PCA based Image Fusion

As exposed in Fig. 1.3, Discrete Wavelet Transform of Image 1 & 2 will be obtained then DWT of Image-1 is injected in to DWT of Image-2. Now, inverse DWT is obtained to obtain the composite image[7], the main objective of this paper is to review the conventional image fusion methodologies and to compare the performance of them with the deep learning based image fusion algorithms in case of medical images.

The paper is divided into four sections, including the introductory part. The second section presents collected works done for carrying out the medical image fusion for real-time medical images. A comparative study of Deep Learning & Conventional Image Fusion is presented in the third section. Fourth section presents conclusion and scope for further research in the proposed area of medical image fusion.

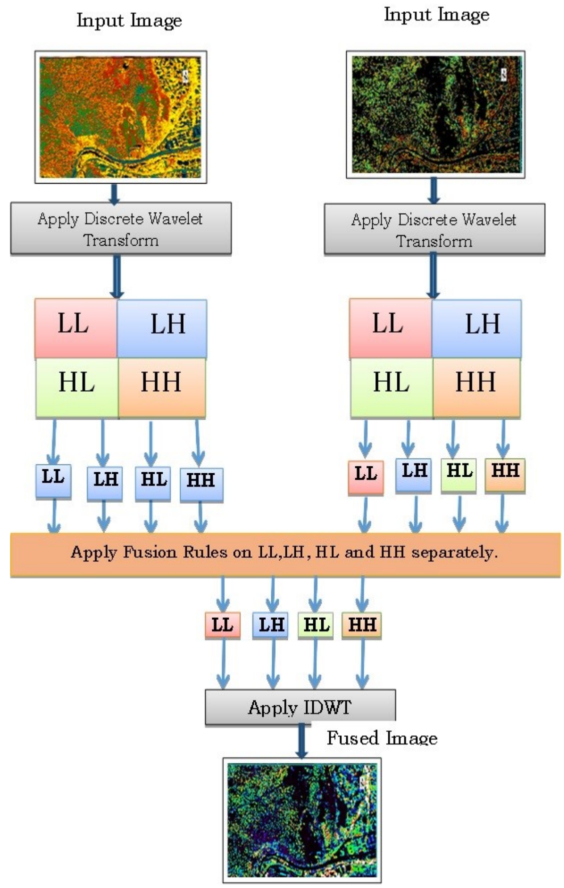

Fig.1. 3. Block Diagram of PCA based Image Fusion

2. LITERATURE REVIEW

Image fusion is used in many real-time image quality enhancements. One noteworthy image fusion application is related to improvement of visibility during the poor weather conditions as existing imaging devices are not sufficient to overcome the visibility degradation. In particular [8] & [9] attempted to solve image degradation problem to haze condition in the atmosphere. Adaptive structure decomposition integration by means of Multi-Exposure Image Fusion (MEF) is used in [8] for obtaining the haze-free images. However, the proposed method in [8] is reported as computational intensive because of linear adjustment of image saturation and adaptive selection of image size requirements. In [9], pixel-wise weight maps based image fusion is proposed using local and global exposedness. It is also reported as the fast dehazing algorithm but its suitability is not yet explored for real-time applications.

In [10], Non-Subsampled Counterlet Transform(NCST) based medical image fusion is used. In particular, Counterlet Transform is applied on image pairs to decompose the source images into high-pass and low-pass sub bands. The integration of high-pass sub bands using phase congruency based function rule performed. However, the NCST domain based method is reported as poor performer for PET-MRI multi modal images fusion. The remaining part of this section discusses firstly, the purpose of using different image fusion methods and then DWT+ PCA for medical image fusion. Secondly, the importance of low dose CT and its images quality improvement.Lastly, the main advantages of deep learning approaches in multi-model image fusion.

Research efforts in the past have established that medical image fusion with wavelet transform will enable better visibility to enhance the visibility of clinically important features. However, the spatial quality of the merged image is poor. For satellite images, microscopy images, medical images, and radar images, the possibility of employing Decimated, Undecimated, and Non-separated DWT techniques of image fusion implementation has been presented in [11]. It can be noted that Decimated DWT is not shift variant and it is negative for linear continuity of spatial features that do not have vertical or horizontal orientation. Whereas the Un-decimated DWT overcomes the problem of shift variance but it will have the poor directionality problem of Decimated DWT. If we examine then the Non-separated DWT wherein it produces only two images. In that one image will be approximation image which is called as scaled image and another image will be detail image which is called wave plane. The Non-separated DWT does not involve decimation and separate filtering. Hence, it overcomes the problem of shift variance and poor directionality at the cost of spectral quality [11]. There are five popular wavelet families used for image fusion. They are as follows i) Haar ii)Daubechies (db) iii)Symlets, iv) Coiflets and v) Biorsplines.

