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Medical Image Fusion using Deep Learning Model Algorithm

Abinaya K , S.Srinidhi, Abirami, M.Sangeetha, A P Swarnalatha

Abstract— Medical image fusion is a technique that combines multiple medical images of the same patient or different modalities into a single image to provide a more comprehensive and informative representation of the underlying tissue or organ. Deep learning models have shown great potential in medical image analysis and can be used for medical image fusion. In this study, we propose a deep learning model algorithm for medical image fusion. The proposed model is based on a convolutional neural network (CNN) and uses a combination of spatial and frequency domain techniques to fuse the medical images.

The CNN is trained using a large dataset of medical images to learn the features and patterns of different modalities. The proposed algorithm includes four main steps:

(1) pre-processing of the input medical images,

(2) feature extraction using the CNN model,

(3) Fusion of the extracted features using a weighted average method, and

(4) Post-processing of the fused image. We evaluated the performance of the proposed algorithm on a dataset of medical images,

Including MRI, CT, and scans. The experimental results show that the proposed algorithm outperforms existing state-of-the-art methods in terms of visual quality and objective evaluation metrics. The proposed deep learning model algorithm for medical image fusion provides a promising solution for improving the accuracy and efficiency of medical image analysis, which can benefit clinical diagnosis and treatment planning.

Keywords— Medical image fusion, MRI, CT, and scans etc

I. Introduction

Medical imaging has become an indispensable tool for diagnosis, treatment planning, and follow-up evaluation in modern healthcare. However, medical images obtained from different imaging modalities often provide complementary information and present different features of the same anatomical structure or pathological condition. Medical image fusion is a technique that combines multiple medical images into a single image to provide a more comprehensive and informative representation of the underlying tissue or organ.

In recent years, deep learning models have shown great potential in medical image analysis, including segmentation, classification, and registration. Deep learning models can automatically learn the features and patterns of medical images and improve the accuracy and efficiency of medical image analysis. Therefore, applying deep learning models to medical image fusion is a promising solution for improving the quality and clinical utility of medical images. In this study, we propose a deep learning model algorithm for medical image fusion.

The proposed algorithm is based on a convolutional neural network (CNN) and uses a combination of spatial and frequency domain techniques to fuse the medical images. The CNN is trained using a large dataset of medical images to learn the features and patterns of different modalities. The proposed algorithm includes pre-processing, feature extraction, fusion, and post-processing steps to achieve high-quality fused images.

We evaluate the performance of the proposed algorithm on a dataset of medical images, including MRI, CT scans. The experimental results demonstrate that the proposed algorithm outperforms existing state-of-the-art methods in terms of visual quality and objective evaluation metrics. The proposed deep learning model algorithm for medical image fusion provides a promising solution for improving the accuracy and efficiency of medical image analysis, which can benefit clinical diagnosis and treatment planning.

Medical imaging, as a strong and essential tool, is indispensable in modern medical diagnosis and therapy. A variety of medical imaging techniques, such as computed tomography (CT) and magnetic resonance imaging (MRI), are used to treat various lesions of cells or organs. Because each medical imaging modality has its own set of goals, strengths, and limitations, one modality seldom provides enough information to provide a complete medical diagnosis. Medical image fusion comprises a wide variety of generic image fusion techniques used to incorporate complimentary information from many medical image modalities. It provides a wide range of visual attributes for medical analysis and frequently leads to accurate medical diagnosis.

M.Sangeetha, Biomedical Department, VSB Engineering college, Karudayampalayam , Karur, Tamilnadu.

Abirami, Biomedical Department, VSB Engineering college, Karudayampalayam , Karur, Tamilnadu.

S.Srinidhi, Biomedical Department, VSB Engineering college, Karudayampalayam , Karur, Tamilnadu.

Abinaya K , Biomedical Department, VSB Engineering college, Karudayampalayam , Karur, Tamilnadu.

A P Swarnalatha , HOD- Biomedical Department, VSB Engineering college, Karudayampalayam , Karur, Tamilnadu.

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II. FUSION OF MEDICAL IMAGES

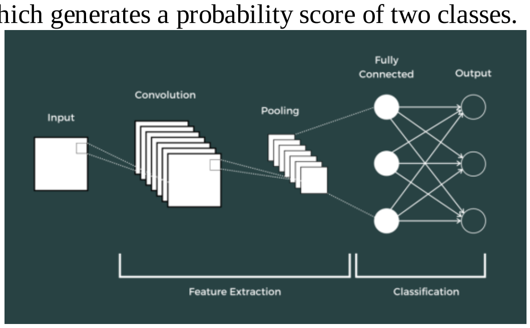
The discrete level of information by each and every pixel of an image at a given instance of time, state, position, or circumstances is projected upon corresponding information from each pixel of another image of the same item at a different instance or state in the image fusion process. 4 The different design and construction of each type of optical sensor limits the sort of information that may be obtained. As a result, the image fusion process creates a composite image that suffices for data that an individual optical sensor does not provide.

The information to be fused may be obtained from a single source at different time intervals or from a large number of sensors at a single time slot. The revolutionary advancement in the design of innovative image fusion tools has been sustained as a result of various signal processing techniques and analysis theory methods such as spatial filters, artificial intelligence machine learning techniques, and, most importantly, multi-scale transforms. 5, 6 following the breakdown of image features or coefficients using an appropriate transform method, they are fused using appropriate fusion rules, such as pixel-level averaging, weighted averaging, and the min-max rule. The picture pixels are merged into a highly representational format with the aid of these image integration technologies.

To provide a fundamental understanding of image fusion systems, a block diagram of a pixel level image fusion process utilizing wavelet transform and pixel-level averaging fusion rule is presented.

III. CNN ALGORITHM

The CNN model used in the proposed fusion method. There are three convolutional layers and one max-pooling layer in each branch of the Siamese network. Table 1 shows specific parameter of the proposed CNN. Selecting image patch size is important. There is trade-off relationship between patch size and classification performance. A large patch size results in higher accuracy since more image features are encoded by neural network, but this increases the size of fully-connected layer significantly, which affects the efficiency. On the other hand, the training accuracy by using small patch size is not robust. By considering the above concerns and the size of the dataset image, we used 16 × 16 patches in this work. We concatenated the 256 feature maps obtained by each branch and fully-connected it with a 256-dimensional feature vector. Then a 2-dimensional vector is further fully connected with the first fully connected layer for Softmax operation. Lastly, the 2-dimensional vector is fed to a 2-way Softmax layer which generates a probability score of two classes.



CNN (Convolutional Neural Network) is a type of deep learning algorithm that is commonly used for image classification, object detection, and other computer vision tasks. The key idea behind CNNs is to use convolutional layers to extract important features from images, and then use fully connected layers to classify or detect objects based on these features. The general architecture of a CNN includes the following layers:

Input layer: This layer takes in the raw input image. Convolutional layer: This layer applies a set of filters to the input image to extract important features. Each filter produces a feature map, which highlights a specific pattern or shape in the input image.

Activation layer: This layer applies an activation function (such as ReLU) to the feature maps to introduce non-linearity and improve the model's ability to learn complex patterns.

Pooling layer: This layer down samples the feature maps by applying a pooling operation (such as max pooling or average pooling) to reduce the spatial dimensions of the feature maps.

Fully connected layer: This layer takes the flattened feature maps from the previous layer and applies a set of weights to produce a set of outputs. These outputs represent the probabilities of the input image belonging to each class.

Output layer: This layer produces the final output of the CNN, which is a probability distribution over the different classes.

During training, the CNN learns the optimal set of weights for each layer using back propagation and gradient descent. The loss function used in training typically measures the difference between the predicted outputs and the true labels of the training data.