It is also worth to note one among the different types of fusion rules such as mean rule, maximum rule, min-max rule and random rule can be adopted while fusing the image. In [12], CT& MRI images are fused using Daubeschies transform with maximum fusion rule. This has the fewest Root Mean Square Error (RMSE) and the maximum Peak Signal to Noise Ratio when compared to earlier wavelet transformations and fusion rules (PSNR). In [13], DWT is used to merge CT and MR images utilising the Maximum Selection rule with window-based consistency checking. The resulting fused image has a higher precision and less variation from the source images. There are two significant variants of DWT and one transform is Shift Invariant DWT (SIDWT) and another transform is Wavelet Transform using a Dual-Tree Complex (DT-CWT) as given in [14]. SIDWT decomposes the input images into shift invariant wavelet representations. The fused image is then created using an appropriate selection scheme and a thorough consistency check. The SIDWT results in reduced RMSE for fused image compared to the DWT at the cost of highly redundant wavelet decomposition [15]. The DT-CWT, also known as the near shift invariant wavelet transform, creates one vector - valued low-pass sub band and six real valued level of operation bands at each level of decomposition. As this method of filtering introduces ½ sample delay in each branch of dual tress, the fused image will be near shift invariant and with perfect reconstruction possible. Asper the results reported in [16], the DT-CWT performance is not good for infrared band.

At the same time, it is worth looking at the properties of another pixel-level picture fusion technique known as Principal Component Analysis, or PCA. The PCA is a statistical fusion method wherein variables with correlation are transformed into uncorrelated variables called Principal Components. In [17], low resolution multi-spectral image is fused with high spatial image using PCA method. The PCA resulted a fused image with better PSNR but low gradient. It means the fused image with PCA will have low sharpness. Hence, it can be concluded that the PCA ignores the requirement of high-quality synthesis of spectral information. Hence, this thesis attempts propose a combination of different fusion methods to produce better spatial quality for fused image while retaining the high quality spectral characteristics to ease the medical diagnosis.

Since the introduction of X-Rays for medical diagnosis, It has been the aim of radiologists to perform medical diagnosis with possible reduction of radiation exposure. In particular, it is always preferable to have low dose CT for medical diagnosis of children. With reference to the discussed requirement of low dose CT, this thesis has attempted improve the quality of low dose CT images by using image enhancement techniques. It is worth to note there are many types Histogram Equalization(HE) methods for image enhancement based on type of images as noted in [18]. In this thesis work, a suitable HE method is used to enhance the low dose CT image then the resultant image is fused with MRI image.

The paper also presents findings in usage of machine learning approach for image fusion and why the machine learning approach is adopted is as follows. In the transforming domain image fusion algorithms, the images are transformed into features using some decompositions or morphological transformations [19-22]. Weighted fusion algorithms are applied to these features to produce a fused image. It is established that spatial domain techniques are suitable for multi focused single domain images fusion whereas the transform domain image fusion is suitable for multimodal images. There are some similarities between transform domain image fusion and newly upcoming Convolutional Neural Network (CNN) based image fusion in terms of features extraction and thereby fusing them. In this dissertation, a novel framework for medical imaging is developed that is based on CNN and has undergone rigorous testing[23-27].

3. PROPOSED CNN BASED IMAGE FUSION:

It is established that spatial domain techniques are suitable for multi focussed single domain images fusion whereas the transform domain image fusion is suitable for multimodal images. In particular, it is observed that there are similarities between transform domain image fusion and CNN based image fusion in terms of feature extraction and there by fusing them.
The main motivation for developing CNN based image fusion framework is because of the following challenges in conventional image fusion:

i. It requires more turnaround time to develop new image transforms and strategies for image fusion to produce better composite image as per the present day requirement of diagnosis
ii. Limited image representation ability in the fused image compared to the source images. This is observed in our first implementation of DWT+PCA
iii. Non availability of standard metrics for evaluating the image fusion results

Deep Learning (DL) has proved to be excellent for feature extraction and data representation for image processing tasks [28]. In particular, it is interesting to know how DL overcomes the above mentioned challenges of conventional image fusion methods before discussing the proposed CNN method of image fusion