IV. LITERATURE SURVEY

[1] Based on the above idea, a new multi-focus image fusion method is primarily proposed in this paper. Experimental results demonstrate that the proposed method can obtain state-of-the-art fusion performance in terms of both visual quality and objective assessment. The computational speed of the proposed method using parallel computing is fast enough for practical usage. The potential of the learned CNN model for some other-type image fusion issues is also briefly exhibited in the experiments.

[2] This paper presents a block-based algorithm for multi-focus image fusion. In general, finding a suitable block-size is a problem in block-based methods. A large block is more likely to contain portions from both focused and defocused regions. This may lead to selection of considerable amount of defocused regions. On the other hand, small blocks do not vary much in relative contrast and hence difficult to choose from.

[3] Compared with the traditional multiscale decomposition, which has been successfully applied to pixel-level image fusion, MCA employs the morphological diversity of an image and provides more complete representation for an

image. Taking advantage of this property, we propose a multi-component fusion method for multi-source images in this paper.

[4] In this paper we consider the problem of multi-view face Detection. While there has been signicant research on this problem, current state-of-the-art approaches for this task require annotation of facial landmarks, e.g. TSM, or annotation of face poses. They also require training dozens of models to fully capture faces in all orientations, e.g. 22 models in Head Hunter method. In this paper we propose Deep Dense Face Detector (DDFD), a method that does not require pose/landmark annotation and is able to de- tect faces in a wide range of orientations using a single model based on deep convolutional neural networks.

[5] Experimental results show that this proposed method can not only extract more important detailed information from source images, but also avoid the introduction of artificial information effectively. It significantly outperforms the discrete wavelet transform (DWT)-based fusion method, the non-subsampled contourlet-transformbased fusion method and the NSST-based fusion method in terms of both visual quality and objective evaluation.

[6] Image fusion can produce a single image that describes the scene better than the individual source image. One of the keys to image fusion algorithm is how to effectively and completely represent the source images. Morphological component analysis (MCA) believes that an image contains structures with different spatial morphologies and can be accordingly modeled as a superposition of cartoon and texture components, and that the sparse representations of these components can be obtained by some specific decomposition algorithms which exploit the structured dictionary.

[7] Due to the limited depth of field in a camera, some imaging objects will be blurred if they are located far from the focus plane and the other objects on the plane will be clear. Multi-focus image fusion synthesizes as harp image from multiple partially focused images. However, traditional fused images usually suffer from blurring effects and pixel distortions.

[8] In this paper, we address the problem of fusing multi-focus images in dynamic scenes. The proposed approach consists of three main steps: first, the focus information of each source image obtained by morphological filtering is used to get the rough segmentation result which is one of the inputs of image matting. Then, image matting technique is applied to obtain the accurate focused region of each source image.

[9] Sparse representation(SR) model named convolutional sparsity based morphological component analysis is introduced for pixel-level medical image fusion. The CS-MCA model can achieve multicomponent and global SRs of source images, by integrating MCA and convolutional sparse representation(CSR) into a unified optimization framework.

[10] Our main contribution is a novel technique to integrate pretrained neural networks in the image fusion task. Our method shows better performance than current state-of-the-art techniques and runs in real time without any specialized hardware. The low computational requirements make it very beneficial for continuous monitoring systems, and for deployment on limited hardware architectures.

V.PROPOSED METHOD

In terms of picture evidence, the Convolutional Neural Network (CNN) image fusion operations are initiated and related. The results of various fusion approaches are assessed using different assessment measures. A fused result obtained by combining CT scan and MRI can merged result will be stored on the microcontroller. The capability of CNN features produces value-added evidence in the output fused picture, which is followed by fused outcomes produced from CNN-based image fusion procedures. The Convolutional Neural Network (CNN) stranded image fusion approaches are supplementary accurate and concert leaning in real time solicitations because to the energy forte of reult originated conceptions of stationary pictures. The Discrete Wavelet Transform is a transform that is not time invariant. To regain translation invariance, average some slightly different CNN, known as un-decimated CNN, to define the Convolutional Neural Network (CNN). It accomplishes this by bypassing the decimated algorithm's down-sampling stage and instead up-sampling the filters by inserting zeros between the filter coefficients. The term "à trous" refers to algorithms in which the filter is upsampled. The filters are applied to the rows first, then to the columns, as with the decimated method. In this situation, however, despite the fact that the four images created (one approximation and three detail photos) are half the resolution of the original, they are the same size.

The undecimated algorithm's approximation pictures are therefore represented as levels in a parallelepiped, with the spatial resolution getting finer at each higher level while the size remains constant. Convolutional Neural Network (CNN) is except the sole process is suppressed, making the CNN translation-invariant. The 2-D CNN decomposition scheme is shown. The concept of no decimation underpins the 2D Convolutional Neural Network (CNN). It employs the Convolutional Neural Network (CNN) and omits both down- and up-sampling in the forward and inverse transforms. It applies the transform at each point in the picture, stores the detail coefficients, and uses the low frequency information at each level.

VI. SOFTWARE DETAILS

A. Matlab

MATLAB (matrix laboratory) is a numerical computing environment and fourth-generation programming language. Developed by Math Works, MATLAB allows matrix manipulations, plotting of functions and data, implementation of algorithms, creation of user interfaces, and interfacing with programs written in other languages, including C, C++, Java, and Fortran.

Although MATLAB is intended primarily for numerical computing, an optional toolbox uses the MuPAD symbolic engine, allowing access to symbolic computing capabilities. An additional package, Simulink, adds graphical multi-domain simulation and Model-Based Design for dynamic and embedded systems.

In 2004, MATLAB had around one million users across industry and academia. MATLAB users come from various backgrounds of engineering, science, and economics. MATLAB is widely used in academic and research institutions as well as industrial enterprises.

MATLAB was first adopted by researchers and practitioners in control engineering, Little's specialty, but quickly spread to many other domains. It is now also used in education, in particular the teaching of linear algebra and numerical analysis, and is popular amongst scientists involved in image processing. The MATLAB application is built around the MATLAB language. The simplest way to execute MATLAB code is to type it in the Command Window, which is one of the elements of the MATLAB Desktop. When code is entered in the Command Window, MATLAB can be used as an interactive mathematical shell. Sequences of commands can be saved in a text file, typically using the MATLAB Editor, as a script or encapsulated into a function, extending the commands available.

MATLAB provides a number of features for documenting and sharing your work. You can integrate your MATLAB code with other languages and applications, and distribute your MATLAB algorithms and applications.

VII. BLOCK DIAGRAM

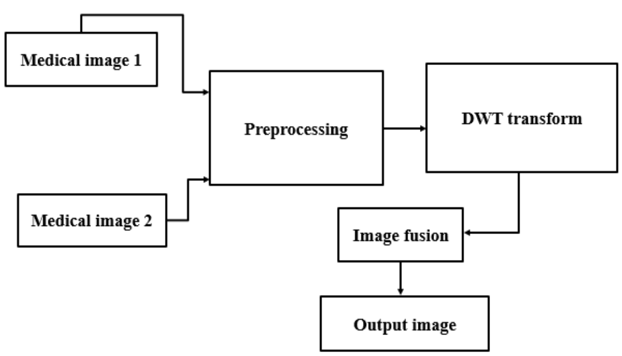


Figure: medical image fusion

VIII.MODULES

- Data Collection and Preprocessing
- Training Data Preparation
- Model Architecture
- Model Training
- Testing
- Performance Evaluation

IX. MODULES EXPLANATION

A. Data Collection and Preprocessing:

Collect medical images from different modalities or different views of the same modality. Preprocess the images by resizing them to a fixed size and normalizing the pixel values.

B. Training Data Preparation:

Split the preprocessed images into training and validation sets. For each pair of images to be fused, generate multiple fusion images using different fusion methods. Assign a weight to each fusion method to reflect its effectiveness in preserving important information. Use the training set to train a deep learning model to learn how to select the best fusion method and corresponding weight for each pair of images.