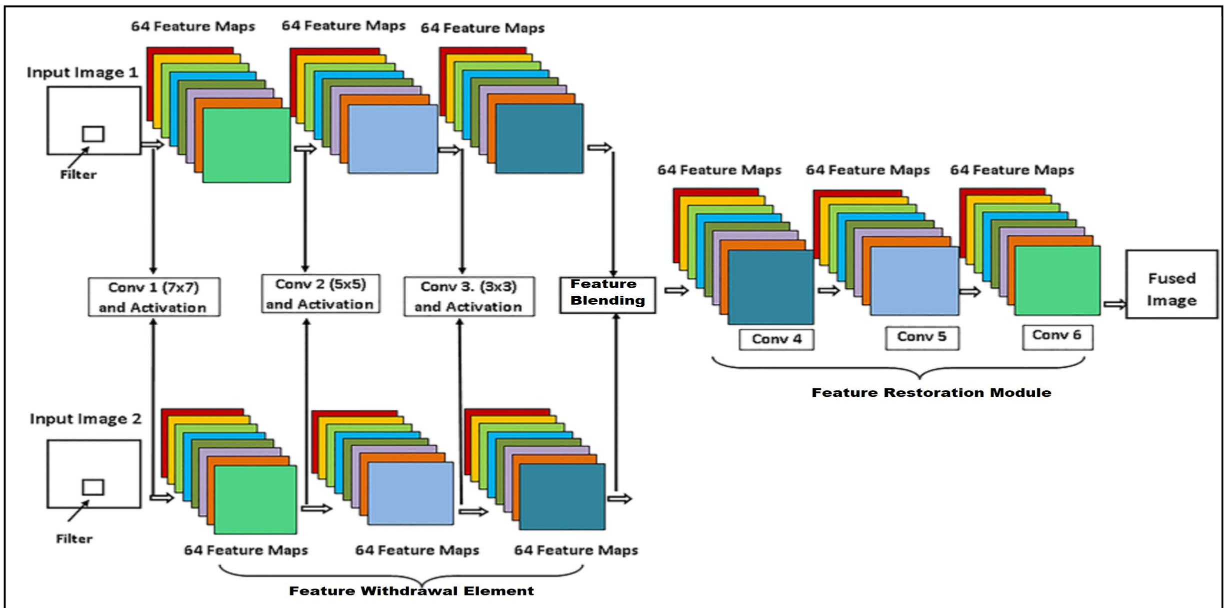

Fig. 4.1. Proposed CNN Model for Image Fusion

The CNN implicitly implements feature extraction and fusion rules for generating the composite image. Hence, it avoids requirement of appropriate image transform development. From literature, it can be found that CNN has capability to characterize complex relation between different signals[29]. This enable the fused image to have spectral characteristics of source images. It is reported that the CNN based local similarity measurement results are far better than conventional methods. Hence, it proves to pave the way for the development of fusion metrics in the near feature.

4. RESULTS AND CONCLUSIONS :

The proposed deep learning methodology shown in Fig.4.1 is based on Convolution Neural Network (CNN) which is implemented using Python 3.7.4. The modelled CNN has a three-stage pipelined architecture with i) Feature Withdrawal Element, ii) Features Blending Module, and iii) Feature Restoration Module. Extensive experimentation during the implementation process has resulted in taking the following measures to retain the salient features of the fused image:

a) The CONV1 is chosen to have Sixty four convolutional kernels of each size 7 ×7 for extracting the effective coarse image features
b) Two more convolution layers CONV2 the image features produced by the CONV1

In the CONV2 layer, sixty-four convolution kernels of size 5X5 are proposed, and sixty-four convolution kernels of size 3X3 are recommended for the CONV3 layer. Besides the above measures, an appropriate activation function *Swish* is chosen to obtain all the image features without any loss of information for the image fusion.

The proposed model in the above Fig.4.1 is trained with hundreds of medical images corresponding to CT, MRI, SPECT and PET. The training set of images is derived from the ILSVRC-2012 validating image collection and contains 50k high-quality images derived from the ImageNet dataset. Two different modalities corresponding to medical images are given as input images for the model. The feature map of each input images is obtained separately. And then, the feature map of one image is fused with the feature map of the other image. And then, the fused feature map is reconstructed to obtain the final fused image.

A mobile work station of HP make with Intel core i-7 having 8 GB RAM, 2. 5 GHz clock frequency and running with Windows 10 operating system is used for training the proposed model. After successful training of the deep neural network, the system is deployed to produce fused images**.** The testing is done with two datasets that are collected from a local diagnostic centre. Dataset-1 provides MRI and SPECT brain pictures, while Dataset-2 has CT and MRI brain images.

Table-1 : Comparison of Different Fusion Methods

Parameter	DWT	PCA	DWT-PCA	CNN		
				Tanh	ReLu	SWISH
Mean	9.5951	10.188	10.263	21.3655	21.6442	23.3266
SD	34.341	34.516	37.790	51.6532	58.6562	56.4652
BIQI	0.0084	0.0164	0.0218	0.0192	0.0185	0.0265
PSNR	27.925	23.6129	28.6339	53.6425	50.2355	55.1212
UIQI	0.5717	0.5813	0.5986	0.5632	0.6254	0.6325
SSIM	0.6754	0.6201	0.6877	0.4126	0.4886	0.5684
Entropy	5.2351	5.2131	5.6524	7.1742	7.5623	7.6584
SF	20.3147	23.3512	25.6363	25.5254	30.5665	31.1532
Elapsed Time in Seconds	6.6512	7.2351	10.2465	15.536	16.0497	18.0497

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Different fusion metrics are used to compare the performance of CNN based image fusion with other selected group of image fusion methods. It is worth to note that average information of fused image given by mean metric, edge information retention given by Standard Deviation(SD), Blind Image Quality Index (BIQI), Peak Signal to Noise Ratio(PSNR), average information per pixel given by Entropy and Special Facial Function (SF) are better for CNN based image fusion as shown in above table. Only Structural Similarity Index (SSIM) is marginally lower for CNN based image fusion.

Hence, it can be concluded that innovation and advancements in technologies will go hand in hand to develop new methods for image fusion, which is going to be useful for better medical diagnosis. The CNN based image fusion methods outperforms when compared to the conventional image fusion algorithms and in particular, the development of low cost time and energy efficient solution for the image fusion technologies is the need of hour. The performance of the CNN based medical image fusion has produced better results than other image methods which is illustrated in the following Table-1.

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