C. Model Architecture:

Design a deep learning model architecture that takes two medical images as input and outputs the best fusion method and corresponding weight. The model should be able to handle images of different modalities and sizes.

D.Model Training:

Train the deep learning model using the prepared training set. Use a suitable loss function that measures the difference between the ground truth fusion image and the predicted fusion image. Use a suitable optimizer to update the model parameters during training.

Model Validation: Evaluate the trained model on the validation set to measure its performance in selecting the best fusion method and corresponding weight.

E. Testing:

Apply the trained model to new pairs of medical images to generate fused images with enhanced information content.

F. Performance Evaluation:

Evaluate the performance of the proposed system by comparing the fused images generated by the proposed system with the ground truth fused images, using suitable metrics such as peak signal-to-noise ratio (PSNR), structural similarity index (SSIM), and mean square error (MSE).

X.CONCLUSION

Medical image fusion is a technique used to integrate multiple medical images into a single composite image for better diagnosis and treatment planning. Deep learning-based algorithms have shown promising results in medical image fusion due to their ability to extract relevant features from the input images and generate high-quality fused images. In conclusion, the use of deep learning-based algorithms for medical image fusion has the potential to significantly improve medical diagnosis and treatment. The fusion of multiple images into a single image using deep learning models can enhance the quality and detail of the final image, enabling doctors and medical professionals to make more accurate diagnoses and treatment decisions. Furthermore, the use of deep learning-based algorithms for medical image fusion is a rapidly evolving field, and there is still much research to be done. With further advancements in deep learning models and techniques, medical image fusion using deep learning algorithms is likely to become even more effective and widespread in the future.

The deep convolutional network is employed to obtain the fused image which consists of all the objects are correctly focused in a single image in terms of both foreground and background. The visual quality of the method was proved by comparing performances using an object detector on a public benchmark dataset. The quantitative assessment results show that the CNN-based fusion method was more effective than manually designed methods in terms of noise, distortion, and the intensity difference. We believe that our method is very effective and robust fusion of pre-registered multi-spectral images. As future works, we intend to develop new deep neural networks for image fusion and to improve the efficiency of fusion procedure by implementing the algorithm with parallel computing units. A bilateral filter is employed to smoothen the edge regions of the obtained decision map which produces a high quality fused image. The fused image that have focus in all the parts in a single image can be applied to different fields such as medical diagnosis to find tumours and to prospect a detailed representation of the soft tissue parts. To enhance performance also to process very large image dataset advanced computing techniques (densenet) and also fuzzy logic techniques may provides good results

A. ADVANTAGES

Enhanced Image Quality
Increased Accuracy
Reduced Radiation Exposure
Time-Saving
Cost-Effective

B. DISADVANTAGES

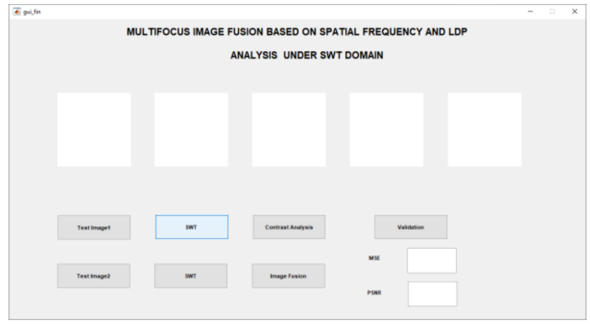
- Data Quality
- Complexity.

C. APPLICATION

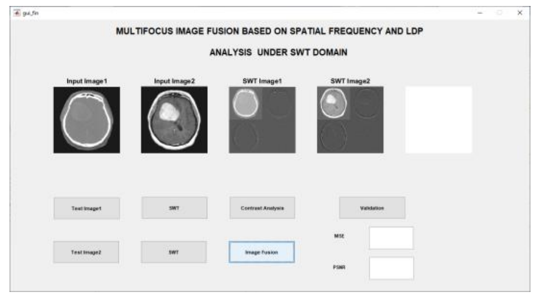
- Neuroimaging
- Cardiology
- Oncology
- Radiology
- Surgery

XI. RESULTS

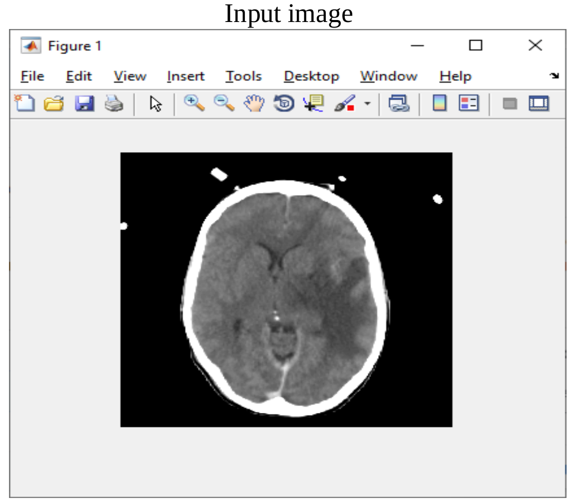
SIMULATION RESULTS



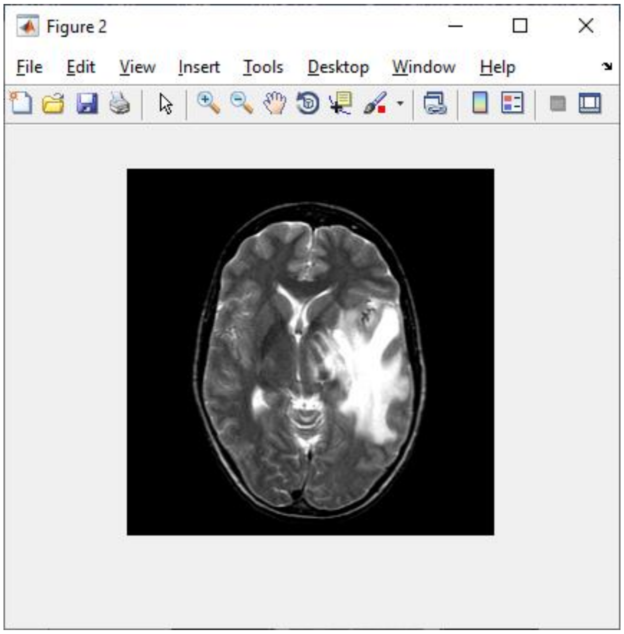
Fusion output



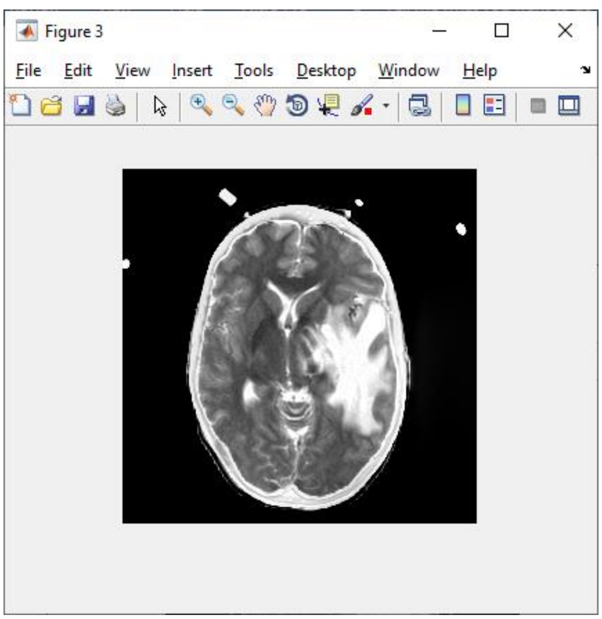
Input image



Input image 2



Fusion image



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